Essays on Stock Performance, Regulation, and Financial Stability of Banks and Insurers

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Felix Irresberger
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Chapter 1

Introduction

1.1 Motivation

In October 2008, the U.S. congress authorized a total of $ 700 billion for the stabilization of heavily distressed financial institutions via the Emergency Economic Stabilization Act. Not only banks but also insurance companies unexpectedly had to be bailed out by the government to rebuild confidence in the stability of the financial system. Since then, financial economists and regulators are having ongoing discussions about the origins and consequences of the near collapse of the financial sector and about the actions required to preserve financial stability in the future.

This dissertation empirically discusses and investigates the impact of regulation, monitoring, and supervision of banks and insurers on financial stability. Further, it investigates how investor sentiment, as a measure of individual or market participants' perceptions of financial institutions and firm fundamentals, affects the shareholder values of insurers and movements in bank deposits.

The financial system faces numerous risks that could lead to its, at least partial, collapse. As the recent financial crisis has revealed, the default of single institutions can create distress across other business partners and thereby, trigger a cascade of events that destabilize the (financial) system. For example, banks that are connected through the interbank market are more likely to be exposed to the default or to toxic assets of a counterparty and thus, face higher systemic risk. On the other hand, the default of financial institutions with a high market share could pose and spread devastating risks across other entities. Clearly, this situation is more likely for larger banks that excessively engage in financial markets. Not only word of mouth but also regulators denote such institutions as “too-big-to-fail”, “too-interconnected-to-fail”, or formally “Systemically Important Financial Institutions” (SIFIs) as their default would cause severe damages to the financial system (see Financial Stability Board, 2011). Consequently, these institutions have a higher probability to be bailed out by governments. Before the financial crisis, these financial institutions were thought to be banks only, but since the government bailout of the insurance company American International Group (AIG), it is clear that systemic risk is not limited to the banking sector. However, the exposure and contribution of insurers to systemic financial distress is thought to be tied to those insurers who engage more in non-core activities such as extensive use of derivatives. In reaction to the global financial crisis, the Bank for International Settlements (BIS), the Financial Stability Board (FSB), and the International Association of Insurance Supervisors (IAIS) published a list of systemically important banks and insurers along with a methodology to identify these relevant banks and insurers (see Financial Stability Board, 2011, IAIS, 2013, BIS, 2011). In this framework, the key indicators of systemic relevance include the size, leverage, complexity, and interconnectedness of a financial firm. Members of this list of institutions are subject to stronger monitoring and have tighter capital restrictions to mitigate the likelihood of failure. While this might be useful to limit the default risk of an individual institution, it could also limit business opportunities as well as profits and create moral hazard since financial managers could be driven to higher risk-taking strategies, e.g., using more investment banking instead of the core banking business to cope with the restrictions.

Another facet that is sometimes neglected in the dicussion of financial stability is the behavioral aspect to analyze investors’ decisions. For example, some insurers experienced huge losses in shareholder value, even though most of the insurers were not distressed and thus, contributors to the banking crisis. This valuation might have originated in the attitudes of investors measuring insurer stocks with the same yardstick as bank stocks. Market-wide or idiosyncratic sentiment not only affects asset prices but also influences decision-making in the real economy. It has been shown that negative sentiment, past experiences, or possible “too-big-to-fail” perceptions can prevent investors from using specific vehicles or institutions for their investments (see, e.g., Osili and Paulson, 2014, Oliveira et al., 2014). Also, a “bank run” as a classical example of the impact of investor behavior on financial stability has long been a motivator for financial regulation. Thus, the importance of analyzing the influence of investor behavior on financial stability is not negligible.

This dissertation contributes to the discussion on financial stability and regulation in the form of five independent articles that empirically explore different facets of systemic risk of banks and insurers.

Chapter two and three deal with the topic of systemic risk in the insurance sector and explore the methodology of regulators to identify systemically important banks and insurers. Before the bailout of AIG, neither economists nor regulators expected insurance companies to suffer from systemic risk effects or to be systemically relevant enough to even contribute to it. Insurers are not as vulnerable to runs or liquidity shortages as banks and also smaller in size and less interconnected. The paper in chapter two is the first to empirically investigate the time evolution of the proposed systemic risk measures for an international panel of insurers. Despite ongoing debates on the key elements that induce systemic risk, there is still no consensus on the proper measurement of such risks. The three most prominent systemic risk measures suggested in the literature are the *Marginal Expected Shortfall* (MES) proposed by Acharya et al. (2010), ΔCoVaR by Adrian and Brunnermeier (2014), and *SRISK* by Brownlees and Engle (2012), which are used in this study. Systemic risk in the insurance sector is expected to be driven by the insurer’s size, its interconnectedness with the rest of the financial sector, and the engagement in non-core activities that do not underwrite risk. Key variables in this analysis include the size and leverage of an insurer but also a measure of interconnectedness introduced in Billio et al. (2012) that is constructed using a principal component analysis of the covariance of financial institutions' stock returns. The regression analyses reveal that the interconnectedness of a large insurer drives its exposure to systemic risk and that the systemic risk contribution is higher for levered insurers. Although the proposed measures are considered by regulators, they have been heavily critized to fall short in measuring systemic risk accurately, since they are mostly based on the equity returns of the firms (see, e.g., Benoit et al., 2013).

The follow-up study presented in chapter three explores the methodology of regulators to identify systemically important banks and insurers using cross-sectional regressions for the crisis period. Using the two common measures MES and ΔCoVaR as dependent variables yields counterintuitive results when employing the key indicators of systemic risk as explanatory variables. For example, size does not play a major role for both exposure and contribution to systemic risk of banks and insurers and higher leverage and interconnectedness even decrease MES and ΔCoVaR. Furthermore, the study explains the nomination of banks and insurers to be "systemically relevant" via probit regressions on proposed drivers of systemic relevance. Interestingly, the size of a bank or insurer seems to be the key indicator when identifying SIFIs.

The fourth chapter of this dissertation is dedicated to the relation of stock performance and differences in regulation and supervision of banks around the world. While economists and regulators are calling for increased supervision and higher capital requirements, banks argue that these tougher restrictions dramatically decrease profits and, eventually, shareholder value and capital buffers. As the first comprehensive study on the interplay of annual stock performance and bank regulation and bank supervision standards in different countries, a large international panel is analyzed over the time period from 1999 to 2012, which makes use of a database on a country's regulatory and supervisory system taken from Barth et al. (2013a). The main finding is that higher capital requirements (Tier-one capital) are indeed negatively related to a bank's stock performance. This relation, however, is reversed in times of crisis, during which stocks of well-capitalized banks perform significantly better.

In great parts, regulation and supervision of financial institutions are intended to limit excessive risk-taking of financial managers and shareholders, which displays the importance of behavioral facets of financial stability. Therefore, the final two chapters of this dissertation deal with the measurement of risks associated with investor behavior. It has long been recognized that sentiment plays an important role in financial markets, e.g., asset prices that are affected by noise traders (see, e.g., De Long et al., 1990), and the decision making of investors. Very often, sentiment measures have been derived by analyzing media outlets and by using linguistic techniques (see, e.g., Tetlock, 2007, Baker and Wurgler, 2006, Antweiler and Frank, 2004). In the information age, however, researchers are given new tools to measure active investor attention to specific topics instead of relying on passive sentiment measures. A new branch of literature is benefiting from internet search volume data, which has been used to detect and predict economic trends, such as unemployment claims or influenza epidemics (see, e.g., Choi and Varian, 2009, Ginsberg et al., 2009). The final two chapters build upon this growing literature and analyze the impact of investor sentiment on insurer stocks and movements in U.S. bank deposits.

Chapter five follows Da et al. (2011) and employs internet search volume data from *Google Inc.* for stock ticker symbols to propose an index for "crisis sentiment". The *Crisis Sentiment Index* is constructed using correlations of search volumes of crisis related search terms and the search volume for ticker symbols to proxy the association of a single insurer stock with financial crises. Using these indices, the hypothesis that insurer stocks suffered to a large extent from bad sentiment and association with adverse effects from the banking crisis is then tested. The results of panel regressions of the insurers' stock performance on market-level and individual crisis sentiment show that stocks of large insurers were indeed negatively affected by idiosyncratic crisis sentiment and thus, were assessed irrationally rather than by actual exposure to the crisis. Also, market-level crisis sentiment is found to be highly significant factor explaining negative insurers' stock performance for the period from 2004 to 2012.

The final chapter of this dissertation empirically investigates the impact of depositor attention and depositor sentiment on movements in bank deposits. Building upon the ideas of the theoretical framework for bank run models from Diamond and Dybvig (1983), the internet search volume on the “Federal Deposit Insurance Corporation” (FDIC) is used as a proxy for household-level attention to deposit insurance to test whether more knowledge of deposit insurance mitigates the likelihood of a bank run. In theory, a deposit insurance scheme is the optimal way to hinder rational and informed depositors from withdrawing their bank deposits out of fear that a bank might fail. Analyzing a panel of FDIC-insured banks in the United States reveals that higher levels of attention to deposit insurance are positively related to quarterly changes in deposits and thus, supports the theoretical results. Additionally, a measure for household sentiment (see Da et al., 2015) is included in the panel regressions and is found to have a strong negative influence on movements in demand and time deposits for smaller and medium-sized banks. For larger banks, however, a higher level of bad sentiment induces positive flows in bank deposits, which is in line with many analyses that propose “too-big-to-fail”-effects for larger banks. Also, the results from logistic panel regressions in chapter six suggest that more information retrieval on deposit insurance mitigates the probability of extreme deposit withdrawals. Thus, the final chapter stresses the importance of an adequate assessment of behavioral risks for preserving financial stability.

This dissertation consists of five chapters that can be read independent of each other and are based on distinct research papers. The following section gives an overview of the papers and provides publication details.

1.2 Publication details

Paper I (Chapter 2):

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:

Journal of Banking and Finance 55, 232-245, 2015.

Paper II (Chapter 3):

Size is everything: How should we measure systemic relevance of banks and insurers?

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. Using a cross-sectional quantile regression approach, we find that Marginal Expected Shortfall and ΔCoVaR as two common measures of systemic risk appear to produce inconclusive results concerning the systemic relevance of banks and insurers during the crisis. Furthermore, we explore 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 global systemically important.

Publication details:

Working paper.

Paper III (Chapter 4):

Bank stock performance and bank regulation around the globe

Authors:

Matthias Pelster, Felix Irresberger, Gregor Weiß

Abstract:

We analyze the effect of bank capital, regulation, and supervision on the annual stock performance of global banks during the period of 1999-2012. We study a large comprehensive panel of international banks and find that higher Tier 1 capital decreases a bank's stock performance over the whole sample period. However, during turbulent times stocks of more highly capitalized banks perform significantly better. Additionally, we find strong evidence that banks that are more likely to receive government bailout during financial distress realize smaller stock performance. In contrast, we find no convincing evidence that banks that generate higher non-interest income have a higher performance.

Publication details:

Working paper.

Paper IV (Chapter 5):

Crisis Sentiment and Insurer Performance

Authors:

Felix Irresberger, Fee König, Gregor Weiß

Abstract:

We propose two simple metrics to proxy for crisis sentiment, i.e., the bearish investor sentiment affecting stocks which was brought on by the recent financial crisis. We first estimate a measure of market-level crisis sentiment by using Google Trends search volume data on crisis-related queries. Second, we estimate the correlation between search request volumes on Google for insurer ticker symbols and crisis-related search terms as a proxy for idiosyncratic crisis sentiment. We then test whether the bad stock performance of insurers during the crisis was due to such negative investor sentiment accounting for the insurer's actual exposure to systemic risk. We find that market-level crisis sentiment was a highly significant predictor of stock performance between 2004 and 2012. During the financial crisis, market-level crisis sentiment affected the performance of all insurers while idiosyncratic crisis sentiment (negatively) influenced the stock performance of large insurers.

Publication details:

Revise and resubmit at the *Journal of Risk and Insurance*.

Paper V (Chapter 6):

Depositor Sentiment

Author:

Felix Irresberger

Abstract:

We use internet search volume data to measure household sentiment and attention for deposit insurance in the U.S. to explain depositor behavior. We find market-level sentiment to cause depositors to withdraw both demand and time deposits from small and medium-sized banks and to run to big banks. By contrast, the attention of households to deposit insurance as revealed by the volume of queries related to the Federal Deposit Insurance Corporation is positively related to changes in deposits. In addition, a higher level of information procurement by households on deposit insurance mitigates the probability of a bank run.

Publication details:

Working paper.

Chapter 2

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

2.1 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)[1] 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,[2] 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

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

[2] 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).[3] 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 (2014b) 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.[4] 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 (2014a) support the too-big-to-fail conjecture for insurers by showing that insurer mergers tend to increase the systemic risk of the acquiring insurers.

[3] 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).

[4] 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 (2014a,b) and employ the Marginal Expected Shortfall (MES) of Acharya et al. (2010) and ΔCoVaR methodology of Adrian and Brunnermeier (2014), 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.[5]

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 2.2 introduces the data and the methodology used in our empirical study. Section 2.3 presents the results of our investigation into the determinants of systemic risk in the insurance industry.

[5]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 2.4.

2.2 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.

2.2.1 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.[6] 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.[7] 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

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

[7] 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 A.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 A.2.

2.2.2 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).[8] 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 (2014), 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 (2014) criti-

[8] 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. (2014), Hovakimian et al. (2012) and White et al. (2012).

cize the MES measure for not being able to adequately address the procyclicality that arises from contemporaneous risk measurement.[9] 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 (2012). 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.

2.2.3 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.

[9] 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.[10] 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.[11]

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

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

[11] 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.[12] 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.[13] 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

[12] 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.

[13] 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.[14] 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

[14]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).

2.2.4 Descriptive statistics

Table 2.1 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 2.1 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 2.1 that the mean MES is relatively constant over time, showing a significant peak during the financial crisis. The exposure to systemic risk

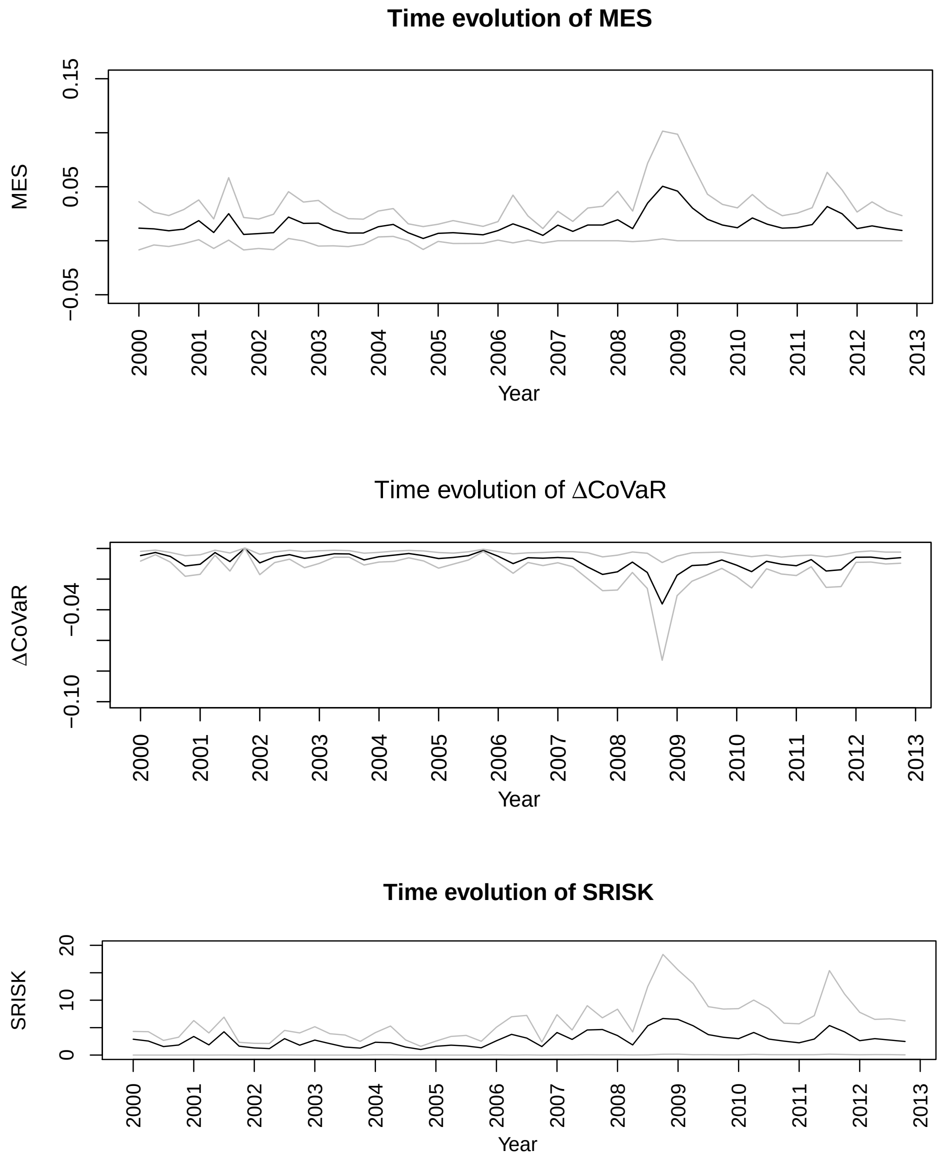
Table 2.1: Descriptive statistics.

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 A.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	0.020	3.44	35.53
ΔCoVaR	4,893	-0.12	-0.04	-0.02	-0.01	0.00	0.00	0.00	0.00	-0.010	0.010	-3.90	29.98
SRISK (in billions)	8,997	0.000	0.000	0.000	0.065	2.457	12.298	42.091	166.22	2.8	8.5	7.56	81.36
Interconnectedness	11,361	0.000	0.000	0.000	0.000	0.158	2.370	123.990	399,010.800	386.980	8,929.084	29.260	982.910
Total assets (in billions)	10,998	0.02	0.59	1.18	29.03	61.37	331.62	865.13	2076.19	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	35.510	21.250	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 2.1: Time evolution of the systemic risk measures in 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 A.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.[15]

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 2.2. 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 2.2, 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 2.2 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).[16]

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

[15]Further summary statistics for our explanatory variables given in Table 2.1 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).

[16]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 2.2: 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 A.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 A.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	6462	0.000	0.000	679.690	0.100	399010.800	11831.450	4899	0.000	0.000	0.879	0.095	350.900	9.680	4.6116***
Total assets (in billions)	6,180	0.020	2.748	43.00	24.13	1,483.00	134.65	4,818	0.114	7.22	94.66	93.280	2,076.00	194.91	-15.706***
Leverage	5,974	1.01	2.89	16.01	8.606	7,100.00	200.04	4,588	1.25	6.25	56.52	16.22	44,180.00	1,308.26	-2.079**
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	0.001	0.000	0.295	0.014	405	0.000	0.000	0.000	0.000	0.000	0.000	1.296
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	2076.00	248.28	-5.120***
Leverage	443	1.32	3.02	11.67	9.88	210.60	23.42	322	1.50	7.18	297.00	22.93	44180.00	3475.01	-1.473

given in Table 2.2 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 2.2 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 2.3, we repeat our analysis of the summary statistics of our systemic risk measures and selected explanatory variables for the nine G-SIIs.

Table 2.3: Descriptive statistics for main variables of interest: Global Systemically Important Insurers.

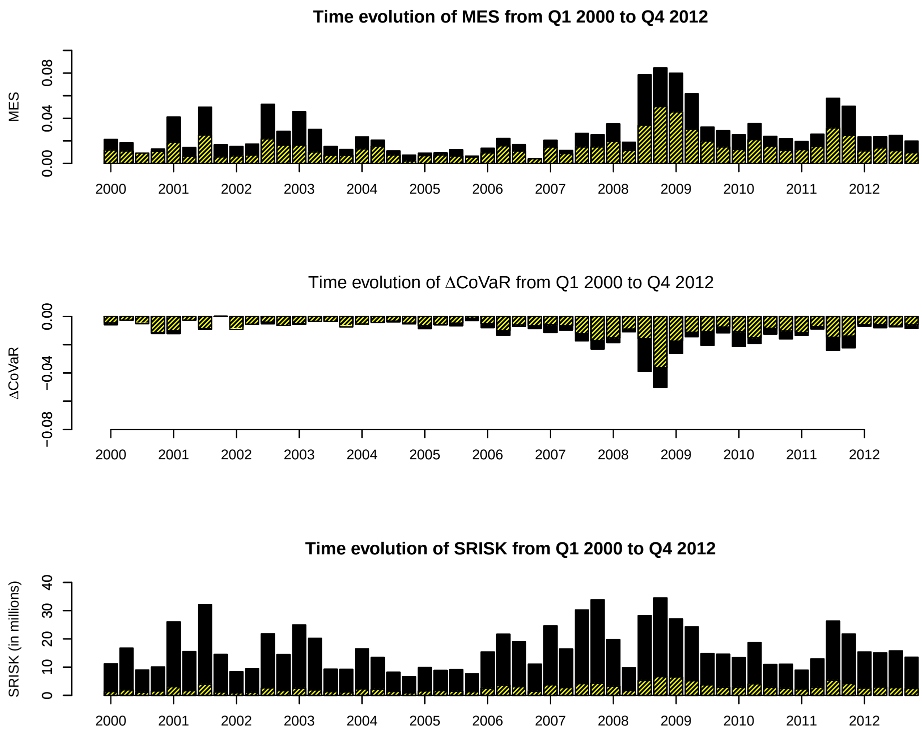
This table shows the respective descriptive statistics for the nine global systemically important insurers (G-SIIs) as defined by the international association of insurance supervisors (IAIS) in the period from Q1 2000 to Q4 2012 (Panel A) and from Q3 2008 to Q2 2009 (Panel B). The nine G-SIIs are Allianz, 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 A.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 2.2.

Figure 2.2: Time evolution of systemic risk measures for (systemically relevant) insurers in 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 A.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.

2.3 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.

2.3.1 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 2.2 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 2.2.3 and Table A.2. The econometric strategy we use is illustrated below.

$$\begin{aligned} SystemicRisk_{i,t} = \beta_0 &+ \beta_1 \cdot Interconnectedness_{i,t-1} + \beta_2 \cdot Leverage_{i,t-2} \\ &+ \beta_3 \cdot Total\ assets_{i,t-2} + \Omega \cdot Insurer\ controls_{i,t-2} \\ &+ \Theta \cdot Country\ controls_{i,t-1} + \varepsilon_{i,t}, \end{aligned} \tag{2.1}$$

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 2.4.

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 economically significant positive sign. In our regressions, a one standard deviation

Table 2.4: 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:

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

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 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 A.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	0.0000	0.0000***	0.0000	0.0000**	-0.0021	0.0000**
	(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	0.0000	0.0000*	0.0000	0.0000	0.0001	-0.0015
	(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	-0.0002**	0.0012**	0.0000	0.0000	-0.0043***	0.0149
	(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	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.226)	(0.875)	(0.441)	(0.947)	(0.521)	(0.461)
ROA	(0.0002)	0.0000	0.0002	0.0000	0.0158	0.1567
	(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	0.0000	0.0000	0.0000***	0.0000***	0.0019	0.0268***
	(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	1333	2658	3569	2508	3426
Adj. R^2	0.5865	0.5752	0.4422	0.4225	0.2040	0.1412

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 (1308.26×0.0002). For comparison, a one standard deviation increase in the leverage of a non-life insurer is associated with an 8% increase in MES (200.04×0.0004). 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 (194.91×1.0075). 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 (134.65×5.5704). 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.

2.3.2 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 2.5.

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 2.5 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 effects in our robustness checks, it is nevertheless instructive to analyze these country

Table 2.5: 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:

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

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 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 A.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	0.0011	-0.0003**	0.0000	0.0005	0.0004	-0.2056
	(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	-0.0001**	-0.0001*	0.0000**	0.0000	0.0000	0.0019
	(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	0.0005	-0.0010	0.0000	-0.0002	0.0100	-0.0592
	(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	0.0000***	0.0000	0.0000	0.0000	0.0000***	0.0000
	(0.003)	(0.767)	(0.872)	(0.774)	(0.004)	(0.306)
ROA	-0.0006*	-0.0007	0.0005*	0.0020*	0.1670	0.9932**
	(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	0.0000	0.0000**	0.0000	0.0001*	-0.0083	0.0686***
	(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

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 2.6.

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 2.7, 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 the same, we only find a statistically significant impact on systemic risk for non-life

Table 2.6: 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:

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

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 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 A.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	0.0000	0.0000***	-0.0001	0.0000*	0.0036	0.0000*	0.0000***	0.0000**	0.0000*	0.0000	0.0000*	-0.0001
	(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	1917	678	1807	812	521	1917	1652	1807	1619
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 2.7: 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 A.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	0.0006	0.0000	0.0000	0.0000	0.0298	-0.0023
	(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	-0.0001	0.0000	0.0000	0.0000	-0.0096*	-0.0011*
	(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	-0.0108***	-0.0017	0.0005	-0.0002	-0.7026	0.0131
	(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	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000**
	(0.224)	(0.429)	(0.182)	(0.970)	(0.597)	(0.021)
ROA	-0.0009	-0.0034**	0.0003	0.0005	0.0776	0.0673
	(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	0.0000	0.0000*	0.0001**	0.0001**	0.0043	0.0346**
	(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

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 ($23.42 \times -0.0003 = -0.7026$). 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 (23.42×0.0006).

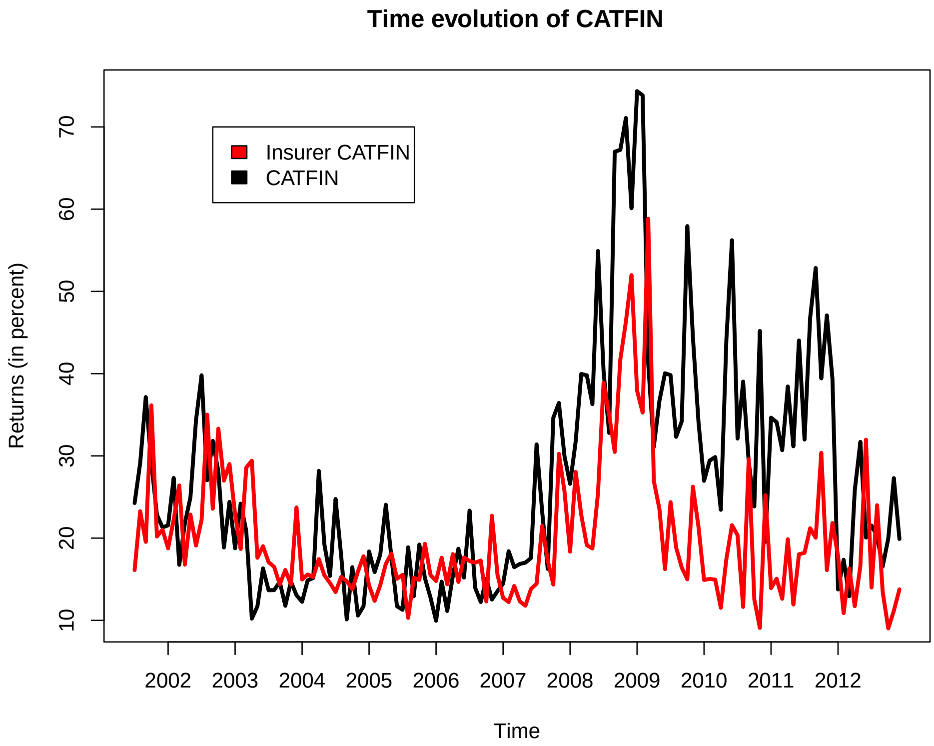
2.3.3 Insurers and the systemic risk in the financial sector

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 2.3 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. Despite the small difference in the magnitude of the peaks of both CATFIN time series,

Figure 2.3: 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.



the plot in Figure 2.3 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 2.3 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.

2.3.4 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.[17] 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 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.

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

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.

2.4 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 3

Size Is Everything: How Should We Measure Systemic Relevance of Banks and Insurers?

"The omission of Standard Chartered from the list of G-Sifis (global systemically important financial institutions) shows size is not everything."

The Observer, 11/06/2011

3.1 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 also 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 18th, 2013, the Financial Stability Board (FSB) together 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, insurers are deemed 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. Similarly, in November 2011, the FSB had previously 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).[18] Furthermore, even the largest international insurers are significantly smaller in size, are 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 create systemic risks.

Based on the experiences from the financial crisis, the IAIS (2013) published in 2012 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.[19]

However, the empirical evidence on the questions whether insurers can become systemically relevant and whether these factors really drive systemic risk is lim-

[18] 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.

[19] 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.

ited. Shortly after the financial crisis, Acharya et al. (2009), Harrington (2009), and Cummins and Weiss (2014) discussed the role of insurers during the financial crisis.[20] 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 (2014b) study the effect of different factors from the IAIS methodology on the systemic risk of U.S. 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, 2014). 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 to counterintuitive. While 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 3.2. The data and variables used in our empirical study are discussed in Section 3.3. The outline and the results of our empirical study are given in Section 3.4. Section 3.5 concludes.

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

3.2 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 to the increasing interconnectedness of insurers to other financial institutions and their activities outside of the traditional insurance business.

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 and 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 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, the effect of additional factor like size, leverage, and profitability on systemic risk in insurance is studied by Weiß and Mühlnickel (2014b).[21] Most impor-

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

tantly, 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. 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 insurance, because larger insurance companies have a wider range of different risks insured and thus are less prone to suffer from cumulative losses (see Hagendorff et al., 2011). 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 payment of interest to investors and to secure firm liquidity. In addition, insurers that engage too heavily in non-core activities as well as derivatives trading could also single-handedly destabilize the financial sector.

Probably the most fundamental question, however, remains whether systemic risk in insurance companies (even if it exists) is large enough to destabilize the whole financial sector. In this respect, Weiß et al. (2014) find systemic risk in the international insurance sector to be small in comparison to previous findings in the literature for banks.

3.3 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.

3.3.1 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 unusually 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*. [22] 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* and we therefore exclude firms where 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 where the most banks (25 out of 148) and insurers (27 out of 98) come from

[22] 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.

the United States. After the U.S., the four most prominent countries in our samples are China (10/2), Japan (16/6), the United Kingdom (11/8), and Germany (8/11). The geographical spread of our sample firms is shown in Table 3.1. [23]

Next, we define and discuss the main dependent and independent variables for our analysis in the subsequent sections. Appendix B.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.

3.3.2 Systemic risk measures

In our study, we employ 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 et al., 2014b,a, Weiß and Mühlnickel, 2014b), we use as our measures of systemic risk the unconditional ΔCoVaR as defined by Adrian and Brunnermeier (2014) 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[24] 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 could 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

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

[24]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.

Table 3.1: 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

its 5% worst outcomes. [25] A positive MES thus indicates a positive exposure to systemic risk rather than a stabilizing effect.

3.3.3 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 on more risks than socially optimal. Consequently, large banks or insurers should 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). 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 book value of equity plus market value of equity, divided by 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.[26] In contrast, managers could be disciplined by higher leverage since they could feel

[25] Additionally, we employ the Dynamic Marginal Expected Shortfall calculated following the procedure laid out by Brownlees and Engle (2012) for robustness checks later on.

[26] 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 as 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 a univariate measure *PCAS* of an institution's interconnectedness with the system of all financial institutions in our sample (i.e., banks and insurers) which is based on a principal component analysis of the correlations between all institutions' stocks. The measure then compute 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).

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 B.1.

3.3.4 Descriptive statistics

Table 3.2 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.[27]

The summary statistics for the banks in our sample are given in Panel A and for the insurers in Panel B of Table 3.2. First, we notice that the means of the variables differ substantially for the banking and 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 MES estimates for 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 mean total assets of $ 158 billion while banks are significantly larger with mean total assets of $ 350 billion. Furthermore, the leverage of banks on average is 13.430 whereas the average insurer has a leverage of 9.285, underlining the usually 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 could hypothesize that size and leverage appear to be driving systemic risk while interconnectedness does not play such an important role for explaining differences in MES and ΔCoVaR.

3.4 The determinants of systemic relevance

In this section, we investigate the question which (possibly differential) factors determine the systemic relevance of banks and insurers. We first present the results of our

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

Table 3.2: 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 B.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

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 influencing systemic relevance as stated by regulators.

3.4.1 Cross-sectional regressions

Instead of only using the standard OLS approach for cross-sectional regressions, we perform our 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[28] 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 leaves us with reasonable benefits compared to OLS regressions. OLS models the relationship between the conditional mean of the dependent variable and the independent variables. Generally, we could have included all active banks and insurance companies from *Datastream* with available data in our study. However, including every firm will bias the results of our regressions, since we would simply add a high number of institutions that are not systemically relevant and thus, skew the values of our systemic risk measures (or the dummy variables for our probit regressions) 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 investigate the 95%-percentile and for ΔCoVaR we are interested in the 5%-percentile, with both indicating extreme systemic risk. The results of our cross-sectional analysis for banks are shown in Table 3.4 and 3.3.

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

Table 3.3: Cross-sectional regression of systemic risk 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 B.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	-	-	-	-

The first three regressions in all settings are concerned with the individual effects of our three main dependent variables, size, leverage and interconnectedness with the financial system, and 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 signifiance 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 lose only some of the significance of interconnectedness and find no statistically significant influence of any other variable on ΔCoVaR.

Table 3.4: Cross-sectional regression of systemic risk 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 B.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	-	-	-	-

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 an 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 of banks 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 3.5 and 3.6, we show the results from the OLS and quantile regressions of ΔCoVaR and MES on the proposed factors of systemic relevance for insurers.

Table 3.5: Cross-sectional regression of systemic risk 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 B.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	-	-	-	-

From Table 3.5, we can see that an insurer's size decreases ΔCoVaR (significant at the 10% level) and thus, indicates a higher contribution to systemic risk by larger

Table 3.6: Cross-sectional regression of systemic risk 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 B.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	-	-	-	-

insurers. This signifiance, however, vanishes when including other control variables and is also never significant when we regress the conditional quantile of systemic risk. A very similar pattern can be found when looking at the results concerning insurer size in Table 3.6, where total assets seems 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 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, but with statistically less significant results.

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 enters 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.

3.4.2 Probit regressions

In this section, we try to explaing the probability of being declared a global systemically important bank or insurer by regulators. To this end, we employ a probit regression approach. 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 3.7.

The Table 3.7 shows the results of several probit regressions on a dummy variables that takes 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 the driving factor for the nomination to be systemically important. 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.

Table 3.7: 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 B.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

The probit regression results for the sample of insurers are shown in Table 3.8.

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 on 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

Table 3.8: 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 B.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

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 cannot explain the point of view of regulators. For them, the systemic importance of a financial institution (regardless whether it is a bank or insurer) is only determined by the institutions size.

3.4.3 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. Therefore, we reestimate the measures using the MSCI World Banks Index and MSCI World Insurance Index, but find no significant changes in 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 appear to be robust to these changes. Also, to control for an insurer's line of business, we include in our cross-sectional analyses a dummy variable that is one if the company is a life insurer (SIC code 6311), and zero otherwise. Including this variable does neither change 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.

3.5 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 syetemically 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 none 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. Although we find some correlation between the probability of being a G-SIFI and G-SII, and the institution's MES (banks) and ΔCoVaR (insurers), these proxies of systemic risk cannot explain the classification of 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. Interestingly, and despite the experiences made during the AIG episode, insurance regulators share the same point of view. Global systemically important insurers are clearly identifieable by a simple look at the total assets in their balance sheet.

Chapter 4

Bank Stock Performance and Bank Regulation Around the Globe

"Banks are somehow making gigatons of money despite onerous new regulations and capital requirements. Why, it's almost like they're not telling the truth when they warn, repeatedly, that these new rules will destroy their profits and the economy."

The Huffington Post, 07/16/2013

4.1 Introduction

Following the collapse of Lehman Brothers, excessive risk-taking caused by a "search for yield" (see Rajan, 2005) and the tendency of deposit-taking banks to earn more non-interest income through activities like, e.g., investment banking have been criticized for contributing to the severity of the recent financial crisis (see, e.g., Laeven and Levine, 2009, Brunnermeier et al., 2012).[29] Responding to these claims, many commentators have called for stricter bank regulation, bank supervision, and, in particular, for higher capital requirements (see, e.g., Kashyap et al., 2008, Acharya et al., 2011, Calomiris and Herring, 2011, Hart and Zingales, 2011).[30] Perhaps most prominently,

[29]The adverse side-effects of bank risk-taking on financial stability have also been addressed earlier by, e.g., Bernanke (1983), Keeley (1990) and Calomiris and Mason (1997).

[30]The diverse causes of and lessons from the recent financial crisis are also discussed by Brunnermeier (2009) and Gorton (2010).

Ben Bernake argued in 2010 that “stronger regulation and supervision [...] would have been a more effective and surgical approach to constraining the housing bubble than a general increase in interest rates”.[31] On the other side, banks have repeatedly and insistently contended that tougher capital requirements will ultimately decrease their profitability, thus in turn decreasing effective capital buffers (see Matutes and Vives, 2000).[32] In the aftermath of the financial crisis, several studies in the financial economics literature have tried to examine these claims more objectively and in more detail (see, e.g., Aiyar et al., 2012, Jiménez et al., 2012). The relation between the different facets of bank regulation and supervision on the one hand and bank performance on the other hand, however, remains empirically unexplored. We investigate in this paper how bank regulation and supervision can explain differences in the performance of banks around the world. In particular, we address the question whether higher capital, tougher supervision, incentives and capabilities for the private sector to monitor banks, and higher capital requirements have led to shrinking bank profits and losses in shareholder value.

The theoretical and empirical literature suggests several distinct channels through which the performance of banks might be related to bank regulation. With bank capital requirements at its core, the regulation of financial institutions predominantly aims at limiting the *risk-taking* of banks by reducing the incentives of shareholders and managers to take on more risks than socially optimal (see Kim and Santomero, 1988). At the same time, requirements to hold more bank capital might also prove counterproductive as banks might react to more stringent capital requirements by pursuing a riskier investment strategy (see Koehn and Santomero, 1980, Buser et al., 1981). Furthermore, Laeven and Levine (2009) show that the relation between bank risk-taking and bank regulation depends critically on each bank’s ownership structure. Turning to the second facet of bank regulation, policy-makers could also attempt to limit bank

[31] Joseph Stiglitz took the same line and argued that the lax regulation of U.S. banks prior to the Subprime crisis was to be blamed for contributing significantly to the build-up of systemic risk.

[32] Economic theory does not completely negate the possibility that higher capital requirements could have adverse side-effects. As, e.g., Diamond and Rajan (2001) show in their model that a bank has to trade off liquidity creation against the cost of a bank run when deciding on its capital structure.

risk-taking by introducing activity restrictions. For example, banks could be prohibited to engage in activities that are not related to deposit-taking and lending and that are deemed to be too risky by regulators (see Boyd et al., 1998). The empirical evidence on the effects of activity restrictions, however, is mixed with findings differing significantly over the past decades. For instance, Cornett et al. (2002) show in their study that Section 20 activities undertaken by banks after 1987 resulted in increased industry-adjusted operating cash flow return on assets with bank risk remaining unchanged. The argument that banks profit from less restrictions on their activities is also taken up by Barth et al. (2004) who argue that activity restrictions reduce competition, limit economies of scope, and may ultimately result in a loss in bank efficiency. Further key aspects of a regulatory regime include entry requirements, the supervisory policy, and governance (see, e.g., Ellis et al., 2014).

As economic theory and empirical work provide conflicting results, our paper contributes significantly to this rich literature in banking. We address the need for a comprehensive analysis of the relation between bank regulation and bank performance and study the determinants of the buy-and-hold return for a large sample of international banks from 1999 to 2012. We concentrate on the banks' regulatory and supervisory environment and estimate panel regressions of the stock performance of banking firms on variables on a country's regulatory and supervisory system taken from the database of Barth et al. (2013a) while controlling for several idiosyncractic factors (e.g., bank size, Tier 1 capital, non-interest income, interconnectedness, and leverage).

We empirically test various hypotheses from the financial intermediation literature on the effects of bank capital, bank regulation, and supervision using a sample of 11,803 bank-year observations from 1,659 publicly listed international banks from 74 countries. Over our complete sample period, we find evidence in support of the view that higher bank capital decreases a bank's stock performance. However, we find strong evidence that higher Tier 1 capital ratios significantly increase banks' stock performance during times of a financial crisis. Additionally, we observe that private monitoring, guidelines on asset diversification, and entry requirements into the banking sector are negatively related to the performance of banking firms. In contrast, we show that with the ability of supervisory authorities to discipline banks, their annual buy-and-hold returns increase. Also, better corporate governance yields better stock performance. Analyzing the effect of implicit government bailout guarantees, we find that banks that are more likely to receive government support realize an inferior stock performance. In particular, we find that both a bank's size and a bank's interconnectedness with the global financial sector are negatively related to its stock performance. Interestingly, while we do find that higher Tier 1 capital decreases performance, we find no convincing evidence that the extent to which banks generate non-interest income significantly influences a bank's performance. Moreover, our analysis of a large sample of international banks yields insights to the influence of financial crises on the drivers of a banking firm's performance. For example, we find that while leverage is not a significant driver of bank performance over the whole sample, it plays a significant role during crisis periods.

The empirical work in this study is related to several recent papers on the factors that influence banks' performance. Our paper is most closely related to the recent study by Berger and Bouwman (2013) which is concerned with the effects of bank capital on both, survival rate and market share. The authors find that capital helps small banks to increase the probability of survival and their market share during crises and normal periods while medium and large banks only have higher survival rates and market shares during crises periods. However, their study is restricted to U.S. banks and focuses on survival rates and market shares. Our analysis on the other hand focuses on the effects of regulation on banks' stock performance for a large panel of international banks. Fahlenbrach et al. (2012) analyze the bank performance of 347 U.S. banks using stock return data for 1998 and 2006. The authors find that banks that performed poorly during the 1998 crisis also performed poorly during the financial crisis of 2006. As they further show, banking firms that relied more on short-term funding and had more leverage are more likely to perform poorly during both crises. However, the authors are only concerned with U.S. banks during 1998 and 2006 while our study exploits the variation in national bank regulation and supervision over the period from 1999 to 2012 to explore the determinants of banks' stock performance. Also, our study is related to Beltratti and Stulz (2012) who study the buy-and-hold stock returns of a sample of large international banks over the crisis period from July 2007 to December 2008. The authors find evidence that banks that rely on short-term financing had poor performance during the crisis. They show that better-performing banks had less leverage and lower returns immediately before the crisis. However, the authors restrict their study to large banks with total assets larger than $50bn and only consider the crisis period. In contrast, our paper studies both crises and non-crises periods for a large comprehensive panel of international banks. Hence, we also include smaller banks in our analyses. Demirgüç-Kunt et al. (2013) analyze the effect of different types of capital ratios on bank stock returns and show that a higher capital position leads to stronger performance during the latest crisis. The authors find that this effect is particularly pronounced for large banks and stronger when higher quality forms of capital are considered. Finally, Fahlenbrach and Stulz (2011) study the connection between bank performance and CEO incentives before the crisis using a sample of 95 U.S. banks from 2006.

The paper proceeds as follows. In Section 4.2, we describe our data and discuss the expected influence of various idiosyncratic and regulatory variables on financial stability. In Section 4.3, we document our main findings on the drivers of systemic risk. Section 4.4 concludes.

4.2 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.

4.2.1 Sample construction

Our initial sample consists of all 22,560 firms included in the active and dead-firm "banks" and "financial services" lists in *Thomson Reuters Financial Datastream*. To rule out the possibility that some commercial and investment banks are erroneously listed in the "financial services" instead of the "banks" category in *Datastream*, we build our initial sample using both lists. We then follow Fahlenbrach and Stulz (2011) and 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). Furthermore, we require a bank to have available accounting data in *Thomson Worldscope* to be included in our sample. Next, we omit a stock from our sample if it is identified in *Datastream* as a non-primary quote, if it is a secondary listing or if it is an American Depositary Receipt (ADR). Additionally, we exclude from our sample all OTC traded stocks and preference shares. Our final sample consists of 3,813 international banks for which we have at least one year of accounting data available. For our sample banks, we need to have daily stock price data available in *Datastream*. Consequently, we remove another 45 banks from our sample, due to missing stock price data. In the following, we apply the filtering process proposed by Hou et al. (2011) and Karolyi et al. (2012).

As noted first by Ince and Porter (2006), stock prices in *Datastream* suffer from several minor data errors. To correct for the confounding effect of these errors, we perform several screening procedures on the daily return of the banks' stock prices. First, we require a bank to have a minimum share price of $1 at the end of a month for the bank-month to be included in our sample. We treat as missing any return above 300 percent that is reversed within one month. In case the number of zero return days exceeds 80 percent of a given month, we follow Hou et al. (2011) and exclude the entire bank-month. Furthermore, we define non-trading days as those days on which 90 percent or more of the listed stocks have zero returns. All non-trading days are then excluded from our sample. Finally, as we are interested in the influence of regulatory capital on banks' stock performance, we exclude all banks with missing data on Tier 1 capital from our sample. In case we have no remaining bank-year for an individual bank, we exclude the bank from our sample. In total, we end up with a sample of 1,659 international banks from 74 countries for the time period 1999 to 2012. Table 4.1 shows the distribution of the 11,803 bank-years across each country.

Table 4.1: Distribution of bank years.

The table shows the distribution of the 11,803 bank years from 1999 to 2012 among the countries in our sample. The international sample consists of 1,659 banks and is constructed as documented in Section 4.2 and by applying several filters as introduced by Ince and Porter (2006) and Hou et al. (2011).

Country	No. of bank-years	Country	No. of bank-years
Abu Dhabi	28	Lebanon	3
Argentina	7	Lithuania	7
Australia	80	Luxembourg	5
Austria	98	Macedonia	4
Bahrain	10	Malaysia	128
Bangladesh	21	Malta	1
Belgium	25	Mauritius	3
Botswana	1	Mexico	2
Brazil	11	Namibia	2
Bulgaria	3	Netherlands	35
Canada	97	Norway	281
Chile	7	Oman	21
China	69	Pakistan	30
Colombia	1	Peru	3
Croatia	4	Philippines	50
Cyprus	11	Poland	40
Czech Republic	9	Portugal	52
Denmark	441	Qatar	54
Dubai	13	Romania	2
Egypt	13	Russian Federation	32
Finland	32	Saudi Arabia	80
France	111	Serbia	3
Germany	167	Singapore	48
Greece	63	Slovakia	10
Hong Kong	97	Slovenia	3
Hungary	12	South Africa	62
Iceland	7	South Korea	9
India	80	Spain	118
Indonesia	25	Sri Lanka	21
Ireland	26	Sweden	63
Israel	79	Switzerland	148
Italy	398	Taiwan	57
Japan	1,263	Thailand	110
Jordan	69	Turkey	74
Kazakhstan	6	Ukraine	1
Kenya	24	United Kingdom	138
Kuwait	35	United States	6,660

4.2.2 Bank characteristics

Our analysis is concerned with the factors influencing stock performances of banks around the globe. Consequently, we use a bank's annual buy-and-hold stock return as dependent variable in our panel regressions. In the following, we describe our independent variables. To begin with, we control for several idiosyncratic bank characteristics that are well-known to influence bank stock prices. Furthermore, for each nation in our sample, we collect a set of country-specific variables that proxy for a bank's regulatory environment and other macroeconomic factors.

First, we include information on a bank's regulatory capital as the main independent variable in our regressions. We use the variable Tier 1 capital which is defined as the ratio of Tier 1 capital to total risk weighted assets. [33] Tier 1 capital is the component of a bank's capital that has the highest quality and is therefore capable to absorb losses without affecting the day-to-day business of the bank and may thus improve overall bank performance.[34] As already pointed out, regulators use capital requirements to limit the risk-taking of banks by having shareholders participate in the losses. For example, Cihák et al. (2012) find that crisis countries used lower actual capital ratios. Conversely, higher Tier 1 capital could induce less profitability of a bank, since it is the most costly form of capital that a bank can raise. Also, bank managers argue that more bank capital might lead banks to a riskier investment strategy. As a result, we do not have an undisputed expectation of the influence on banks' stock performance. By including Tier 1 capital in our regression analyses, we (indirectly) control for possible positive and negative effects of stricter capital requirements on a bank's stock performance.

Next, we control for differences in the size of a bank by taking the natural logarithm

[33] Das and Sy (2012) study the usefulness of risk weighted assets and argue that they do not predict market measures of risk. Additionally, Mariathasan and Merrouche (2014) find that risk weighted assets predict bank failure only when the risk of a crisis is very low. See, e.g., Gauthier et al. (2012), Hanson et al. (2011) for a more detailed discussion of the potential disadvantages associated with the use of risk weighted assets. Further studies concerning risk weighted assets include, e.g., Acharya et al. (in press).

[34] We focus on the effect of Tier 1 capital on bank performance as, e.g., Anginer and Demirgüç-Kunt (2014) show that Tier 2 capital has a destabilizing effect as it is less able to absorb losses.

of a bank's total assets at the end of the fiscal year. The literature reveals ambiguous findings on the interplay of the size of a bank and its individual stock performance. 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. They show that this finding is due to the pricing of implicit bailout guarantees by stock market investors. Irrespective of the banks' leverage, larger commercial bank stocks have significantly lower risk-adjusted returns than small- and medium-sized bank stocks. Underlining this finding, Aebi et al. (2012) show that bank size was negatively related to the stock performance of banks during the recent financial crisis. On the other hand, increased bank size might result in a higher market power and as a consequence increase stock performance. As a result, we have no clear prediction for the sign of the coefficient on bank size in our panel regressions.

In our analysis, we use several measures to control for different types of bank risk. To proxy for a bank's systematic risk and thus a bank stock's sensitivity to a given benchmark market index, we employ in our regressions the bank's beta. We calculate a bank's beta as the covariance between the returns on the bank's stock and the returns of the MSCI World index divided by the variance of the bank's stock returns. A higher beta denotes a positive correlation of the benchmark index and the stock's movements and should therefore reflect a good performance during good economic times and worse stock performance in financial crises.

To additionally control for the systemic risk of a bank, we use two measures for the exposure and contribution of an individual bank to systemic risk. To be precise, we employ two prominent measures of systemic risk from the literature: the Marginal Expected Shortfall (MES) and a bank's ΔCoVaR. Formally, the Marginal Expected Shortfall is defined as

$$MES^{j}_{p\%} = \mathbb{E}\left[\frac{w^j_1}{w^j_0} - 1 \middle| I_{p\%}\right],$$

where $\frac{w^j_1}{w^i_0} - 1$ are the net equity returns of bank j during the bad market outcomes and $I_{p\%}$ is an indicator variable for the market return being in its left $p\%$-tail. Hence, the

Marginal Expected Shortfall is then computed as the average return on any given bank (R_b) conditional on the market return being in the p% left tail:

$$MES^{\,b}_{p\%} = \frac{1}{\#\ days} \sum_{system\ is\ in\ p\%\ tail} R_{b,t}.$$

In our analysis, the MES of an individual bank's stock is calculated as the negative average stock return on the days the MSCI World Index experienced its 5% worst outcomes (see Acharya et al., 2010). Adrian and Brunnermeier (2014) define the unconditional ΔCoVaR as the difference of the Value-at-risk (VaR) of a financial sector index conditional on the distress (in the 5% quantile) of a particular bank and the VaR of the sector index conditional on the median state of the bank. Formally, the $CoVaR^{j|i}_{\alpha}$ of the financial sector s is defined as the Value-at-Risk (VaR) given by $Pr(R_i \leq VaR^i_{\alpha}) = \alpha$ conditional on some event $\mathbb{C}(R_i)$ of institution i, where R_i is the return of institution i for which the VaR^i_{α} is defined. The $CoVaR^{s|i}_{\alpha}$ is implicitly defined by the α-quantile of the conditional probability distribution:

$$Pr\left(R_s \leq CoVaR^{j|\mathbb{C}(R_i)}_{\alpha} \mid \mathbb{C}(R_i)\right) = \alpha.$$

Thus, the contribution of institution i to the VaR of the financial system s is given by

$$\Delta CoVaR^{s|\mathbb{C}(R_i)}_{\alpha} = CoVaR^{s|R_i=VaR^i_{\alpha}}_{\alpha} - CoVaR^{s|R_i=Median^i}_{\alpha}.$$

Consequently, the measure captures an individual bank's contribution to systemic risk. Hence, $\Delta CoVaR^{s|\mathbb{C}(R_i)}_{\alpha}$ or simply $\Delta CoVaR^i_{\alpha}$ denotes the difference between the financial system's VaR conditional on a particular financial institution i being in distress and the VaR of the financial system conditional on the median state of the institution i.[35] We would expect a bank's exposure to crises to be negatively associated with the bank's stock performance. At the same time, however, we also expect a bank's contribution to systemic risk to be negatively correlated with its stock performance as higher systemic

[35]We use the MSCI World Index for our calculations.

importance increases the probability of a bailout (and thus reduces the risk premia in stock returns).

As a way of measuring firm value, we employ a bank's market-to-book ratio calculated as the market value of common equity divided by the book value of common equity. Fahlenbrach et al. (2012) for instance find evidence for a positive relation of a bank's buy-and-hold returns and the market-to-book ratio. Therefore, we would expect a positive impact of market-to-book ratio on a bank's stock performance. Next, we include in our analysis the variable return on assets (ROA) as a standard measure of a firm's profitability. Naturally, we would expect a positive relation between a bank's profitability and its stock performance. Finally, to control for differences in the banks' stocks, we employ the Amihud measure of an individual stock's illiquidity adjusted following the procedure proposed by Karolyi et al. (2012) as a further control variable (Liquidity).[36]

We include several variables to control for differences in the business model of a bank. First, we define the variable Loans as the ratio of a bank's total loans to total assets. When loans are higher, banks' regulatory capital is expected to be less impacted by increases in credit spreads, which could reduce the values of securities (see, e.g., Beltratti and Stulz, 2012). Additionally, we define the variable Loan loss provisions as the natural logarithm of a bank's expenses set aside as allowances for uncollectable or troubled loans divided by total loans. Uhde and Heimeshoff (2009) show that this proxy for a bank's quality of its loan portfolio is negatively related to the bank's performance.

Another bank-specific variable we consider in our main regressions is Deposits, which is calculated as total deposits divided by total liabilities. A higher value for Deposits indicates a less fragile funding of the bank, which could serve as a stabilizing factor for firm performance.[37] On the other hand, a bank that is mainly funded by

[36]Note that, in contrast to the original Amihud measure, the adjusted Amihud measure proposed by Karolyi et al. (2012) is increasing in the stock's liquidity.

[37]A low value for Deposits indicates high overnight money market funding and hence, fragile funding. A a consequence, Basel III integrates a ratio for stable funding.

deposits might be less active in non-traditional banking activities, which could limit possible streams of income. To investigate this hypothesis, we also include the ratio of non-interest income and total interest income in our main regressions. In a related study, Brunnermeier et al. (2012) empirically show that banks that generate higher non-interest income have a higher contribution to systemic risk than traditional banks. Next, we consider a bank's funding in our analyses by including the variable Debt maturity. The latter is the ratio of total long term debt (due in more than one year) to total debt. Fahlenbrach et al. (2012) find evidence that the poor performance of banks during the recent financial crisis was partly due to a stronger reliance on short-term funding. In our analyses, we expect the coefficient of debt maturity to enter our regressions with a positive sign (see also Adrian and Shin, 2010). Fahlenbrach et al. (2012) find empirical evidence that the leverage of a bank has a negative influence on a bank's stock return during the crisis period. Therefore, we add a proxy for a bank's leverage to our set of independent variables. In particular, we follow Acharya et al. (2010) and calculate the variable leverage as book value of assets minus book value of equity plus market value of equity, divided by market value of equity and expect it to enter our regressions with a negative coefficient.

4.2.3 Regulatory and macroeconomic environment

The focus of our empirical study lies on an analysis of the relation between the regulation of domestic banking sectors and an individual bank's stock performance. In particular, we investigate whether differences in stock performance can be explained by differences in the bank's country-specific regulatory environment. We obtain data on the regulatory environments from the database of Barth et al. (2013a) that is based on four surveys performed between 1999 to 2012 on the regulation and supervision of banks in 180 countries. Unfortunately, not every variable is available for every year of our full sample period from 1999 to 2012. Nevertheless, we update missing data points with the most recent data since adjustments of the regulatory and supervisory environment are relatively rare and result from a relatively slow political process (see Barth et al., 2004, Anginer et al., 2014b). First, we employ a measure of the degree to which official supervisory authorities are allowed to actively prevent or correct instances of corporate wrongdoing by banks. The index of the official supervisory power ranges from zero to 14, where higher values denote greater power of the authorities. One could argue that more powerful regulators are able to prevent excessive risk-taking by banks before and during crises. At the same time, however, more powerful supervisors could also limit banks in their range of investment opportunities. Therefore, we have no expectation regarding the sign of the coefficient in our regressions.

As our next step, we take advantage of a variable that proxies for differences across countries in the way firms are restricted in their engagement in banking activities or are ostracized from banking markets. For example, Ongena et al. (2013) find that the lower the barriers to entry and the tighter the restrictions on bank activities in domestic markets are, the more they are associated with lower banking standards in domestic and foreign markets. Additionally, empirical investigations show that the risk-taking of banks is sensitive to domestic regulation and restrictions on (foreign) market entry and bank activities (see, e.g., Barth et al., 2004, Laeven and Levine, 2009, Buch and DeLong, 2008). Ellis et al. (2014) identify key planks of any well-defined regulatory regime, one of which are entry requirements. As a consequence, we also control for differences in entry requirements in a country by employing an index of the legal requirements that need to be fulfilled before a banking license is issued. The entry requirements index ranges from zero to eight, where eight denotes the greatest stringency. Next, we consider the private monitoring index and diversification index from the database of Barth et al. (2013a). The former describes the incentives and capabilities that are provided by regulatory and supervisory authorities to encourage the private monitoring of banks. Cihák et al. (2012) find evidence that the private sector in crisis countries had weaker incentives to monitor banking firms' risks. Additionally, Caprio Jr. et al. (2014) find that higher levels of private monitoring negatively impinge the probability of a crisis. Thus, we expect that a small score of the index (which ranges from 0 to 12) is associated with weaker stock performance. The diversification index proxies for a country's guidelines for asset diversification and loan giving abroad. Higher guidelines on diversification lead to a more balanced investment portfolio. However, diversification does not necessarily increase value for shareholders. Also, one might argue that more diversification leads to the lack of a core business. This line of argumentation is also supported by the rich literature on mergers (see, e.g., DeYoung et al., 2009). Additionally, Mercieca et al. (2007) find no evidence in support of beneficial effects of direct diversification on bank performance. Finally, we control for the stringency of capital regulation on the banking system. The capital regulatory index captures whether capital requirement reflects certain risk elements and deducts certain market value losses from capital before minimum capital adequacy is determined. It ranges from zero to ten, where ten indicates the highest degree of stringency of capital regulation. Barth et al. (2013a) show that capital requirements have been adjusted to greater stringency over the last decade. Unfortunately, the capital regulatory index is not available for all countries in our sample for the whole sample period.

To control for the overall economic conditions and possible business cycle fluctuations in each country, we obtain data from the World Bank's World Development Indicator (WDI) database on the annual growth rate of the real gross domestic product (in %) and the inflation rate. We suspect that a bank's opportunities for investments are correlated with different business cycles. These opportunities might arise in times of economic growth and, consequently, have a positive effect on the overall performance of a bank. For example, Demirgüç-Kunt and Detragiache (1998) find evidence that both a low GDP growth and a high inflation rate increase the likelihood of systemic banking sector problems which could worsen a bank's stock performance due to spillover effects.

Finally, to control for the competition in a given country's banking sector, we employ the Herfindahl-Hirschman Index computed as the sum of the squared market shares of a country's domestic and foreign banks. Anginer et al. (2014a) find a positive relation between bank competition and systemic stability as greater competition encourages banks to take on more diversified risks, hence making the banking system as a whole less fragile to shocks. Consequently, we expect an ambiguous effect of competition on banks' stock performances. On the one hand, competition should decrease the profit margins of banks, leading to less pronounced buy-and-hold returns. However, on the other hand, following the argumentation of Anginer et al. (2014a), competition protects investors from an otherwise higher exposure to systemic risk, thus leading to a better bank stock performance.

4.2.4 Additional variables controlling for possible government bailouts

It could be argued that a bank's interconnectedness rather than its size drives its systemic risk and thus the probability of a potential bailout by the government in a scenario of market stress.[38] Consequently, a bank's stock performance could also be affected by the bank's degree of interconnectedness with the financial sector as investors price implicit bailout guarantees for too-interconnected-to-fail banks. To control for this, we employ our variable Interconnectedness which is defined as the number of in- and outgoing granger causalities of the banks' stock returns as proposed by Billio et al. (2012). As before for bank size, we expect an ambiguous influence of interconnectedness on the banks' stock performance.

Next, Bertray et al. (2013) show that bank shareholders differentiate between a bank's absolute size and its systemic size. Thus, while we check for size and systemic relevance of a bank, it is crucial to include an indicator of systemic relevance relative to the local economic environment in our regressions. Therefore, we define the variable Systemic size as the ratio of a bank's total liabilities to national GDP. As Bertray et al. (2013) show that growing to a size that is systemic is not in the interest of a bank's shareholders, we expect a negative influence of systemic size on banks' stock performance.

[38] For the importance of the interconnectedness of financial institutions for global financial stability, see, e.g., Black et al. (2013), Arnold et al. (2012) and Billio et al. (2012).

Another key plank of a well-defined regulatory regime is governance (see Ellis et al., 2014). Hence, in our further analyses, we additionally include an index that measures the quality of corporate governance in a given country. As Santos (2001) notes, capital standards may be an important instrument to implement the optimal governance of banks because they can be used to define the threshold for the transfer of control from shareholders to regulators. Ideally, a good governance environment should be the basis of a smooth bank business operation and should therefore be reflected in the annual stock performance. Ellis et al. (2014) argue that this aspect of a regulatory regime is often neglected. We calculate two versions of a corporate governance index, employing the Worldwide Governance Indicators provided by the World Bank. The simpler version is calculated as the arithmetic mean of the six constituent variables. Additionally, we consolidate the six factors using a principal component analysis to account for possible commonalities in the variables (see also Barth et al., 2013b). Aebi et al. (2012) study bank performance during the financial crisis 2007/2008 and find evidence that better corporate governance is related to better performance.

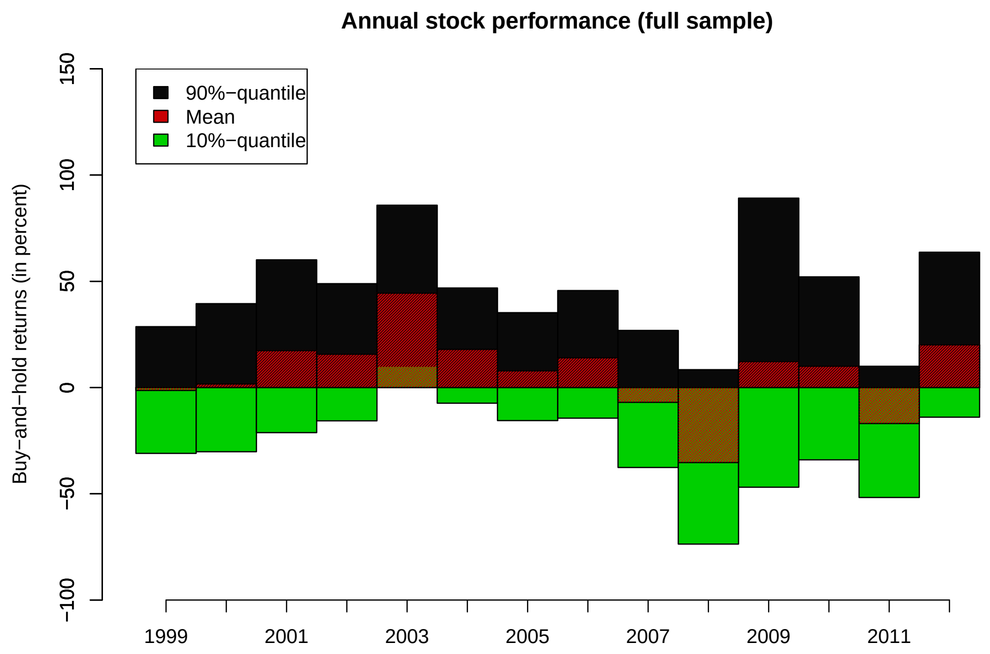
4.2.5 Bank stock performance

In the first step of our empirical study, we analyze several descriptive statistics of our sample banks' stock performance, the bank-specific explanatory variables as well as our controls regarding the banks' regulatory environment. Figure 4.1 plots the time evolution of the mean, 10%-, and 90%-quantile of the sample banks' buy-and-hold returns across our full sample.

Average stock performance peaked in the year 2003 during which banks even in the 10% quantile of stock performance experienced a stock performance of above 10%. As expected, overall stock performance dropped in the years of the financial crisis with its minimum in the year 2008. Here, the top-performing bank stocks achieved an annual return of 8.4% on average. A similar result holds for the year 2011. Interestingly, the 90%-percentile of the annual buy-and-hold returns had its peak in 2009, directly

Figure 4.1: Time evolution of bank stock performances.

The figure shows the time evolution of the annual buy-and-hold returns across our full international sample of banks. We report the 90%-quantiles (black bars) and the 10%-quantiles (green bars) as well as the mean values (red areas) of annual buy-and-hold returns.

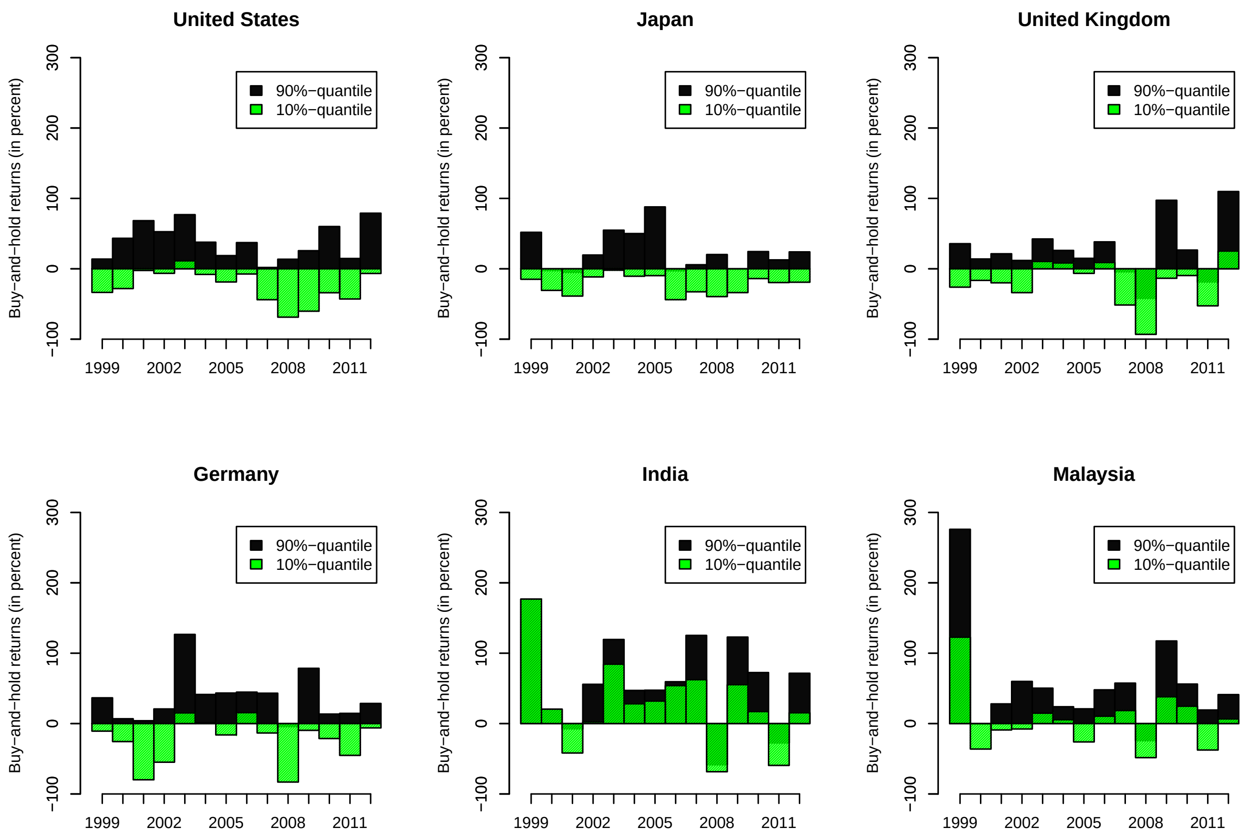


after the crisis years, whereas the bottom percentiles remain relatively low. These first findings show that bank stocks performed quite differently both before, during, and after the financial crisis, thus underlining the importance of our main research question. In Figure 4.2, we further investigate this differential stock performance of banks in our sample by comparing the stock performance of banks in six selected countries.

A first striking finding in Figure 4.2 is that while the U.S. banking sector's average stock performance began to rise from 1999 to 2003, the 90%-quantile of the stock performance of Japanese banks declined. Interestingly, the opposite trend can be observed for the period from 2003 to 2005. However, for all of the six countries, we find a sudden and steep drop in the average bank's stock performance in 2008 with only slightly positive buy-and-hold returns in the 90%-quantile in the U.S. and Japan. After the crisis, the bank stocks recovered to a certain amount with some banks in the United Kingdom and Germany having annual buy-and-hold returns of above 50%. In

Figure 4.2: Time evolution of banks' stock performances by country.

The figure shows the time evolution of the annual buy-and-hold returns across our full international sample of banks. We report the 10%- (green area) and 90%-percentiles (black bars) of annual buy-and-hold returns in a given country.



contrast, banks in India and Malaysia had extremely high stock returns both before and after 2008, with banks in the top 90%-percentile of annual buy-and-hold returns being well above 100%.

Next, we comment on several descriptive statistics for our dependent and independent variables presented in Table 4.2 that are later used in our panel regressions.

From Table 4.2, we can see that all our variables exhibit significant variation, both across time and across banks. First, we can see that banks in our sample differ considerably with respect to their respective business model and funding strategy. In particular, the variables Loans and Non-interest income as well as Leverage and Debt Maturity show significant variation in our panel data set. On average, the variable Loans decreases steadily across all banks in our sample (from 65% to 61%) while Non-interest income increases significantly. However, Non-interest income shows a significant spike in 2009 and 2010. Also, the debt maturity of banks increases, on average, across all banks in our sample, as does leverage. However, the average leverage of banks exhibits a significant drop between 2005 and 2007.

Even more interestingly, the amount of regulatory capital also shows significant variation, both across time and banks. For example, several banks from the United States feature high Tier 1 capital ratios, whereas 143 banks from different countries show regulatory capital ratios below 1% over our entire sample period. However, from 1999 to 2012, we observe a significant upward trend in average Tier 1 capital ratios.[39]

As far as the Interconnectedness between banks is concerned, we find that the ten most interconnected banks from our sample are all from the United States. Surprisingly though, we observe the highest degree of interconnectedness in 2000. This is surprising because, for example, Engle et al. (2014) argue that the degree of interconnectedness between banks has increased as a result of rising globalization. Nevertheless, we find average values of our measure of a bank's interconnectedness to have increased from 1999 to 2012. Finally, we also find significant time variation in the variables on the

[39]These findings are also underlined by Cohen and Scatigna (2014) who confirm that capital ratios have increased steadily since the financial crisis and analyze different channels of adjustment.

Table 4.2: Summary statistics.

This table shows selected descriptive statistics of variables used in our regressions. The sample consists of 1,659 publicly traded international banks from 74 countries over the period 1999-2012. Stock market data are retrieved from *Thomson Reuters Financial Datastream* while financial accounting data are taken from the *Worldscope* database. Regulation variables come from Barth et al. (2013a) and country characteristics are retrieved from the World Bank's World Development Indicator (WDI) Database. Definitions of variables as well as descriptions of the data sources are given in Appendix C.1. Total assets is measured in billion U.S. Dollars; the Systemic Size is given in terms of 10^{-3}.

Variable	Observations banks	Observations bank-years	Mean	Std. Dev.	Min	Max	Between Variation	Within Variation
Buy-and-hold return	1,659	11,803	0.053	0.398	-0.982	4.273	0.209	0.372
Beta	1,659	11,803	0.041	0.083	-0.531	1.760	0.092	0.045
MES	1,659	11,803	0.015	0.075	-0.111	1.819	0.042	0.066
CoVaR	1,656	10,566	-0.897	4.947	-37.615	37.301	2.983	4.450
Total assets	1,659	11,803	0.005	0.233	0.0000	4.770	0.167	0.109
Market-to-book	1,656	11,761	1.538	3.203	-293.851	93.803	2.126	2.823
Leverage	1,656	11,761	14.969	21.523	1.033	716.452	14.102	16.678
Non-interest income	1,659	11,806	0.362	4.890	-0.909	468.005	6.500	2.449
Loans	1,603	11,270	0.677	0.138	0	0.933	0.134	0.059
Loan loss provisions	1,600	11,248	0.007	0.019	-0.226	1.570	0.025	0.012
Debt maturity	1,644	11,648	0.499	0.293	0	1	0.256	0.191
Deposits	1,659	11,801	0.768	0.191	0	0.9922	0.184	0.059
Return on assets	1,558	10,644	1.090	1.417	-27.600	20.640	1.525	0.964
Tier 1 capital	1,659	11,803	0.088	0.703	0.001	0.224	0.171	0.672
Liquidity	1,643	11,362	-0.001	0.003	-0.140	0.000	0.003	0.002
Interconnectedness	1,599	9,619	0.073	0.065	0.009	0.578	0.050	0.053
Systemic size	1,659	11,803	0.060	0.335	0.000	10.97	0.249	0.117
Official Supervisory Power	1,586	10,114	12.281	2.169	4	16	2.002	0.795
Diversification Index	1,645	11,513	1.404	0.502	0	2	0.393	0.367
Entry requirements	1,645	11,440	7.480	0.789	0	8	0.697	0.477
Private Monitoring Index	1,628	11,295	8.966	1.189	5	11	0.999	0.798
Capital Requirements	925	3,678	6.785	1.322	3	10	1.211	0.637
Corp. Governance (PCA)	1,659	11,803	-0.231	1.173	-4.157	3.207	1.088	0.325
Corp. Governance	1,659	11,803	1.192	0.500	-1.177	1.986	0.629	0.088
GDP growth	1,656	11,802	2.445	2.672	-13.127	26.750	2.552	1.607
Inflation	1,643	11,700	2.276	3.264	-21.582	75.271	3.688	2.139
HHI	1,448	10,039	0.088	0.066	-2.459	0.760	0.060	0.021
Crisis dummy	1,659	11,803	0.270	0.444	0	1	0.302	0.377

banks' regulatory environment.

In Table 4.3, we present the Pearson correlations between the independent variables used in our regression analyses.

As can be seen from the estimates in Table 4.3, most variables are not significantly correlated with each other. However, several of our regulatory variables exhibit stronger correlations with the macroeconomic controls. Consequently, these variables are not used jointly in the regressions presented in the next section to minimize the risk of multicollinearity biasing our findings.

In the upcoming sections, we try to explain the found differences in the stock performance of banks by estimating panel regressions in which we employ both our country-specific variables on bank regulation and the idiosyncratic bank characteristics.

4.3 The influence of regulation on stock performance

In this section, we present the results of our panel regression in which we analyze the determinants of the banks' stock performance. We begin by analyzing whether stricter regulation, e.g., in the form of higher regulatory capital requirements leads to a decrease in stock performance. Next, we investigate whether bank stock performance is significantly affected by regulators via implicit bailout guarantees. Finally, we take a closer look at the determinants of banks' stock performance during times of financial crises.

4.3.1 Does stricter bank regulation lead to worse stock performance?

For the analysis of the determinants of a bank's stock performance, we estimate panel regressions with time-fixed and bank-fixed effects. The standard errors are clustered at

Table 4.3: Correlations of independent variables.

This table shows Pearson correlations between the independent variables used in our main regressions. The sample consists of 1,659 publicly traded international banks from 74 countries over the period 1999-2012. Stock market data are retrieved from *Thomson Reuters Financial Datastream* while financial accounting data are taken from the *Worldscope* database. Regulation variables come from Barth et al. (2013a) and country characteristics are retrieved from the World Bank's World Development Indicator (WDI) Database. Definitions of variables as well as descriptions of the data sources are given in Appendix C.1.

	Log return	MES	ΔCoVaR	Beta	Total assets	Market-to-book	Leverage	Non-interest income	Loans	Loan loss provision	Debt maturity	Deposits	Return on assets
MES	-0.07												
ΔCoVaR	0.10	-0.01											
Beta	0.02	-0.27	0.21										
Total assets	-0.17	0.20	-0.18	-0.07									
Market-to-book	-0.18	0.10	0.00	-0.04	0.27								
Leverage	-0.10	-0.07	-0.08	-0.10	0.03	-0.15							
Non-interest income	0.04	0.15	-0.13	-0.18	0.41	0.05	-0.03						
Loans	-0.09	-0.10	-0.09	0.05	-0.15	0.01	0.00	-0.36					
Loan loss provisions	0.01	-0.08	-0.07	-0.11	-0.07	-0.12	0.16	-0.03	0.12				
Debt maturity	0.15	-0.09	0.02	0.04	-0.30	-0.14	0.07	-0.16	0.13	0.08			
Deposits	0.26	-0.04	0.22	0.03	-0.58	-0.16	-0.15	-0.20	-0.02	0.10	0.21		
Return on assets	0.05	0.10	-0.05	0.16	0.24	0.25	-0.38	0.08	-0.01	-0.50	-0.10	-0.22	
Tier-1-capital	0.12	-0.08	0.10	0.20	-0.37	-0.21	-0.18	-0.18	-0.07	-0.00	0.10	0.10	0.11
Systemic size	-0.27	0.05	-0.13	-0.10	0.58	0.14	0.24	0.10	-0.11	-0.08	-0.22	-0.51	0.04
Liquidity	0.01	-0.05	0.04	0.24	0.37	0.16	-0.23	0.17	-0.10	-0.09	-0.17	-0.07	0.26
Interconnectedness	-0.04	-0.19	0.17	0.51	-0.03	0.01	-0.05	-0.14	0.03	-0.02	0.09	0.09	0.07
Capital requirements	0.32	-0.14	0.07	0.17	-0.25	-0.03	-0.03	-0.10	-0.01	-0.06	0.20	0.15	0.19
Entry requirements	0.38	0.02	0.14	0.10	-0.21	-0.07	-0.15	-0.06	-0.16	-0.06	0.16	0.33	0.09
Diversification index	0.12	0.11	-0.08	-0.05	0.45	0.17	0.04	0.09	-0.01	-0.13	-0.09	-0.38	0.21
Official Supervisory Power	0.11	-0.06	0.12	0.10	-0.52	-0.26	0.01	-0.07	-0.05	0.03	0.29	0.37	-0.11
Private monitoring index	0.23	-0.08	0.18	0.12	-0.57	-0.31	-0.02	-0.09	-0.17	0.06	0.32	0.57	-0.23
Governance	0.04	0.11	0.13	-0.15	-0.20	-0.13	0.06	0.05	-0.11	-0.09	0.08	0.12	-0.27
Governance (pca)	0.15	0.15	0.10	0.00	-0.11	-0.10	-0.06	-0.00	-0.11	-0.02	0.02	0.32	-0.08
GDP-growth	-0.17	-0.01	-0.12	-0.08	0.46	0.39	-0.07	0.02	0.07	0.01	-0.25	-0.27	0.21
HHI	0.01	0.25	-0.01	-0.18	0.30	0.12	-0.03	0.12	-0.09	-0.08	-0.18	-0.09	-0.00

Table 4.4: Correlations of independent variables (continued).

	Tier-1-capital	Systemic size	Liquidity	Inter connect-edness	Capital re-quirements	Entry require-ments	Diversifica. index	Official Supervisory Power	Private moni-toring index	Governance	Governance (pca)	GDP growth
MES												
ΔCoVaR												
Beta												
Total assets												
Market-to-book												
Leverage												
Non-interest income												
Loans												
Loan loss provisions												
Debt maturity												
Deposits												
Return on assets												
Tier-1-capital												
Systemic size	-0.32											
Liquidity	-0.01	0.12										
Interconnectedness	0.05	-0.04	0.12									
Capital requirements	0.21	-0.32	-0.05	0.09								
Entry requirements	0.09	-0.22	-0.07	0.06	0.46							
Diversification index	-0.33	0.35	0.07	-0.04	0.03	0.23						
Official Supervisory Power	0.34	-0.32	-0.10	0.09	0.52	0.13	-0.54					
Private monitoring index	0.32	-0.55	-0.13	0.08	0.33	0.44	-0.45	0.55				
Governance	0.02	0.06	-0.04	-0.12	-0.22	0.17	-0.10	0.21	0.33			
Governance (pca)	0.08	-0.10	-0.03	-0.01	-0.31	0.31	-0.19	-0.18	0.24	0.28		
GDP-growth	-0.30	0.24	0.13	-0.04	-0.29	-0.26	0.38	-0.77	-0.56	-0.55	-0.12	
HHI	-0.25	0.19	0.08	-0.16	-0.59	0.04	0.42	-0.60	-0.23	0.31	0.53	0.29

the bank level.[40] More formally, we will estimate regressions of the following form:

$$\begin{aligned}\text{Buy-and-hold return}_{i,t} = \beta_1 \cdot \text{Tier-1-capital}_{i,t-1} + \beta_{\text{Bank controls}} \cdot X_{i,t-1} \\ + \beta_{\text{Regulatory}} \cdot Y_{i,t-1} + \beta_{\text{Country controls}} \cdot Z_{i,t-1} + u_i + v_t + \epsilon_{i,t}.\end{aligned}$$

We run several regressions to identify the determinants of a bank's stock performance. In all our regressions, we use the banks' yearly log buy-and-hold returns as our dependent variable. First, we regress a banks's stock performance on a set of bank-specific variables. We control for any unobserved variables with time-fixed and bank-fixed effects. In further regressions, we include additional control variables on the banks' regulatory and macroeconomic environment to determine which country-specific factors drive the stock performance of banks. We lag all our explanatory variables by one year to mitigate the problem that our dependent variables and some of our independent variables could be determined simultaneously. The results of our baseline panel regressions are shown in Table 4.5.

In our baseline regressions in Table 4.5, we use the banks' yearly log buy-and-hold return as the dependent variable. The results of our baseline panel regressions show that a bank's Tier 1 capital ratio is negatively related to the bank's stock performance. This result is statistically significant at the 1% level. At least for our full sample, however, this result is only marginally economically significant as a one standard deviation increase in Tier 1 capital yields a decrease in a bank's annual stock return of just 0.2% (0.003×0.6787311). This finding contributes to the on-going discussion of the regulation of banks' equity capital. On the one hand, Tier 1 capital represents a bank's capital of the highest quality. Consequently, public opinion and regulators repeatedly call for tougher capital regulations. In a recent paper, Bostandzic et al. (2014) find that higher Tier 1 capital decreases both the exposure and contribution of individual banks to systemic risk. On the other hand, bank managers argue that higher capital requirements

[40] As the residuals are not correlated across both time and banks, this procedure is valid. For further comments see, e.g., Thompson (2011) or Beck and De Jonghe (2013).

Table 4.5: Regressions of a bank's stock performance.

The regressions estimate the relation between stock performance and bank characteristics as well as regulatory variables over the period 1999-2012. We use the banks' log annual buy-and-hold return as our dependent variable. The sample consists of 1,659 publicly traded international banks from 74 countries. Stock market data are retrieved from *Thomson Reuters Financial Datastream* while financial accounting data are taken from the *Worldscope* database. Regulation variables come from Barth et al. (2013a) and country characteristics are retrieved from the World Bank's World Development Indicator (WDI) Database. The regressions include all banks from our sample and we apply panel regression with time-fixed and bank-fixed effects using clustered robust standard errors (at the bank level). P-values are given in parentheses, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Adj. R^2 is adjusted R-squared. Definitions of variables as well as descriptions of the data sources are given in Appendix C.1.

Variable	Model (1)		Model (2)		Model (3)		Model (4)		Model (5)		Model (6)		Model (7)		Model (8)	
Bank-level characteristics																
Lagged return	-0.142	***	-0.153	***	-0.093	***	-0.125	***	-0.15	***	-0.136	***	-0.139	***	-0.099	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
MES	-0.171	**			-0.157	**	-0.184	**	-0.144	**	-0.178	**	-0.159	**	-0.187	**
	(0.018)				(0.036)		(0.011)		(0.047)		(0.014)		(0.030)		(0.015)	
Beta	-0.205	**	-0.193	**	-0.118		-0.223	**	-0.2	**	-0.195	**	-0.208	**	-0.101	
	(0.021)		(0.029)		(0.200)		(0.013)		(0.028)		(0.029)		(0.024)		(0.273)	
Total assets	-0.205	***	-0.219	***	-0.199	***	-0.208	***	-0.2	***	-0.214	***	-0.202	***	-0.204	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Market-to-book	-0.052	***	-0.049	***	-0.065	***	-0.05	***	-0.048	***	-0.05	***	-0.045	***	-0.062	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Leverage	0.000		0.000		0.000		0.000		0.000		0.000		0.001		0.000	
	(0.747)		(0.813)		(0.735)		(0.676)		(0.688)		(0.498)		(0.467)		(0.574)	
Non-interest income	-0.021		-0.033		-0.008		-0.018		-0.026		-0.023		-0.022		-0.008	
	(0.225)		(0.199)		(0.655)		(0.306)		(0.136)		(0.184)		(0.208)		(0.668)	
Loans	-0.266	***	-0.209	***	-0.197	**	-0.236	***	-0.241	***	-0.247	***	-0.236	***	-0.189	**
	(0.000)		(0.007)		(0.011)		(0.001)		(0.001)		(0.001)		(0.001)		(0.016)	
Loan loss provisions	-2.137	**	-2.334	**	-1.783	*	-1.764	*	-2.577	***	-2.221	**	-2.317	**	-1.999	*
	(0.020)		(0.011)		(0.099)		(0.065)		(0.007)		(0.021)		(0.017)		(0.072)	
Debt maturity	-0.013				-0.029		-0.018		-0.016		-0.02		-0.018		-0.032	
	(0.563)				(0.221)		(0.429)		(0.478)		(0.373)		(0.422)		(0.178)	
Deposits	0.212	***			0.216	**	0.199	**	0.172	**	0.21	**	0.197	**	0.229	***
	(0.009)				(0.013)		(0.017)		(0.035)		(0.011)		(0.017)		(0.009)	
Return on assets	0.034	***	0.034	***	0.042	***	0.036	***	0.034	***	0.035	***	0.035	***	0.041	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Tier-1-capital	-0.003	***	-0.003	***	-0.003	***	-0.003	***	-0.003	***	-0.003	***	-0.003	***	-0.003	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Liquidity	-8.245	***	-7.544	***	-9.705	***	-9.676	***	-7.654	***	-8.076	***	-7.749	**	-9.077	**
	(0.000)		(0.003)		(0.007)		(0.007)		(0.000)		(0.000)		(0.032)		(0.013)	
ΔCoVaR			0.000													
			(0.621)													
Regulatory environment																
Offical Supervisory Power					0.014	**									0.015	**
					(0.025)										(0.019)	
Private monitoring index							-0.029	***					-0.013	*	-0.028	***
							(0.000)						(0.051)		(0.001)	
Diversification index									-0.116	***			-0.095	***		
									(0.000)				(0.000)			
Entry requirements											-0.057	***	-0.053	***	-0.042	**
											(0.000)		(0.000)		(0.013)	
Fixed effects	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
N	10,032		9,112		8,687		9,670		9,835		9,762		9,580		8,567	
R^2	0.321		0.307		0.347		0.318		0.329		0.324		0.324		0.349	
Adj. R^2	0.319		0.305		0.345		0.316		0.327		0.322		0.322		0.347	

negatively affect bank performance. Blum (1999) shows that increasing capital requirements could also lead to increased risk-taking. Our result supports the conjecture that stock investors view higher capital ratios as being detrimental to a bank's ability to generate profits. However, this result is economically of marginal magnitude. We attribute this finding to the fact that while investors might consider high capital ratios undesirable in normal times, investors could, at the same time, favor stocks or highly capitalized banks during a financial crisis. Berger and Bouwman (2013) find empirical results in support of this line of argumentation as they show that capital helps banks to increase the probability of survival and their market share during crises periods. On average, however, we show for our full sample that high ratios of regulatory capital are seen critically by stock investors.

Next, we find that a bank's exposure to systemic risk is associated with a lower stock performance (model (1)). The result is also economically significant as a one standard deviation increase in our proxy for a bank's systemic risk exposure (MES) yields a decrease of the annual stock return of -3.7% (0.171×0.2172). This result is line with our intuition as a bank with a higher systemic risk exposure is hit harder in the event of a system-wide crash. In regression (2), we substitute the MES by the bank's estimate of ΔCoVaR as a measure of its contribution to systemic fragility. In contrast to our previous finding, a bank's contribution to systemic risk does not have any statistically significant impact on the institution's stock performance. Hence, our finding underlines that these two measures, even though both are associated with systemic risk, capture different aspects of systemic risk.

Additionally, we find strong evidence that supports the notion that size is negatively correlated with bank performance. As banking firms increase in size, so does their systemic importance and the implicit probability of a government bailout in case of default. These findings are in line with the results of Gandhi and Lustig (2015) who argue that size is a priced factor in the cross-section of bank stock returns due to implicit bailout guarantees. Furthermore, our findings are in support of Demirgüç-Kunt and Huizinga (2013) who argue that for large banks downsizing or splitting up might increase their value.

Additional results also show that high-valued stocks yield a lower buy-and-hold return than stocks with low valuation. This result is statistically significant at the 1% level, economically significant, and large, as a one standard deviation increase yields a decrease in performance of -56.3%. Further along, we control for differences in the banks' lagged performance and find evidence for reversal in the banks' returns. To be specific, we find that a bank's performance is negatively influenced by its lagged performance. Not surprisingly, banks that earn a high return on their assets also have a better annual stock performance. This effect is of large economic importance. A one standard deviation increase in return on assets implies an increase in the annual log buy-and-hold return of 36%. We also control for differences in the banks' stock liquidity. Underlining the findings of Han and Lesmond (2011), we find that an individual stock's illiquidity is negatively associated with its performance. Turning to a bank's business model, we find that by taking deposits, banks increase their annual buy-and-hold stock return in our sample period while giving loans decreases the annual stock return. We trace this back to the fact that loans are associated with a small profit margin and thus, banks with a large loan portfolio are realizing a decreased performance. Of major importance is the quality of the loan portfolio measured by loan loss provisions. As the quality of the loan portfolio decreases, so does the annual buy-and-hold return of the banking firm. The economic importance of this influence is large. Furthermore, banks with more deposits have a less fragile funding structure than, for example, banks that invest in overnight money market funds. As a result, deposits are associated with better stock performances. Surprisingly, neither a firm's degree of leverage nor its non-interest income has significant influence on the buy-and-hold returns in our large comprehensive panel. Also the amount of short-term funding measured by debt maturity has no significant influence on the performance.

In regressions (3) to (8), we add several variables that describe the banks' regulatory and supervisory environment to our models. In models (3) to (6), we start by adding one regulatory variable at a time while in models (7) and (8), we include more than one regulatory variable at the same time. As mentioned earlier, some of our regulatory variables are highly correlated both with each other and with our macroeconomic control variables. For example, the index of the Official Supervisory Power and the Diversification Index are negatively correlated with a correlation of -54%. As a consequence, we can only include one of these two variables in our regressions at a time. Additionally, we observe a strong negative correlation between variables that proxy for the supervisory environment of a country and country-specific controls such as GDP growth, inflation, and the Herfindahl-Hirschman index. To minimize multicollinearity problems, we do not use highly correlated variables simultaneously in a regression. In additional unreported regressions, we include the country control variables instead of our regulatory variables. The results on the idiosyncratic bank characteristics remain qualitatively unchanged.[41]

Turning to the influence of the regulatory and supervisory environment on a bank's annual buy-and-hold return, we find that with more supervisory power, the stock performance of banks increases. With increasing power of supervisors, banking problems are recognized earlier and corrected more promptly. In contrast, higher incentives for a better private monitoring are associated with a lower stock performance of banks. We argue that increased capabilities for the private sector to monitor banks are linked to additional efforts for the banking firms. Consequently, these additional cost lead to a worse stock performance. Another possible explanation for this result is that with more incentives for the private sector to monitor banks, banks are more cautious with their investment strategies and consequently earn lower profits.

Next, higher values of the Diversification index that captures the guidelines for asset diversification are also associated with a lower stock performance. Our results show that more asset diversification leads to a poorer stock performance of banks in our full sample. We argue that with stricter guidelines for asset diversification, banking firms lack a core business. At the same time, banks have better diversified asset portfolios.

[41] We do not report the additional results as the focus of our paper is on the influence of the regulatory and supervisory environment on banking performance.

Consequently, our findings support both lines of argumentation as with stricter guidelines for diversification, the stock performance of banks decreases.

Finally, we find evidence that additional legal entry requirements to obtain a banking license lead to a lower stock performance of banks in a given country. Ongena et al. (2013) argue that lower barriers to entry are associated with lower bank lending standards abroad. Hence, investors could be more cautious which in turn leads to smaller annual buy-and-hold returns.

In regressions (7) and (8), we include several variables that proxy for our sample countries' regulatory environments simultaneously and confirm our findings from the previous regressions. In additional unreported results, we include a dummy variable that captures the existence of a deposit insurance scheme in a given country. However, we find no convincing evidence of any influence of the variable on the annual stock performance of banks. Also, we study the influence of capital requirements captured by the Capital Regulatory Index introduced by Barth et al. (2013a) on a bank's stock performance. However, we do not find any convincing evidence that the annual buy-and-hold return is related to the stringency of capital requirements. Hence, we conclude that investors rather base their investment decisions on idiosyncratic bank characteristics than on country-level characteristics. Additionally, the Capital Regulatory Index captures capital stringency, but is not directly based on a required minimum capital ratio. In contrast, the variable Tier 1 capital captures a bank's actual amount of regulatory capital within a single (realized) ratio.

To further analyze this result, we split our sample into halves based on the banks' Tier 1 capital ratio in a given bank-year. The top half consists of all banks that feature Tier 1 capital ratios above the mean while the bottom half consists of all banks whose Tier 1 capital ratio is below the average. Our conjecture is that stock market investors favor banks that are not undercapitalized but divest from banks that hold too much capital relative to their competitors within a regulatory regime.

We then run separate panel regressions for each subsample using time-fixed and bank-fixed effects as well as clustered robust standard errors (at the bank level) to test this conjecture. The results of our additional panel regressions are shown in Table 4.6.

Table 4.6: Tier 1 capital and banks' stock performance.

The regressions estimate the relation between stock performance and bank characteristics as well as regulatory variables over the period 1999-2012. We use the banks' log annual buy-and-hold return as our dependent variable. The sample consists of 1,659 publicly traded international banks from 74 countries and is divided into two subsamples. The first subsample (Model (1)) consists of banks whose Tier 1 capital ratio is above the mean while the second subsample (Model (2)) consists of banks whose Tier 1 capital ratio is below the mean. Model (3) includes all banks for which a Capital Requirements Index realization is available. Stock market data are retrieved from *Thomson Reuters Financial Datastream* while financial accounting data are taken from the *Worldscope* database. Regulation variables come from Barth et al. (2013a) and country characteristics are retrieved from the World Bank's World Development Indicator (WDI) Database. The regressions include all banks from our sample and we apply panel regression with time-fixed and bank-fixed effects using clustered robust standard errors (at the bank level). P-values are given in parentheses, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Adj. R^2 is adjusted R-squared. Definitions of variables as well as descriptions of the data sources are given in Appendix C.1.

	Model (1)		Model (2)		Model (3)	
Sample	Top half Tier 1 capital		Bottom half Tier 1 capital		CRI Sample	
Bank-level characteristics						
Lagged return	-0.116	***	-0.178	***	-0.183	***
	(0.000)		(0.000)		(0.000)	
MES	-0.045		-0.289	***	-0.250	*
	(0.697)		(0.001)		(0.070)	
Beta	-0.143		-0.309	*	-0.455	**
	(0.171)		(0.071)		(0.017)	
Total assets	-0.214	***	-0.224	***	-0.401	***
	(0.000)		(0.000)		(0.000)	
Market-to-book	-0.125	***	-0.033	***	-0.112	***
	(0.000)		(0.005)		(0.000)	
Leverage	0.003	**	0		0.004	***
	(0.023)		(0.852)		(0.000)	
Non-interest income	-0.022		-0.003		-0.048	
	(0.496)		(0.860)		(0.440)	
Loans	-0.269	**	-0.208	*	-1.012	***
	(0.039)		(0.053)		(0.000)	
Loan loss provisions	-2.72	**	-1.544		-2.793	*
	(0.031)		(0.335)		(0.077)	
Deposits	0.137		0.266	*	1.025	***
	(0.280)		(0.070)		(0.000)	
Return on assets	0.024	**	0.048	***	0.046	***
	(0.016)		(0.001)		(0.004)	
Tier-1-capital	-0.002	***	0.003		0.778	
	(0.000)		(0.997)		(0.151)	
Liquidity	-8.082	***	-5.690		-15.036	*
	(0.000)		(0.302)		(0.066)	
Capital Requirement Deviation					-0.038	**
					(0.027)	
Fixed effects	Yes		Yes		Yes	
N	4,923		5,109		3,320	
R^2	0.389		0.329		0.404	
Adj. R^2	0.385		0.325		0.399	

We observe that Tier 1 capital ratios are negatively associated with annual buy-and-hold returns for banks that feature above-average regulatory capital ratios. At the same time, this result disappears for banks that demonstrate below-average capital ratios. Consequently, our results indicate that our finding of a negative relation between Tier 1 capital and banks' stock performance is mainly driven by banks with high Tier 1 capital ratios. At the same time, we find no evidence that below-average capital ratios increase bank performance. Another interesting result from the regressions based on subsamples is that a bank's stock performance is not related to its MES or Beta if the bank is highly capitalized (Model (1)). In this scenario, the default probability decreases and, consequently, different types of risk are no longer relevant for investors. However, as capital ratios decrease, both, MES and Beta, are negatively associated with banks' stock performance (Model (2)).

Next, we try to shed more light on the question whether the capitalization of banks relative to their competitors is priced by stock market investors. Irrespective of the overall capital requirements that affect all banks in a given country, investors could favor the stocks of those banks that hold more (or less) capital than the average competitor. To this end, we introduce the new variable *Capital Requirement Deviation* which we define in the following way. First, we calculate the mean of the variable Tier 1 capital for all banks with the same realization of the Capital Regulatory Index, or, more exactly, for all banks that face a similar capital stringency. In a second step, we calculate the differences between the individual banks' Tier 1 capital and the respective mean values for each bank. Hence, our variable Capital Requirement Deviation captures the extent to which a bank's capital deviates from the average of peers in the same CRI group, i.e., the average value of regulatory capital of banks within the same group of capital stringency.[42] We then repeat our baseline regression and additionally include the new variable Capital Requirement Deviation (Model (3)). We find a statistically significant (5% level) negative influence of the Capital Requirement Deviation

[42]Note that the Pearson correlation between the variables Tier 1 capital and the Capital Requirement Deviation is 38%.

on a bank's stock performance. At the same time, the previously observed influence of the variable Tier 1 capital disappears. The results on our other idiosyncratic bank characteristics remain qualitatively unchanged. Our results are thus strongly supportive of the notion that investors indeed value bank stocks based on their relative rather than their absolute capitalization. Banks that had more Tier 1 capital relative to their peers working under a similar capital stringency had significantly lower annual buy-and-hold returns. This result supports the argumentation of Calem and Rob (1999). The authors argue that the relationship between bank capital and risk is U-shaped.

4.3.2 Implicit bailout guarantees and bank stock performance

In additional analyses, we are interested in the relation between a bank's stock performance and possible implicit bailout guarantees. The results from our main regressions in Table 4.5 highlighted the significant influence of a bank's size on its stock performance. More precisely, we find that with increasing size measured by the logarithm of a bank's total assets, the annual buy-and-hold return of banking firms decreases. Also, we find evidence that an increased exposure to systemic risk measured by a bank's MES is associated with a declining stock performance. To further analyze the relation between a bank's stock performance and implicit bailout guarantees, we now turn to several additional regressions in which we focus on indicators of systemic risk and possible bailout guarantees. Again, to detect the determinants of a bank's stock performance, we estimate panel regressions with time-fixed and bank-fixed effects using standard errors clustered at the bank level. The results of our additional panel regressions are shown in Tables 4.7 and 4.8.

In our models (1) through (5) in Table 4.7, we run regressions that are very similar to our baseline regressions. In contrast to the regressions in the previous section, however, we also include our proxy for an individual bank's interconnectedness with the financial sector in the regressions. Just like with bank size, we expect more interconnected banks to be more systemically important (see also Chan-Lau, 2010) and thus provide

Table 4.7: Regressions of a bank's stock performance and interconnectedness.

The regressions estimate the relation between stock performance and a bank's interconnectedness with other banks, bank characteristics, and regulatory variables over the period 1999-2012. We use the banks' log annual buy-and-hold return as our dependent variable. The sample consists of 1,659 publicly traded international banks from 74 countries. Stock market data are retrieved from *Thomson Reuters Financial Datastream* while financial accounting data are taken from the *Worldscope* database. Regulation variables come from Barth et al. (2013a) and country characteristics are retrieved from the World Bank's World Development Indicator (WDI) Database. The regressions include all banks from our sample and we apply panel regression with time-fixed and bank-fixed effects using clustered robust standard errors (at the bank level). P-values are given in parentheses, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Adj. R^2 is adjusted R-squared. Definitions of variables as well as descriptions of the data sources are given in Appendix C.1.

Variable	Model (1)		Model (2)		Model (3)		Model (4)		Model (5)	
Bank-level characteristics										
Lagged return	-0.201	***	-0.189	***	-0.214	***	-0.199	***	-0.21	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
MES	-0.187	**	-0.2	***	-0.165	**	-0.189	**	-0.19	**
	(0.015)		(0.010)		(0.034)		(0.015)		(0.017)	
Total assets	-0.218	***	-0.228	***	-0.219	***	-0.233	***	-0.224	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Market-to-book	-0.049	***	-0.048	***	-0.046	***	-0.048	***	-0.042	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.001)	
Leverage	0.000		0.000		0.000		0.000		0.000	
	(0.995)		(0.912)		(0.982)		(0.716)		(0.738)	
Non-interest income	-0.009		-0.003		-0.013		-0.01		-0.004	
	(0.734)		(0.907)		(0.643)		(0.712)		(0.893)	
Loans	-0.368	***	-0.338	***	-0.349	***	-0.355	***	-0.348	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Loan loss provisions	-2.93	**	-2.408	*	-3.216	**	-2.904	**	-2.822	**
	(0.018)		(0.059)		(0.013)		(0.024)		(0.030)	
Debt maturity	0.01		0.006		0.008		0.005		0.008	
	(0.704)		(0.820)		(0.766)		(0.837)		(0.771)	
Deposits	0.244	***	0.242	***	0.211	**	0.247	***	0.25	***
	(0.008)		(0.010)		(0.021)		(0.008)		(0.007)	
Return on assets	0.037	***	0.04	***	0.039	***	0.039	***	0.041	***
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)	
Tier-1-capital	-0.004	***	-0.003	***	-0.003	***	-0.003	***	-0.003	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Liquidity	-10.679	***	-11.287	***	-9.678	***	-10.568	***	-9.442	**
	(0.002)		(0.008)		(0.005)		(0.003)		(0.029)	
Interconnectedness	-0.181	**	-0.17	**	-0.195	***	-0.17	**	-0.163	**
	(0.014)		(0.023)		(0.008)		(0.020)		(0.028)	
Regulatory environment										
Private monitoring index			-0.044	***					-0.031	***
			(0.000)						(0.000)	
Diversification index					-0.098	***			-0.07	***
					(0.000)				(0.003)	
Entry requirements							-0.066	***	-0.064	***
							(0.000)		(0.000)	
Fixed effects	Yes		Yes		Yes		Yes		Yes	
N	8,078		7,768		7,902		7,843		7,696	
R^2	0.34		0.337		0.347		0.342		0.344	
Adj. R^2	0.338		0.335		0.345		0.339		0.341	

weaker stock performance. Our results provide strong evidence that more interconnected banks realize a smaller annual buy-and-hold stock return than other banks. The results are statistically (at the 5% level) and economically significant. Again, we find support for the notion that investors view more interconnected banks to have an increased probability of receiving a government bailout (see also Bertray et al., 2013).

Next, we analyze in more detail the question whether different indicators of systemic risk also drive banks' stock performance. One could argue that the sheer size of a banking firm as it is captured by the logarithm of a bank's total assets is not the best indicator to measure whether the institution is too-big-to-fail. For example, Bertray et al. (2013) propose to use the systemic size of an institution rather than its total assets as a proxy for systemic relevance. The authors use the ratio of liabilities over GDP to identify systemically important banks. Table 4.8 shows the results of our analyses in which we employ systemic size as an alternative proxy for the systemic importance of a bank.

In models (1) through (8), we replace the variable Total assets by the variable Systemic size. Interestingly, we cannot find any statistical evidence that the Systemic size of a banking firm has influence on the stock performance of the institution. Our other results remain qualitatively unchanged. This result underlines the findings by Bertray et al. (2013) who argue that investors distinguish between banks' absolute size and systemic size. However, the variable systemic size also captures the costs of a bailout for the government. Hence, the variable systemic size additionally measures the degree to which a country is affected by a possible bailout of a banking firm in case of financial distress. As a consequence, the systemic size of a bank captures two contra-directional features. Accordingly, the variable does not significantly influence the annual buy-and-hold return of a bank

In models (3) and (4), we additionally include a variable that measures the quality of the corporate governance of a given country. The variables are calculated using the Worldwide Governance Indicators provided by the World Bank. The variable Governance is an arithmetic mean of the six indicators on Corporate Governance provided by the World bank. However, a better index of Corporate Governance might consist of some underlying commonality found in the six indicators. Consequently, we perform a principal component analysis to extract the common factor of the individual indicators and include the variable Governance (pca) in an additional regression. Regardless of the calculation method of the index we include to measure the quality of the corporate governance in a country, we find evidence for the notion that better corporate governance yields better stock performance. Consequently, we find evidence that supports the hypothesis that a better corporate governance environment allows banks to run their business more soundly and solidly, which in turn results in higher annual buy-and-hold returns.

Table 4.8: Systemic size and bank's stock performance.

The regressions estimate the relation between stock performance and bank characteristics as well as regulatory variables over the period 1999-2012. We use the banks' log annual buy-and-hold return as our dependent variable. The sample consists of 1,659 publicly traded international banks from 74 countries. Stock market data are retrieved from *Thomson Reuters Financial Datastream* while financial accounting data are taken from the *Worldscope* database. Regulation variables come from Barth et al. (2013a) and country characteristics are retrieved from the World Bank's World Development Indicator (WDI) Database. The regressions include all banks from our sample and we apply panel regression with time-fixed and bank-fixed effects using clustered robust standard errors (at the bank level). P-values are given in parentheses, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Adj. R^2 is adjusted R-squared. Definitions of variables as well as descriptions of the data sources are given in Appendix C.1.

Variable	Model (1)		Model (2)		Model (3)		Model (4)		Model (5)		Model (6)		Model (7)		Model (8)	
Bank-level characteristics																
Lagged return	-0.129	***	-0.141	***	-0.131	***	-0.131	***	-0.082	***	-0.112	***	-0.138	***	-0.123	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
MES	-0.233	***			-0.224	***	-0.229	***	-0.203	***	-0.25	***	-0.201	***	-0.241	***
	(0.001)				(0.001)		(0.001)		(0.005)		(0.000)		(0.005)		(0.001)	
Beta	-0.392	***	-0.398	***	-0.384	***	-0.388	***	-0.284	***	-0.411	***	-0.374	***	-0.39	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.001)		(0.000)		(0.000)		(0.000)	
Systemic size	-43.847		-36.983		-40.431		-50.773		-199.782	**	-119.369		-77.285		-101.203	
	(0.280)		(0.346)		(0.341)		(0.201)		(0.049)		(0.161)		(0.398)		(0.225)	
Market-to-book	-0.049	***	-0.046	***	-0.047	***	-0.049	***	-0.063	***	-0.047	***	-0.045	***	-0.047	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Leverage	0.000		0.000		0.000		0.000		0.000		0.000		0.000		0.001	
	(0.694)		(0.696)		(0.725)		(0.704)		(0.700)		(0.659)		(0.635)		(0.434)	
Non-interest income	-0.011		-0.013		-0.012		-0.011		-0.001		-0.01		-0.019		-0.013	
	(0.536)		(0.591)		(0.502)		(0.521)		(0.953)		(0.573)		(0.275)		(0.453)	
Loans	-0.259	***	-0.233	***	-0.254	***	-0.24	***	-0.165	**	-0.238	***	-0.243	***	-0.251	***
	(0.000)		(0.004)		(0.001)		(0.001)		(0.035)		(0.002)		(0.001)		(0.001)	
Loan loss provisions	-2.162	**	-2.44	***	-2.223	***	-2.076	**	-1.883	*	-1.915	**	-2.781	***	-2.369	***
	(0.011)		(0.006)		(0.009)		(0.016)		(0.067)		(0.032)		(0.002)		(0.009)	
Deposits	0.434	***	0.423	***	0.42	***	0.426	***	0.413	***	0.409	***	0.38	***	0.433	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Return on assets	0.032	***	0.033	***	0.032	***	0.032	***	0.038	***	0.033	***	0.032	***	0.033	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Tier-1-capital	-0.003	***	-0.003	***	-0.003	***	-0.003	***	-0.003	***	-0.003	***	-0.003	***	-0.003	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Liquidity	-8.467	***	-9.205	***	-8.413	***	-8.539	***	-12.245	***	-12.008	***	-8.091	***	-8.389	***
	(0.000)		(0.001)		(0.000)		(0.000)		(0.001)		(0.001)		(0.000)		(0.000)	
ΔCoVaR			0.000													
			(0.960)													
Regulatory environment																
Governance (pca)					0.033	**										
					(0.042)											
Governance							0.102	*								
							(0.077)									
Official Supervisory Power									0.014	**						
									(0.020)							
Private monitoring Index											-0.033	***				
											(0.000)					
Diversification Index													-0.129	***		
													(0.000)			
Entry requirements															-0.051	***
															(0.000)	
Fixed effects	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
N	10,149		9,108		10,149		10,149		8,793		9,782		9,951		9,875	
R^2	0.307		0.294		0.307		0.307		0.335		0.304		0.316		0.308	
Adj. R^2	0.305		0.292		0.305		0.305		0.333		0.302		0.314		0.306	

4.3.3 Banks' stock performance during crises times

Our analyses so far have revealed strong correlations between bank capital, bank size, and bank stock performance. As mentioned above, however, these effects could differ significantly during times of financial crisis. As a result, we now turn to an in-depth analysis of the factors that drive a bank's performance during turbulent times. Complementing the main regressions discussed in the previous subsections, we also investigate the robustness of our results during crisis- and non-crisis times, respectively. To identify periods of financial crisis, we rely on the new database on systemic banking crises provided by Laeven and Valencia (2012). We then perform several regressions in which we employ the same set of variables as in Table 4.5 but additionally include a dummy variable that takes on the value one if a country experienced a financial crisis in a given year, and zero otherwise. Moreover, we include several interaction terms with our crisis dummy to test the differential effect of several explanatory variables on bank performance during and outside of crises. Again, we estimate panel regressions of the annual buy-and-hold return with clustered robust standard errors (at the bank level) as well as time-fixed and bank-fixed effects. The results are presented in Table 4.9.

Models (1) through (5) in Table 4.9 provide us with first evidence on the effect of turbulent times on a bank's performance. The results show that during crisis periods, a higher Tier 1 capital ratio significantly increased a bank's stock performance. The result is economically significant and large. A one standard deviation increase in Tier 1 capital yields an increase in the dependent variable of 84%. Thus, while a higher Tier 1 capital yields only a marginal decrease in stock performance during calm times, during turbulent times, a higher Tier 1 capital ratio induces a significantly better stock performance. This result supports the argumentation that Tier 1 capital shields banks from adverse effects spilling over from the financial sector to individual institutions. Also, this result is in line with the argumentation of Berger and Bouwman (2013) that banks with more capital also have a higher probability of survival, a possibly higher

Table 4.9: Bank-specific and regulatory interactions.

The regressions estimate the relation between stock performance and bank characteristics, a bank's interconnectedness with other banks, and regulatory variables over the period 1999-2012. Table 4.5 reports the results of our baseline regressions over the period 1999-2012 using banks' log annual buy-and-hold return as our dependent variable. In addition to our multivariate analyses, we include several interaction terms. The sample consists of 1,659 publicly traded international banks from 74 countries. Stock market data are retrieved from *Thomson Reuters Financial Datastream* while financial accounting data are taken from the *Worldscope* database. Regulation variables come from Barth et al. (2013a) and country characteristics are retrieved from the World Bank's World Development Indicator (WDI) Database. The regressions include all banks from our sample and we apply panel regression with time-fixed and bank-fixed effects clustered robust standard errors (at the bank level). P-values are given in parentheses, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Adj. R^2 is adjusted R-squared. Definitions of variables as well as descriptions of the data sources are given in Appendix C.1.

Variable	Model (1)		Model (2)		Model (3)		Model (4)		Model (5)	
Bank-level characteristics										
Tier-1-capital	-0.003	***	-0.003	***	-0.003	***	-0.003	***	-0.003	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Leverage	0.000		0.005	***	0.000		0.000		0.000	
	(0.542)		(0.000)		(0.749)		(0.786)		(0.963)	
Debt maturity	-0.014		-0.012		-0.015		-0.019		0.012	
	(0.539)		(0.593)		(0.504)		(0.402)		(0.620)	
Loans	-0.270	***	-0.274	***	-0.273	***	-0.149	*	-0.318	***
	(0.000)		(0.000)		(0.000)		(0.060)		(0.000)	
Interconnectedness									0.028	
									(0.685)	
Crisis	-0.079	***	0.113	***	0.008		0.300	***	0.006	
	(0.003)		(0.000)		(0.747)		(0.000)		(0.799)	
Interactions										
Tier-1-capital × Crisis	1.238	***								
	(0.000)									
Leverage × Crisis			-0.006	***						
			(0.000)							
Debt maturity × Crisis					0.005					
					(0.904)					
Loans × Crisis							-0.421	***		
							(0.000)			
Interconnect. × Crisis									-0.911	***
									(0.000)	
Bank-level controls	Yes		Yes		Yes		Yes		Yes	
Fixed effects	Yes		Yes		Yes		Yes		Yes	
N	10,032		10,032		10,032		10,032		8,078	
R^2	0.323		0.328		0.321		0.324		0.345	
Adj. R^2	0.321		0.326		0.319		0.322		0.343	

market share, and thus a better stock performance.

Further along, we find that while Leverage does not have a significant influence on a bank's stock performance over the whole sample period, during crisis times, more highly levered banks realize a significantly lower return than other banks. The economic significance of this result is large (66.5% decrease in our dependent variable for a one standard deviation increase in leverage). This finding is also underlined by Fahlenbrach et al. (2012) who confirm that the leverage of a bank had a negative influence on the bank's stock performance during the financial crisis. One possible explanation for this finding could be that banks with higher leverage also had a more fragile funding and were thus more vulnerable during the recent crisis. However, we find no statistical evidence that a bank's debt maturity is significantly related to a bank's annual buy-and-hold return.

While we find some evidence for our full sample that banks with more loans in their portfolio realize smaller annual buy-and-hold stock returns, this effect is even more pronounced during crises times. We find strong empirical evidence (significant at the 1% level) that banks with more loans have significantly lower stock returns during a crisis. The result is also economically significant and in line with the results of Cihák et al. (2012) who find that for the global financial crisis, countries had less stringent regulations on the treatment of bad loans. Also, the finding underlines the argumentation of Engle et al. (2014) who argue that leverage is more serious when the economy is weak.

Finally, we analyze the relation between the interconnectedness of a bank with other banking firms during times of a financial crisis. We show that during crisis times, a bank's stock performance decreases significantly as its interconnectedness increases. Again, this result is significantly more pronounced during crisis times than for the complete sample period. In line with our intuition, this evidence highlights the importance of interconnectedness among financial institutions during crises. As interbank linkages are to some degree unknown, for highly interconnected firms the risk of contagion increases during crises periods. To be specific, only direct linkages to other banks are known, while information about linkages of higher degrees are rare. As a result, with increasing interconnectedness a bank's stock performance decreases.

4.4 Conclusion

In this paper, we investigate the effects of bank capital, bank regulation, and supervision on banks' stock performance. We analyze a comprehensive panel of international banks over the period of 1999-2012 with 11,803 bank-year observations from 1,659 banks in 74 countries. We employ panel regressions to study the determinants of each bank's annual buy-and-hold return using bank-specific as well as country-specific and regulatory explanatory variables.

The key result of our empirical study is that higher regulatory capital in the form of Tier 1 capital is negatively related to the banks' stock performance over our complete sample period from 1999 to 2012. However, during turbulent times, higher regulatory capital significantly increases a bank's annual stock performance. In addition, we find evidence that supports the notion that implicit government bailout guarantees decrease bank stock performance. To be specific both, a bank's size measured by its total assets and a bank's interconnectedness with other banking firms, are related to weaker stock performance. Furthermore, we find evidence that better supervision and corporate governance are beneficial to bank stock performance. At the same time, schemes supporting the private monitoring of banks are negatively related to annual buy-and-hold returns.

The implications of our results are twofold. First, while higher bank capital indeed decreases overall bank performance, this result is of marginal magnitude. However, as higher Tier 1 capital ratios significantly increase performance during crisis times, regulation appears to be on the right track, increasing regulatory capital requirements around the world since the recent financial crisis. Finally, we confirm in our panel setup that size and systemic relevance of banks negatively influence banks' stock performance. In line with earlier findings in the literature, bank stock returns are significantly lower for larger and systemically more important banks that are more likely to receive a government bailout.

Chapter 5

Crisis Sentiment and Insurer Performance

"The financial crisis generally had a limited effect on the insurance industry [...]. Aggregate stock prices of publicly traded life insurers [...] had declined by a total of 79 percent by February 2009."

United States Government Accountability Office, 07/29/2013

5.1 Introduction

Looking back at the recent financial crisis, it appears that not only shareholders of banks but also investors of insurer stocks were hit hard by the turmoil in international stock markets. In fact, insurer stocks suffered even higher losses than stocks of banks. The question remains what exactly caused stocks of insurers to experience such massive declines (see Figure D.1 in Appendix D for a comparison of the stock returns of banks and insurers in the U.S. during the financial crisis). In this paper, we analyze whether the abnormally high losses on insurer stocks during the financial crisis can be explained by investor sentiment that intensified during the financial crisis. More precisely, we argue that investors were measuring both banks and insurance companies by the same yardstick during the crisis and exited stock investments of financial institutions indiscriminately and regardless of the institutions' actual exposure to the crisis. If this were the case, investors would have been punishing insurers beyond the degree to which they were actually exposed to the adverse effects of a crisis that originated from the banking sector. We find that market-level crisis sentiment was a highly significant predictor of stock performance between 2004 and 2012. During the financial crisis, market-level crisis sentiment affected the performance of all insurers while idiosyncratic crisis sentiment (negatively) influenced the stock performance of large insurers. Our results imply that investors exited insurer stocks mainly due to irrational crisis sentiment rather than a rational assessment of the insurers' actual exposure to the crisis.

Intuitively, we would expect insurers to suffer to a lesser extent than banks during a financial crisis for several reasons: First, insurers are neither vulnerable to bank runs by depositors (see Diamond and Dybvig, 1983) and creditors (see Duffie, 2010, Gorton and Metrick, 2012) nor to liquidity shortages arising from the interbank market as seen during the financial crisis. On the contrary, insurer stocks should experience a flight to quality during an episode of turmoil in the financial sector as investors exit their investments in volatile bank stocks. However, the recent financial crisis has seen dramatic losses on the stocks of insurers worldwide. Insurer performance is clearly influenced by a multitude of determinants which have been thoroughly discussed in the literature. He and Sommer (2011) investigate the impact of ownership structure, i.e., mutual versus stock ownership, on the relation between firm performance and CEO turnover in the U.S. property-liability insurance industry. Similarly, Mayers and Smith (2010) establish a connection between board structure and the extent to which executive compensation is linked to the performance of mutual insurers. They find that dysfunctional managerial incentives can be controlled through governmental mechanisms. Berry-Stölzle et al. (2013) look at the effect of product diversification on performance of insurers and find it to be heterogeneous across countries and dependent on company size. Looking at the relationship of market structure and the performance in property-liability insurers, Choi and Weiss (2005) come to the conclusion that a higher insurance market concentration leads to lower prices and higher profits and that both cost and revenue efficiency have considerable influence on firm performance. Most of the existing literature on insurer performance is restricted to the U.S. market, with few exceptions such as Renbao and Wong (2004), who focus on the financial health of Asian property-liability and life insurance companies. In a related study, Lai and Limpaphayom (2003) examine the effects of organizational structure on performance in the Japanese non-life insurance industry. The latter find that the keiretsu[43] form of organization increases insurer performance. Complementing these findings, an alternative explanation for the bad performance of insurers during the crisis could be that investors were driven by extreme bearish sentiment together with high uncertainty regarding a respective insurer's involvement in the credit derivatives market. This investor sentiment might also have been increased during the financial crisis by the near-collapse of American International Group, which led to a reassessment of the insurance sector's potential to cause systemic risk.

In this paper, we argue that insurer performance during the financial crisis was significantly driven by irrational components such as general negative investor sentiment. To proxy for an individual insurer's susceptibility to the adverse effects of the crisis as perceived by market investors, we propose two new measures of "crisis sentiment". First, we extend the FEARS index of Da et al. (2015) and propose to use the first principal component of several Google search volumes for crisis-related queries (e.g., "financial crisis", "subprime crisis") to measure the level of market-wide crisis sentiment. To measure the extent of idiosyncratic crisis sentiment, we improve the investor attention proxy of Da et al. (2011) based on Google Trends data to obtain a measure for the correlation of the search volume of individual insurers' ticker symbols with search terms such as "bank crisis", "financial crisis" or "credit crisis". Thus, we extend the original idea of Da et al. (2011) by measuring not only the amount of attention paid to the insurance market by investors, but the degree to which investors are negatively

[43] *Keiretsu* refers to the corporate structure of a company that is closely tied to a bank that provides debt financing and owns a considerable part of the company's equity, see Lai and Limpaphayom (2003).

influenced by the financial crisis in their perception of the insurance market. We estimate our proposed measure of crisis sentiment for a sample of international insurance companies and carry out regressions of the stock performance of global insurers before, during and after the financial crisis on the two new measures of crisis sentiment and various control variables. Most importantly, we control for the insurers' individual exposure to losses in the financial sector's aggregate stock prices by using the Marginal Expected Shortfall (MES) measure of Acharya et al. (2010).

Our results show that our measure of market-level (or general) crisis sentiment significantly predicts an insurer's quarterly buy-and-hold returns.[44] Higher values of general crisis sentiment induce a worse stock performance of insurers in the following quarter. As we control for both the insurer's exposure to systemic risk (proxied by their Marginal Expected Shortfall) and the crisis-related downturn of the general economy (measured by the GDP growth and inflation rates), we find robust evidence that the extreme losses on insurer stocks during the crisis were indeed due to (irrational) bearish investor sentiment. In contrast, we find that idiosyncratic crisis sentiment is only significant in the regressions of the stock performance of large insurers during the crisis. Consequently, (retail) investors did indeed act on the sentiment of a general economic downturn rather than a differential and rational assessment of the idiosyncratic exposure of insurers to the crisis.

Our paper is related to few but influential previous studies on the usefulness of internet search data.[45] Ginsberg et al. (2009) were among the first to use search engine queries to detect health trends and predict influenza epidemics. In an economic context, the usefulness of Google search volume data for portfolio diversification and investment strategies has recently been investigated by Kristoufek (2013) and Preis et al. (2013). Methodically, our empirical approach differs from theirs in that we make use

[44] In contrast to related studies on investor sentiment (see, e.g., Tetlock, 2007, Da et al., 2011), we concentrate in this study on quarterly buy-and-hold returns rather than daily stock returns. In this way, our results are immediately comparable to related studies by Beltratti and Stulz (2012) and Fahlenbrach et al. (2012) on the stock performance of banks during the financial crisis.

[45] As noted by Choi and Varian (2009), search data from Google may have the potential to describe interest in a variety of economic variables.

of the search volume index (SVI) provided by Google Trends while Ginsberg et al. (2009) compute a time series of weekly counts for the most common search queries themselves. The usefulness of quantifying internet search behaviour has also been studied in the finance literature, most notably through the work of Da et al. (2011) and Da et al. (2015). In the latter, the authors also study investor sentiment measured through internet search behaviour but focus on the pricing of financial assets. Their approach resembles ours with respect to the construction of a new index of investor sentiment. Their so called FEARS index is based on the SVI of sentiment revealing search terms such as “recession” or “bankruptcy”, which they find to increase in the years around the financial crisis. However, Da et al. (2015) focus on the effect investor sentiment has on asset prices, volatility and fund flow from equity mutual funds to bond funds. Our paper differs significantly from previous studies, however, as we measure the correlation between two sets of search terms and provide the first use of big data from Google in the empirical insurance literature. In addition, our work also complements the findings on the relation between investor mood and asset prices (see, e.g., Shu, 2010). But instead of using mood proxies, such as biorhythms or whether, we employ a direct measure of the bearish sentiment of investors. Finally, our paper is also related to the recent study by Wisniewski and Lambe (2013) which examines the impact of negative media speculation on the performance of bank sector indices. In contrast to their paper, we refine the notion of negative sentiment by analyzing crisis sentiment and concentrate on the performance of individual insurers rather than the whole financial sector.

The rest of our paper is structured as follows. In Section 5.2, we briefly describe the construction of our data sample, followed by an outline of the measures we employ to proxy for insurer performance. We then explain how we build our two measures of crisis sentiment and describe the control variables that have been shown to influence insurer performance. Section 5.3 presents the results of our analysis into the question whether insurer performance during the crisis was driven by crisis sentiment. Section 5.4 concludes.

5.2 Data and variables

5.2.1 Sample selection

We study the hypothesis that insurer stock performance during the financial crisis was driven by crisis sentiment in a comprehensive cross-country analysis. Using a sample of international insurers in our empirical study is instructive for several reasons. First, we strongly expect crisis sentiment to vary significantly across countries due to cross-country differences in internet availability and usage. As such, we expect the effect of crisis sentiment on insurer stock performance to be attenuated in countries with fewer internet users and vice versa. Second, we also expect crisis sentiment to have a differential effect on the performance of insurers in the U.S. (being the country the financial crisis originated from) and Non-U.S. countries.

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 our investigation it is essential for an insurer to be large enough in terms of total assets to receive sufficient attention by retail investors on the internet. We therefore exclude all insurers with less than $ 1 billion of total assets. We then omit all firms for which stock price data is unavailable in *Datastream*. Next, we eliminate all secondary listings and nonprimary issues from our sample. Finally, we also 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.

5.2.2 General crisis sentiment

In the early works on asset pricing and efficient markets, it is regularly assumed that new information is immediately processed by investors and priced. In reality, however, the limited attention investors can allocate to an asset (see Kahnemann, 1973) raises severe doubts about the validity of the assumption of the instantaneous pricing of information. There now exists an extensive literature on the effects of limited information and heterogeneous investor attention and asset pricing (see, e.g., Merton, 1987, Gervais et al., 2001, Sims, 2003, Hirshleifer and Teoh, 2003, Grullon et al., 2004, Seasholes and Wu, 2007, Barber and Odean, 2008, Hou et al., 2009). While most of these studies relied on indirect measures of investor attention, recent work has used data based on Google search volumes to directly measure investor attention (see Da et al., 2011, 2015). Closely related to investor attention, asset prices could also be driven by investor sentiment. If uninformed noise traders base their investment decisions on sentiment rather than rational information, changes in investor sentiment and pessimism will be reflected in asset prices (see De Long et al., 1990) if not in the long run, then at least in the short run (see Kogan et al., 2006, 2011).[46] As such, extreme noise trading brought on by the financial crisis might have been responsible for the extreme downward price movements in insurer stocks.

In this paper, we propose a direct measure of the pessimistic investor sentiment caused by the financial crisis. We argue that the media coverage of the financial distress at banks during the crisis urged noise traders to exit investments in insurer stocks even though these divestitures may not have been justified by an increased default probability of insurers. Moreover, if uninformed traders suspected insurers to be similarly exposed as banks to runs in the money market (see Gorton, 2010) and counterparty risk in credit derivatives markets, missing too-big-to-fail guarantees in insurance could have additionally driven investors to sell the shares of insurers. To measure investor sentiment towards the vulnerability of insurers to the banking crisis, we use the *Google Trends* analytics tool. *Google Trends* allows the user to download (normalized) data on the weekly search volume for a given word or list of words.[47] First, we obtain the Google Search Volume Index (GSVI) for multiple search terms related to the financial

[46] In fact, Tetlock (2007) shows that high media pessimism does not only explain contemporaneous stock returns, but also predicts downward stock price movements which are followed by a reversion to fundamentals.

[47] The graphical output of the Google Trends Analytics tool is illustrated in Figure D.2 in Appendix D.

crisis. The GSVI measures the number of searches for a given term relative to the total amount of searches on Google over a given time period as a proxy for investor attention. As the naming of the financial crisis evolved through the years, just like the crisis evolved from a relatively limited crisis in the subprime lending sector to a global financial crisis, we collect data on several variations of the search term “financial crisis”. In particular, we use the words “financial crisis”, “credit crisis”, “subprime crisis” and “bank crisis”.[48] We do not use more general, negatively connotated terms, like Da et al. (2015), since we are specifically interested in investors’ (irrational) perception of the effect the crisis had on individual insurers’ stock returns. Following the approach of Baker and Wurgler (2006), the observations of the GSVI for these search terms are then used in a principal component analysis. More precisely, we first employ the 52 weekly GSVI values of the four crisis-related search terms in the year 2004 and estimate the first principal component of the four time series. The resulting values of the first principal component are then used to proxy for the Google search volume of crisis-related search terms during the year 2004. To estimate the GSVI of crisis-related terms in each remaining week in our sample, we use rolling windows that are enlarged by one week after each estimation (i.e., the principal component analysis used to compute the first principal component in week t is performed on data for weeks one through week t). Obviously, the principal component analysis could have also been performed on our complete data set. The estimation procedure described above, however, guarantees that the time series of the first principal component of crisis-related search terms does not suffer from a look-ahead bias. Then, let Z_t be the resulting value of the first principal component of the GSVI of the four search terms at time t, scaled to the range of 0 to 100.[49] We then consider the estimate of Z_t to be our primary proxy for the general crisis sentiment of investors. The time evolution of the market-level crisis sentiment Z_t together with the GSVIs of the four original search terms is shown

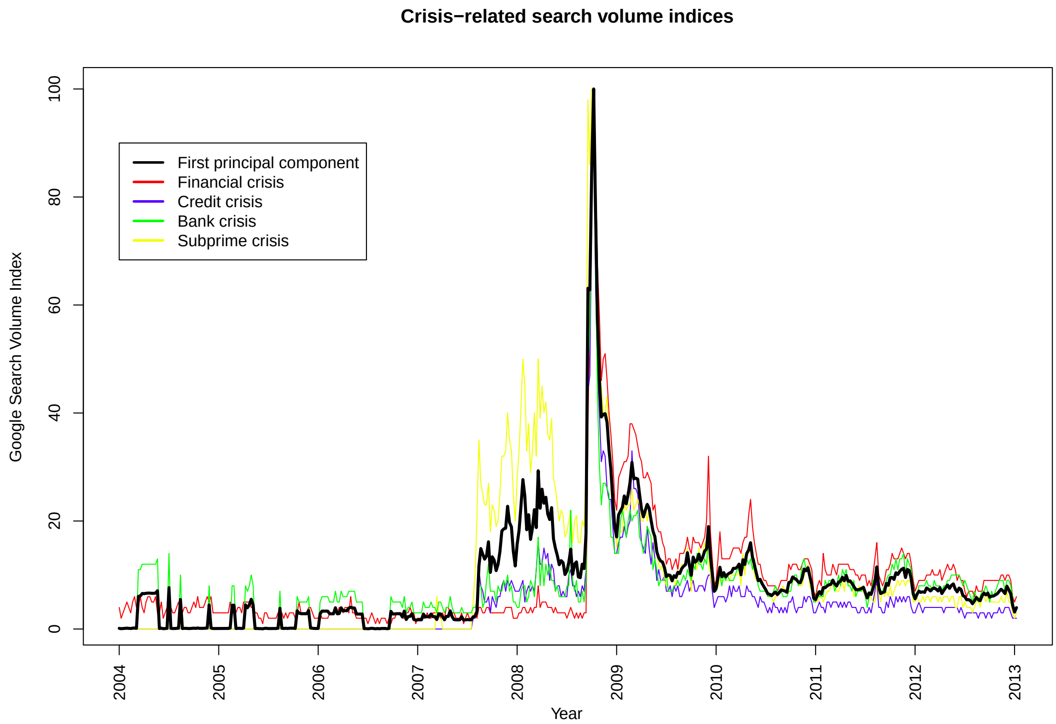
[48] Note that we do not use search terms that differ only marginally from the terms we use like, e.g., “the financial crisis” or “banking crisis”. As these alternative terms are highly correlated with the terms we employ in our empirical study, we restrict Google searches to the small set of terms mentioned above.

[49] The scaling is done as in the Google Trends tool through dividing by the maximum value of the series and then multiplying by 100.

in Figure 5.1.

Figure 5.1: Google search volume indices for "financial crisis" and related search terms.

The figure shows the plots of the five Google Search Volume Indices from 2004 to the end of 2012 for the search terms "financial crisis", "credit crisis", "subprime crisis", "bank crisis" and the first principal component of the four indices. The principal component is iteratively calculated using an enlarging window, starting with the values of the year 2004 and then scaled to the range of 0 to 100. All data are taken from *Google Trends*.



Two observations from Figure 5.1 are noteworthy: First, and not surprisingly, crisis sentiment increased in summer 2007 and rose steeply around the collapse of Lehman Brothers in 2008. Nevertheless, search volume indices also varied significantly before and after the collapse of Lehman. Second, differences between the GSVI of the individual search terms can be quite high as evidenced, e.g., by the high search volumes for "subprime crisis" in late 2007 and early 2008 thus underlining the need to consolidate the search volume data via our principal component analysis.

5.2.3 Crisis Sentiment Index

Whereas our proxy for the general crisis sentiment as constructed above is supposed to capture the overall angst of investors towards the financial crisis, we additionally introduce a measure of the relation between individual insurers and the financial crisis as perceived by investors.

We follow Da et al. (2011) and retrieve weekly data from *Google Trends* on the GSVI for each insurer for the time period between 2004 and 2012 using the firm's ticker symbol as the search query (our retrieval of Google data parallels the approach by Da et al., 2011).[50] Although Google Trends allows to retrieve search results for specific regions, we conduct world-wide searches as we want to capture international investors' attention to insurers. Moreover, as the GSVI does not provide the search volume in total, but in relative terms, measuring investors' attention countrywise would make comparisons between individual countries difficult. Next, we estimate time-varying correlations ρ_t^i between the general crisis sentiment Z_t and the search volume index $GSVI_t^i$ of insurer i. We follow Da et al. (2011) and compute $GSVI_t^i$ using insurer i's ticker symbol and, if only a numeric ticker symbol was available, the insurer's company name as given in *Datastream* as search terms in Google Trends. To avoid a possible look-ahead bias in the estimation of the correlations, we estimate ρ_t^i using rolling windows of length 52 weeks using data up to week t (the rolling windows are skipped ahead one week for each estimation). Finally, we construct our *Crisis Sentiment Index (CSI)* by combining the dynamic correlation between the first principal component Z_t and a firm's $GSVI_t^i$, multiplying the estimated correlation with the sum $(GSVI_t^i + Z_t)$ and then dividing the resulting term by 200:

$$CSI_t^i := \left(\frac{GSVI_t^i + Z_t}{200} \right) \cdot \rho_t^i. \tag{5.1}$$

This specific construction of the CSI accounts for several issues. First, by employ-

[50] In case the ticker symbol was ambiguous, most notably Japan, official company names instead of ticker symbols are used in Google Trends to retrieve the GSVI.

ing the time-varying correlations of the first principal component and the normalized search volume index of the firms we capture the time variation in the crisis-related attention retail investors and noise traders (together with the general public) paid to the insurance firms in our sample. This correlation, however, does not provide us with any information on the actual level of the search volumes in a given week. As such, it could be that both the insurer's GSVI and the crisis-related search terms are highly correlated simply because both their search volume indices were zero. We correct this issue in equation (5.1) by multiplying the dynamic correlation with the sum of the indices and the scaling factor of $\frac{1}{200}$ (each of the two GSVIs has a range of 0 to 100).

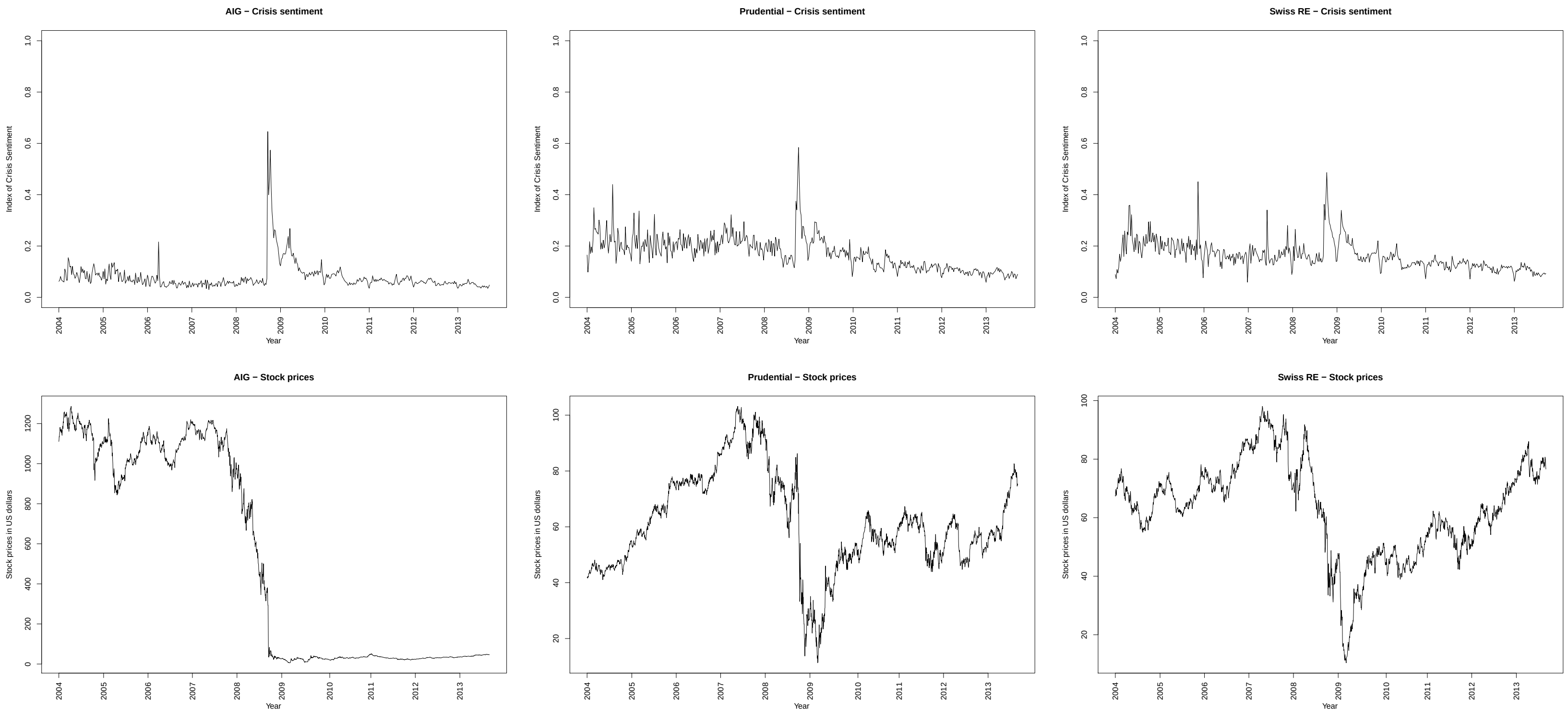
In Figure 5.2, we plot the estimated values of the Crisis Sentiment Index of three global insurers (AIG, Prudential and Swiss RE) against the stock (mid) prices of the three respective insurers during the period 01/01/2004 to 08/31/2013.

The plots in the upper panel of Figure 5.2 highlight both the time variation of idiosyncratic crisis sentiment during our full sample period and the particularly high levels of crisis sentiment during the financial crisis. Moreover, consistent with the fact that AIG received more media coverage during the crisis than any other insurance company, the peak in the CSI is most pronounced for AIG while crisis sentiment was considerably lower, e.g., for Swiss RE. A comparison of the plots of crisis sentiment and the three insurers' stock prices in the lower panel of Figure 5.2 already hints at a high correlation between stock prices and contemporaneous idiosyncratic crisis sentiment. In our panel regression analysis, we will later explore the questions whether this contemporaneous correlation also holds in our full sample and whether lagged values of the general and idiosyncratic crisis sentiment proxies can also be used to predict an insurer's stock performance.[51]

[51] In Figure D.3 in Appendix D, we also plot the time evolution of CSI for the mean values and for the 10%- and 90%-quantiles of CSI.

Figure 5.2: Crisis sentiment and insurer stock prices 2004-2013.

The figure shows plots of the (weekly) values of the Crisis Sentiment Index (first line) and daily stock prices (second line) for American International Group (first column), Prudential (second column) and Swiss RE (third column). The data on the stock prices are taken from the *Thomson Reuters Financial Datastream* database and cover the period from 01/01/2004 to 08/31/2013. The Crisis Sentiment Index is computed using data from *Google Trends* via $CSI_t^i := \left(\frac{GSVI_t^i + Z_t}{200}\right) \cdot \rho_t^i$. where Z_t is the first principal component of the Google Search Volume Indices (GSVI) for several crisis-related search query terms, $GSVI_t^i$ is the GSVI for insurer ith ticker symbol (or company name in case of a numeric ticker symbol) and ρ_t^i is the (dynamic) correlation between Z_t and $GSVI_t^i$.



5.2.4 Further control variables

In addition to our two proxies of crisis sentiment, we also employ several control variables that have been shown in the literature to affect insurer performance in our panel regressions.[52]. Data on the insurer characteristics we use are obtained from the *Thompson Worldscope* database. To begin with, we control for two standard accounting performance measures and use an insurer's Return on Equity (ROE) and Return on Assets (ROA). ROE is calculated as earnings per share of the last 12 months divided by prorated book value per share times 100. ROA is the pre-tax return of the insurer on its total assets. As previous research has shown (see, e.g., Berry-Stölzle et al., 2013), firm performance is unquestionably related to firm size. We therefore include the natural logarithm of an insurer's total assets as well as net revenues, given by the log total of an insurer's operating revenue, to proxy for size and the market-to-book-ratio, defined by market value of common equity divided by book value of common equity, to proxy for each insurer's firm value. As a further proxy for performance, we include the loss ratio, built by adding claim and loss expenses to long term insurance reserves and dividing by premiums earned. Moreover, we expect performance to be influenced by leverage, which is obtained by subtracting the book value of equity from the book value of assets, adding market value of equity and dividing the total by market value of equity. Empirical evidence has shown both a negative (see, e.g., Acharya et al., 2010) and a positive (see Vallascas and Hagendorff, 2011) correlation between performance and leverage. We therefore have no expectations as to the sign of the coefficient of leverage in our regressions. Furthermore, we include a proxy for an insurer's investment success in our panel regressions. More precisely, we use the ratio of investment income to net revenues, as well as the related proxy Investment Activity, which is defined as the ratio of the insurer's absolute investment income to the sum of absolute investment income and absolute earned premiums. The latter proxies for the degree to

[52]The determinants of insurer performance have also been addressed by Lai and Limpaphayom (2003), Choi and Weiss (2005), Lai et al. (2011), He and Sommer (2011), He et al. (2011), Fields et al. (2012) and Berry-Stölzle et al. (2013).

which an insurer derives income from investing in assets instead of earning premiums from underwriting. To assess an insurer's activity outside the insurance business, we also regress insurer performance on non-policyholder liabilities, obtained by dividing the total on balance sheet liabilities by total insurance reserves. Since corporate governance has been shown to affect firm performance during crises (see Johnson et al., 2000), we include the variables Board Size and Board Independence in our regressions. Board Size is measured by the natural logarithm of the number of directors whereas Board Independence describes the percentage of independent outside directors on the board of directors.

Although we argue that the bad stock performance of insurers was driven by irrational crisis sentiment, it could also be the case that insurer stock performance was driven by rational divestitures at systemically more exposed insurers. To control for this effect, we include a measure of systemic risk in our analysis which has been extensively discussed in the previous literature. We compute an insurer's Marginal Expected Shortfall to control for an insurer's actual exposure to systemic risk. We follow Acharya et al. (2010) and define the Marginal Expected Shortfall as the average return on an individual insurer's stock on the days the Datastream Bank Index experienced its 5% worst outcomes during the time period of January 2004 to December 2012. To control for country-specific, i.e., economic or political differences across countries in our sample, we include several country controls, such as the annual real GDP growth rate in per cent or Inflation, defined as the log of the annual change of the GDP deflator.[53] Finally, as we expect cross-country differences in internet availability and usage to influence our Crisis Sentiment Index, we include the variable Internet use, which is given as the percentage of people with access to the world wide web in a given country in our regression analysis. Data on internet availability is taken from the World Development Indicator database of the World Bank.

[53]Inflation is known to influence insurer performance, see for instance Berry-Stölzle et al. (2013).

5.2.5 Insurer performance and descriptive statistics

Descriptive statistics on our dependent variables, our measures of crisis sentiment and various control variables are given in Table 5.1.

The descriptive statistics in Table 5.1 summarize the data of all 253 firms over the complete sample period from Q2 2004 to Q4 2012. We intentionally choose quarterly returns instead of data of higher frequency in order to keep our study comparable to related studies by Beltratti and Stulz (2012) and Fahlenbrach et al. (2012). It is noteworthy that the overall stock performance of insurers measured by the insurers' quarterly buy-and-hold returns was insignificant over our full sample period. However, stock performance was significantly negative during the financial crisis [54] with insurer stocks plummeting by -5.19% on average. Similarly, our Crisis Sentiment Index has a mean of zero in our full sample with the values of the CSI increasing significantly during the financial crisis. The descriptive statistics for the proxy for the market-level crisis sentiment are in line with the evidence presented in Figure 5.1 that our sample period is characterized by a high variation in the level of general crisis sentiment with peaks during 2008.

In addition, several findings from studying the descriptive statistics are noteworthy. First, average internet use is high with approximately 69.54% of households having access to the internet in our full sample. As the internet appears to be pervasively available in our sample, we can safely assume that retail investors regularly use the internet to gather information on stocks (regardless of the question whether they also base their trading decisions on this information). Cross-country differences, however, are significant with some countries having an internet availability of only 7%. Second, the average exposure of insurers to systemic risk during our full sample period was at an economically significant 2%. During the financial crisis, the average exposure of insurers to externalities stemming from the banking sector was even higher with the average MES being 2.33%. Several insurers were thus heavily exposed to systemic

[54]Following Fahlenbrach et al. (2012) we define the crisis period as Q3 2007 to Q4 2009.

Table 5.1: Descriptive statistics.

The table presents descriptive statistics on quarterly buy-and-hold returns of the 253 sample insurers for the period from Q2 2004 to Q4 2012. Additionally, descriptive statistics for the General crisis sentiment, Crisis Sentiment Index and the various control variables we use in our regression analyses are given on a quarterly basis. We report the number of observations, minimum and maximum values, percentiles and moments. Except for the number of observations, skewness and (excess) kurtosis, all entries are denominated in %. All variables and data sources are defined in Appendix D.1.

			Percentiles							Moments			
	Obs	Min	1st	5th	20th	80th	95th	99th	Max	Mean	St. Dev.	Skewness	Exc. Kurt.
Insurer performance and main explanatory variables													
- Buy-and-hold returns	8714	-1.00	-0.47	-0.24	-0.08	0.10	0.26	0.55	29.00	0.02	0.39	49.40	3431.26
- CSI	8855	-0.30	-0.11	-0.04	0.00	0.01	0.07	0.16	0.43	0.01	0.04	1.47	14.91
- General crisis sentiment	35	0.32	0.32	0.39	1.77	13.44	24.75	48.39	48.39	8.96	9.36	2.25	6.57
Control variables													
- Leverage	6247	1.17	1.50	1.93	3.12	15.02	37.03	133.23	44180.69	49.04	1137.83	37.55	1447.15
- Net revenues	6297	7.12	11.42	12.70	13.81	16.50	17.84	18.63	18.97	15.16	1.59	-0.26	0.79
- Total assets	6321	11.65	13.54	14.21	15.25	18.20	19.91	20.72	21.45	16.78	1.71	0.26	-0.25
- Debt maturity	5761	0.00	0.00	0.07	0.75	1.00	1.00	1.00	1.00	0.84	0.27	-2.05	3.24
- Loss ratio	5999	-1717.91	-0.06	40.81	63.17	114.85	267.37	864.40	8439.29	114.27	271.23	20.26	597.57
- Market-to-book ratio	6247	-0.76	0.20	0.50	0.81	2.03	3.30	5.51	45.12	1.54	1.50	16.13	439.99
- Non-policyholder liabilities	6027	0.56	1.01	1.07	1.14	1.79	5.06	36.52	704.97	5.04	40.78	14.04	205.65
- Return on assets	6318	-30.22	-5.80	-1.01	0.45	3.67	6.76	10.21	34.57	1.91	3.19	-0.39	25.74
- Investment activity	5998	-5.39	0.01	0.05	0.08	0.31	0.69	0.93	7.12	0.22	0.32	3.80	213.21
- Investment success	6035	-22.10	0.03	0.18	0.59	0.89	0.95	1.16	4.13	0.71	0.65	-28.63	995.07
- MES	8744	-1.14	-0.02	0.00	0.00	0.03	0.06	0.10	0.40	0.02	0.03	-7.03	420.48
- Return on equity	5845	-77.86	-66.22	-6.84	5.66	16.29	25.82	34.29	36.69	10.16	12.84	-3.39	19.27
- Internet use	8835	7.30	8.43	35.00	64.76	81.03	86.77	91.30	95.00	69.54	15.54	-1.80	3.66
- Board size	2953	3.00	6.00	8.00	9.00	14.00	20.00	26.00	28.00	12.09	3.82	1.32	2.45
- Board independence	2694	0.55	2.84	9.23	38.53	86.98	91.33	94.45	94.67	62.58	26.61	-0.77	-0.60
- GDP growth	8624	-8.54	-5.49	-3.11	-0.36	3.27	5.45	8.22	14.78	1.68	2.66	-0.46	1.96
- Inflation	8624	-14.45	-2.16	-0.89	0.88	3.23	5.97	8.30	27.57	2.25	2.02	1.19	15.43
- Stock market turnover	8680	0.15	1.70	6.28	73.17	189.06	348.58	404.07	404.07	144.33	93.06	1.09	1.25

risk. However, variation in the MES estimates across time and in the cross-section is high thus underlining the notion that some insurers suffered heavily from the financial crisis while others were not exposed to systemic risks. Furthermore, insurers had positive mean profitability ratios and leverage ratios that lie mostly between 3.12 (20%-quantile) and 15.02 (80%-quantile). Mean leverage was 49.04, although this estimate is biased in part by few extreme outliers with a negative book value of equity. We chose to keep these insurer-quarter observations in our sample as they belong to insurers that most likely were in distress during the financial crisis and as dropping these observations would lead to a survivorship bias.

We start our analysis of the hypothesized relation between crisis sentiment and insurer performance by conducting a univariate analysis of our full sample of insurer-quarter observations. We first compute descriptive statistics for insurer-quarter observations in the bottom and top (general) crisis sentiment quartile based on our full sample (2004-2010). Not surprisingly, general crisis sentiment and the Crisis Sentiment Index do not statistically significantly differ for insurer-quarters in the top and bottom general crisis sentiment quartiles (despite the fact that both subsamples are constructed in this way). Both measures of crisis sentiment are, however, higher in the top crisis sentiment quartile. Quarterly buy-and-hold returns are slightly higher in the top crisis sentiment quartile (0.7%) although returns in both the top and bottom quartile (0.68%) are economically negligible. As results from this univariate analysis based on data starting in 2004 offer a possibly biased picture due to the fact that crisis sentiment only started to affect stock investors in 2006, we repeat this analysis for the subsample of Q1 2006 to Q4 2010. The results of this analysis are reported in Table 5.2.

Surprisingly, buy-and-hold returns do not significantly differ between the insurers in the top and bottom CSI quartiles. By construction, firm-specific and general crisis sentiment are significantly higher in the top CSI quartile. However, results for some of our independent variables indicate significant differences between insurers which possessed a high CSI during the crisis and those that were in the bottom CSI quartile. For instance, insurers with a high value of the Crisis Sentiment Index had a higher loss

Table 5.2: Descriptive statistics for insurer-quarters in the first and fourth crisis sentiment quartiles (Q1 2006 - Q4 2010).

This table compares the characteristics of insurers below the bottom quartile of the Crisis Sentiment Index (CSI) relative to those above the top quartile of the CSI. Our sample consists of 253 international insurers (listed in Appendix D.2) and covers the period from Q1 2006 to Q4 2010. We report the mean, 5%- and 95%-quantiles, and the standard deviation of our dependent and independent variables. The equality of means of the different variables is tested using a standard t-test. All variables and data sources are defined in Appendix D.1. ***,**,* denote estimates that are significant at the 1%, 5%, and 10% level, respectively.

	Bottom crisis sentiment quartile				Top crisis sentiment quartile				*t*-test
	Mean	St. Dev.	5% quantile	95% quantile	Mean	St. Dev.	5% quantile	95% quantile	
Dependent variable and main explanatory variables									
- Buy-and-hold returns	-0.0032	0.2055	-0.3047	0.2614	0.0058	0.3029	-0.3305	0.3427	0.6846
- CSI	-0.0418	0.0375	-0.114	-0.002	0.0633	0.0649	0.003	0.2033	39.5295***
- General crisis sentiment	12.9959	11.3707	0.3155	24.7483	14.9866	13.2231	2.0653	48.3862	3.1199***
Control variables									
- Leverage	14.57	30.23	1.80	57.28	17.067	54.02	1.94	51.64	1.02
- Net revenues	15.37	1.58	12.76	18.00	15.49	1.79	12.63	18.29	1.21
- Total assets	16.98	1.84	14.24	20.13	17.13	1.95	14.31	20.26	1.36
- Debt maturity	0.85	0.26	0.14	1	0.86	0.23	0.27	1	0.43
- Loss ratio	86.33	219.69	32.07	363.22	117.71	267.00	31.90	366.33	2.15**
- Market-to-book ratio	1.48	0.92	0.51	3.30	1.31	0.80	0.48	2.87	-3.17***
- Non-Policyholder liabilities	4.55	29.60	1.09	8.47	1.80	2.82	1.08	2.90	-2.00**
- Return on assets	2.31	3.35	-0.64	7.25	1.83	3.28	-0.82	6.72	-2.48**
- Investment activity	0.23	0.27	0.05	0.77	0.23	0.28	0.05	0.78	0.29
- Investment success	0.72	0.28	0.21	0.96	0.70	0.38	0.10	0.95	-1.44
- MES	0.02	0.03	-0.00	0.07	0.03	0.03	-0.00	0.09	2.86***
- Return on equity	9.47	12.53	-20.36	24.76	7.05	14.92	-19.24	20.45	-2.85***
- Internet use	70.05	13.82	40.79	85.03	68.88	13.92	37.99	82.3	-1.62
- Board size	11.78	3.83	6	20	12.23	3.54	8	20	1.65*
- Board independence	63.48	26.51	11.62	90.60	67.06	24.68	20.54	91.89	1.77*
- GDP growth	1.19	2.86	-4.81	5.40	0.62	2.92	-5.13	4.43	-3.77***
- Inflation	2.31	2.26	-0.93	5.38	2.33	1.88	-0.45	5.40	0.19
- Stock market turnover	187.49	111.54	33.37	404.07	185.99	114.17	30.58	404.07	-0.26

ratio, were less profitable and had a higher exposure to systemic risk according to their mean MES.

The results of the univariate analysis so far have presented only weak evidence in support of the hypothesis that idiosyncratic crisis sentiment drove insurer performance during the financial crisis. The extremely bad stock performance of insurers could, however, be due to high levels of market-wide crisis sentiment that affected all financial institutions indiscriminately. Moreover, idiosyncratic and general crisis sentiment could have a differential impact on small and large insurers as absolute media coverage for these groups differ as well. We therefore explore the relation between crisis sentiment and insurer performance in a panel regression setting in the following section.

5.3 Does crisis sentiment drive insurer performance?

5.3.1 Baseline panel regressions

In this section, we explore the determinants of the stock performance of international insurers during the last decade. To this end, we perform several panel regressions of the insurers' quarterly buy-and-hold returns on our two proxies of crisis sentiment together with various control variables. To limit the possibility of reverse causality driving our results, we lag all explanatory variables by one quarter.[55] Our sample is composed of 8,855 insurer-quarter observations for the sample period Q1 2004 to Q4 2012. As we strongly suspect the sensitivity of insurer performance to investor sentiment to vary with firm size (and thus media coverage), and as this could possibly bias our findings, we estimate separate regressions for quintiles of insurer-quarter sorted by the insurers' total assets. Everything else equal, we would expect the influence of crisis sentiment on insurer performance to be highest for large insurers as they are the ones with the most

[55] It is quite easy to imagine a possible source of reverse causality in the setting of our regression of insurer performance on crisis sentiment. In a contemporaneous view, attention and sentiment of retail investors could simply reflect a reaction of investors to the evolution of past stock prices. Although we cannot completely rule out reverse causality, we believe that our regressions of performance on lagged values of crisis sentiment mitigate this possibility to a large extent.

extensive media coverage. To account for unobservable heterogeneity across insurers and time, we estimate panel regressions with insurer- and time-fixed effects and robust standard errors. Results from our baseline panel regressions are shown in Table 5.3.

Models (1) through (5) in Table 5.3 constitute our baseline panel regressions of insurer performance on our Crisis Sentiment Index based on insurer-quarter observations sorted in quintiles of total assets. The results of these regressions show a clear picture. Insurer performance is not affected by our measure of an insurer's individual sensitivity to crisis sentiment. Based on these findings, at least in our full sample there appears to be no indication for a significant relation between individual crisis sentiment and insurer performance. Instead, several of our idiosyncratic control variables like, e.g., the insurers' market-to-book ratios are found to be driving buy-and-hold returns (regardless of the firm size quintile the regression is based on). In models (6) to (10), we repeat our baseline panel regressions but substitute the CSI by our measure of the market-wide crisis sentiment. The findings of these regressions offer a completely different picture than our models that employ the CSI. Our measure of the general crisis sentiment of investors is a highly statistically significant determinant of the stock performance of insurers in our complete sample period. Moreover, we find the market-level crisis sentiment to be highly significant for small, medium-sized and large insurers with the effect being largest in magnitude for insurers in the top quintile of total assets. Higher levels of market-wide crisis sentiment imply lower quarterly buy-and-hold returns of insurers in the future. This effect is also economically significant as a one standard deviation increase in our proxy of general crisis sentiment decreases the average quarterly returns of, e.g., small insurers by -4.31% (-0.0045×9.58). Similarly, a one standard deviation increase in the market-wide crisis sentiment leads to a decrease in future returns on the stocks of large insurers of -5.12% (-0.0054×9.48).

Again, we find that insurer performance is also driven by the firms' market-to-book ratios and to some extent by their profitability as measured by the insurers' return on assets. In all regression specifications, leverage seems to be negatively related to insurer

Table 5.3: Panel regressions of insurer performance 2004-2012.

This table shows results of panel regressions of quarterly buy-and-hold returns of international insurers on two proxies of general and firm-individual crisis sentiment and various control variables. The panel regressions are performed on subsamples of insurer-quarter observations sorted into quintiles of the insurers' total assets. All panel regressions are estimated with insurer- and quarter-fixed effects. The sample includes 8,855 insurer-quarter observations of 253 international insurers over the time period Q1 2004 to Q4 2012. Robust standard errors are reported in parantheses and all explanatory variables are lagged by one quarter. For all regressions, we present results separated by quintiles of the insurers' total assets. Results for the country-specific variables GDP growth, Inflation and Stock market turnover are suppressed. Variable definitions and data sources are provided in Table D.1 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:	Quarterly buy-and-hold returns									
Total assets quintile:	Small-Q1	Q2	Q3	Q4	Large-Q5	Small-Q1	Q2	Q3	Q4	Large-Q5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CSI	0.0622	-0.0988	-0.3073	0.1063	-0.1635					
	(0.721)	(0.385)	(0.316)	(0.381)	(0.136)					
General crisis sentiment						-0.0045***	-0.0033***	-0.0040***	-0.0036***	-0.0054***
						(0.001)	(0.000)	(0.000)	(0.003)	(0.000)
MES	0.6991*	0.4269*	0.4282	1.3340*	0.9249	0.6999*	0.4368*	0.4051	1.3320	0.9252
	(0.082)	(0.099)	(0.445)	(0.077)	(0.150)	(0.081)	(0.090)	(0.475)	(0.077)	(0.153)
Total assets	0.0375**	0.0315	0.0545	0.0802**	-0.0048	0.0381**	0.0305	0.0516	0.0830**	-0.0055
	(0.027)	(0.521)	(0.217)	(0.026)	(0.839)	(0.024)	(0.537)	(0.245)	(0.026)	(0.817)
Market-to-book ratio	0.0053***	0.0517***	0.0422***	0.0294***	0.0150	0.0053***	0.0520***	0.0412***	0.0292***	0.0147
	(0.000)	(0.002)	(0.000)	(0.002)	(0.132)	(0.000)	(0.002)	(0.000)	(0.002)	(0.132)
Return on assets	0.0019**	-0.0008	0.0109***	0.0174***	0.0070	0.0020**	-0.0007	0.0115***	0.0171***	0.0067
	(0.041)	(0.833)	(0.000)	(0.000)	(0.124)	(0.039)	(0.843)	(0.000)	(0.000)	(0.139)
Leverage	-0.0023*	0.0000	-0.0005***	-0.0001***	-0.0010***	-0.0024*	0.0000	-0.0005***	-0.0001***	-0.0010***
	(0.099)	(0.828)	(0.001)	(0.000)	(0.008)	(0.075)	(0.830)	(0.000)	(0.000)	0.010
Investment activity	0.2066**	-0.0063	-0.0282	-0.0080***	-0.0192*	0.2086**	-0.0063	-0.0303	-0.0079***	-0.0207**
	(0.030)	(0.368)	(0.181)	(0.003)	(0.056)	(0.028)	(0.368)	(0.142)	(0.004)	(0.026)
Non-Policyholder Liabilities	0.0047	-0.0227***	-0.0001*	-0.0001	0.0000	0.0050	-0.0226***	-0.0001*	-0.0001	0.0000
	(0.236)	(0.002)	(0.075)	(0.116)	(0.981)	(0.127)	(0.002)	(0.089)	(0.129)	(0.975)
Loss ratio	0.0000	-0.0001*	0.0001	0.0000*	0.0001**	0.0000	-0.0001*	0.0001	0.0000*	0.0001***
	(0.748)	(0.089)	(0.144)	(0.089)	(0.014)	(0.710)	(0.086)	(0.131)	(0.092)	(0.010)
Debt maturity	-0.0017	-0.0167	-0.0141	0.0210	-0.0624**	-0.0025	-0.0150	-0.0121	0.0195	-0.0690**
	(0.933)	(0.184)	(0.555)	(0.526)	(0.044)	(0.899)	(0.203)	(0.642)	(0.557)	(0.033)
Internet use	0.0015	0.0013	-0.0013	-0.0036**	-0.0036***	0.0015	0.0012	-0.0013	-0.0037**	-0.0035***
	(0.298)	(0.259)	(0.319)	(0.042)	(0.004)	(0.325)	(0.287)	(0.276)	(0.040)	(0.004)
Country controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Insurer-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	865	993	1085	1212	1198	865	993	1085	1212	1198
R^2	0.251	0.352	0.373	0.455	0.561	0.251	0.351	0.370	0.455	0.560
Adj. R^2	0.209	0.320	0.344	0.433	0.543	0.210	0.320	0.342	0.433	0.542

performance for medium-sized and large insurers. Interestingly, an insurer's exposure to systemic risk as measured by its Marginal Expected Shortfall is not significantly correlated with insurer performance. Although one might expect large insurers to be especially susceptible to turmoil in the financial sector, the MES is not significant in five out of our ten regressions in Table 5.3 and only significant at the 10% level in the remaining models. Most strikingly, MES enters the latter regressions with a weakly significant positive sign. Finally, the adjusted R^2 in all regressions are all well above 20% with the regressions (5) and (10) of the performance of large insurers possessing an adjusted R^2 of 54.3% and 54.2%, respectively. Our baseline regressions thus provide us with ample evidence in support of our hypothesis that market-wide crisis sentiment is a significant driver of insurer stock performance.

In the following subsection, we test the robustness of our main results by performing several further regression analyses.

5.3.2 Robustness checks

The results of our baseline panel regressions show that insurer performance between 2004 and 2012 was negatively related to the level of market-wide crisis sentiment of investors. In the following, we present the results of various robustness checks of this main finding.

First, one could argue that our measure of the general crisis sentiment simply reflects the influence of the market portfolio or of changes in economic growth on an individual firm's stock performance. Both arguments can be confuted as we control for both the insurers' MES and the respective GDP growth rate. Controlling for both variables in our regressions does not affect the high economic and statistical significance of the general crisis sentiment.

Next, we estimate several additional panel regressions in which we employ additional or alternative control variables to check the robustness of our main finding. All regressions are again estimated with insurer- and time-fixed effects employing the full set of control variables. The results of these robustness checks are presented in Table 5.4. For simplicity, the results on the control variables in these regressions are omitted from the table.

Table 5.4: Robustness checks.

This table shows results of further panel regressions of quarterly buy-and-hold returns of international insurers on two proxies of general and firm-individual crisis sentiment and various control variables. The panel regressions are performed on subsamples of insurer-quarter observations sorted into quintiles of the insurers' total assets. All panel regressions are estimated with insurer- and quarter-fixed effects. The sample includes 8,855 insurer-quarter observations of 253 international insurers over the time period Q1 2004 to Q4 2012. Robust standard errors are reported in parantheses and all explanatory variables (if not indicated otherwise) are lagged by one quarter. For all regressions, we present results separated by quintiles of the insurers' total assets. Variable definitions and data sources are provided in Table D.1 in the Appendix. Panel A shows the results of a panel regression in which the general crisis sentiment index is lagged by two quarters. Panel B presents a regression in which a subsample of observations between 2006 to 2010 is used. Panels C and D present the results of regressions in which the general crisis sentiment index is interacted with total assets and the availability of the internet, respectively. Panels E, F and G use alternative measures of an insurer's size, profitability and investment activity. Panel H presents the results of three regressions in which the MES is estimated using different sector indexes. All regressions include our full set of control variables. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. Adj. R^2 is adjusted R-squared.

Dependent variable:	Quarterly buy-and-hold returns				
Total assets quintile:	Small-Q1	Q2	Q3	Q4	Large-Q5
Panel A: double-lagged					
General crisis sentiment$_{t-2}$	-0.0034**	-0.0034**	-0.0122***	-0.0090***	-0.0144***
	(0.030)	(0.030)	(0.000)	(0.000)	(0.000)
Panel B: subsample 2006-2010					
CSI	-0.1057	-0.1267	-0.9064**	0.2303	-0.4102**
	(0.565)	(0.487)	(0.010)	(0.330)	(0.040)
General crisis sentiment	-0.0036*	-0.0056***	-0.0106***	-0.0071***	-0.0067***
	(0.087)	(0.002)	(0.000)	(0.000)	(0.002)
Panel C: interaction total assets					
General crisis sentiment	0.0163	0.0163	-0.0043	-0.0232	0.0220
	(0.377)	(0.377)	(0.924)	(0.398)	(0.130)
Total assets	0.0362*	0.0362*	0.0694	0.0373	-0.0047
	(0.063)	(0.063)	(0.140)	(0.302)	(0.836)
General crisis sentiment × Total assets	-0.0014	-0.0014	-0.0001	0.0011	-0.0014*
	(0.295)	(0.295)	(0.979)	(0.497)	(0.055)
Panel D: interaction internet use					
General crisis sentiment	-0.0006	-0.0006	-0.0077**	-0.0065***	-0.0023
	(0.849)	(0.849)	(0.026)	(0.002)	(0.547)
Internet use	0.0012	0.0012	0.0013	-0.0015**	-0.0023*
	(0.287)	(0.287)	(0.147)	(0.035)	(0.056)
General crisis sentiment × Internet use	0.0000	0.0000	0.0000	0.0000	-0.0001
	(0.355)	(0.355)	(0.515)	(0.279)	(0.329)
Panel E: alternative size proxy					
General crisis sentiment	-0.0033***	-0.0033***	-0.0060***	-0.0047***	-0.0057***
	(0.005)	(0.005)	(0.000)	(0.000)	(0.000)
Net revenues (Total assets)	0.0103	0.0103	0.0208	-0.0270	-0.0382*
	(0.521)	(0.521)	(0.348)	(0.214)	(0.063)
Panel F: alternative profitability proxy					
General crisis sentiment	-0.0030	0.1526*	-0.0059***	-0.0047***	-0.0062***
	(0.114)	(0.075)	(0.000)	(0.000)	(0.000)
ROE (ROA)	0.0018	0.0021	-0.0005	0.0089**	0.0116
	(0.951)	(1.000)	(0.851)	(0.032)	(0.270)
Panel G: alternative investment activity proxy					
General crisis sentiment	-0.0030	0.1528*	-0.0059***	-0.0047***	-0.0061***
	(0.108)	(0.075)	(0.000)	(0.000)	(0.000)
Investment success (Inv. Activity)	-0.0418	0.0160	0.0064	0.0467	0.0220
	(0.584)	(0.560)	(0.890)	(0.525)	(0.506)
Panel H: alternative MES estimation					
General crisis sentiment (MES1)	-0.0022	0.1595*	-0.0042***	-0.0031***	-0.0059***
	(0.251)	(0.062)	(0.000)	(0.002)	(0.000)
General crisis sentiment (MES2)	-0.0022	0.1596*	-0.0042***	-0.0031***	-0.0059***
	(0.255)	(0.062)	(0.000)	(0.002)	(0.000)
General crisis sentiment (MES3)	-0.0023	0.1593*	-0.0042***	-0.0031***	-0.0059***
	(0.235)	(0.063)	(0.000)	(0.002)	(0.000)
Other control variables:	Yes	Yes	Yes	Yes	Yes
Insurer-fixed effects	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes

We start by addressing concerns that despite lagging our main explanatory variable by one quarter, both the general crisis sentiment and the insurers' quarterly buy-and-hold returns could be simultaneously determined. To this end, we estimate panel regressions in Panel A of Table 5.4 in which we employ the measure of market-wide crisis sentiment lagged by two quarters. The results indicate that general crisis sentiment remains statistically significantly related to insurer performance even if lagged by two quarters. Also, this result remains valid for all subsamples of different insurer size.

Our main findings were based on an analysis of our full sample of insurer-quarter observations between 2004 and 2012. However, crisis sentiment was low to non-existent before the onset of the financial crisis in early 2006. It could thus be argued that our results are biased by including insurer-quarters in which both our measures of crisis sentiment were practically zero. To control for this, we estimate a panel regression in Panel B in which we only employ observations from the time period of 2006 to 2010. The results show that the effect of the general crisis sentiment on insurer performance is even more pronounced during the financial crisis than in our full sample. Even more importantly, we find that our proxy of insurer-individual crisis sentiment is highly significant for mid-sized insurers and insurers in the top total assets quintile. In other words, the stock performance of large insurers during the financial crisis was significantly determined by both market-wide and individual crisis sentiment, possibly because larger insurers receive more attention through searches on Google, especially in times of financial turmoil. This effect is highly economically significant as a one standard deviation increase in the CSI leads to a -2.74% decrease in insurer stock returns (-0.4228×0.0649).

Furthermore, we investigate whether the negative correlation between market-wide crisis sentiment and insurer performance is affected by insurer size and the availability of the internet. For this purpose, we estimate panel regressions in Panels C and D of Table 5.4 in which we interact the general crisis sentiment index with total assets and our variable Internet use, respectively. Our results so far indicate that the effect of crisis sentiment on performance is aggravated by the size of the insurer. This finding is weakly corroborated by the negative sign of the coefficient of the interaction term in Panel C which is stat. significant at the 10% level. Also, it could be argued that a better availability of the internet increases the effect of crisis sentiment. The results in Panel D, however, show that the interaction term enters none of our regressions with a significant sign. A possible explanation for this is that our sample is predominantly composed of insurers from developed countries in which the internet was readily available even at the beginning of our sample period. Differences in the availability of the internet across countries thus do not seem to influence our results.

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 insurer's investment income to net revenues instead of the ratio of the insurer's absolute investment income to the sum of absolute investment income and absolute earned premiums), respectively. The results presented in Panels E to G clearly show that market-wide crisis sentiment remains a significant driver of insurer performance. While the negative effect on performance is slightly attenuated in the subsamples of smaller insurers, our main findings remain unchanged for mid-sized and large insurers.

Next, it could be argued that our results are driven by the specific manner in which we estimate the Marginal Expected Shortfall of insurers. If this were the case, our proxies of crisis sentiment could simply capture the systemic risk exposure of insurers that is not adequately captured by our MES estimates in the baseline regressions. To control for this potential bias, we recalculate the MES using three alternative indexes. To be precise, we employ the *World DS Full Lin Insurer Index* (labeled MES1 in Panel H), the *MSCI World Banks Index* (MES2) and the *MSCI World Insurance Index* (MES3) taken from *Datastream*. The results show that our conclusions remain unchanged. Additionally, we also estimate regressions in which we employ data on the size and the independence of the insurers' boards to control for possibility that the differences in performance are due to differences in corporate governance. Again, we find that our results remain unaffected by the addition of these variables in our regressions.

Another concern with our results is that our proxies of crisis sentiment simply measure the overall volume of search queries on Google rather than the specific search queries for crisis-related terms. If this were the case, any index constructed from arbitrary Google search terms related to the economy should have a similarly significant effect on insurer performance. To test this hypothesis, we construct several different indices from Google search volumes for search terms that are related to the economy but do not carry a negative connotation and that are not related to the financial crisis.[56] We then use these indices in unreported placebo panel regressions of insurer stock performance. We find that none of these alternative Google search volume indices is statistically significant in the placebo regressions. Related to this concern is the argument that insurer stock prices could be influenced by general bad sentiment not specifically tied to crisis-related topics. To refute this train of thought, we run several regressions including the FEARS factor introduced in Da et al. (2015).[57] We regress the insurers' stock performance on the FEARS index along with our control variables (excluding the other two sentiment measures) in the quintiles of the insurers' total assets and find no statistical significance of the FEARS factor. Additionally, we rerun these regressions and also include the CSI and then the general crisis sentiment index, respectively. As before, the coefficients of the FEARS index remain insignificant from zero while the general crisis sentiment index is highly significant with a negative effect on the insurers' stock performance. The CSI, again, is insignificant in the regressions.

In unreported regressions, we include the quarterly Chicago Board Options Exchange Market Volatility Index (VIX)[58] and find the same results for the CSI and the general crisis sentiment index as before.[59]

Finally, one could argue that not all search queries concerning the financial crisis or related phrases were done in English. Citizens of every country are more likely

[56] For example, we use search times like "economy", "employment", "inflation", "GDP", etc.

[57] We construct the index using weekly data and aggregate the results to quarterly data by averaging the weekly values.

[58] The data for VIX is obtained from `http://research.stlouisfed.org/fred2/series/VIXCLS/downloaddata`.

[59] In particular, we rerun the usual panel regressions with the VIX instead of the sentiment measures and find it to be of little statistical significance.

to enter search terms in their own mother tongue. We therefore construct a multilingual version of our proxy for the general crisis sentiment by translating the four crisis-related phrases used before into each insurers' home country's official language. Unfortunately, Google Trends does not provide data for many of the translated words, simply because the search volume of these words was too low. Consequently, we have to restrict ourselves to seven main languages with available data for at least one of the four search terms. [60] Afterwards, we proceed with the calculation of the multilingual index in the same way as the general crisis sentiment. Despite the inclusion of several other languages, we find that our main findings remain unchanged. A high correlation of 96.1% between the general crisis sentiment and its multilingual version underlines this result.

5.4 Conclusion

Shareholders of insurers lost significantly on their investments during the recent financial crisis. Although insurers did not suffer from the risk of a bank run or faced the detrimental effects of interbank funding drying up, the stocks of insurers nevertheless plummeted between 2006 and 2009 to an extent that was similar to the losses of banks. In this paper, we argue that the bad stock performance of insurers during the crisis was in part due to the crisis sentiment of investors, i.e., the perceived susceptibility of insurers to the financial crisis. We propose two proxies of an insurer's individual crisis sentiment and the market-wide general crisis sentiment and estimate these measures using Google Trends data.

These two measures of crisis sentiment are then used in panel regressions of international insurers' quarterly buy-and-hold stock returns. In these regressions, we control for several other idiosyncratic and country-specific determinants of insurer performance from the literature. Most importantly, we also control for the insurers' exposure to systemic risk as proxied by their Marginal Expected Shortfall. Our findings clearly

[60] We use the following languages to construct the multilingual version of the CSI and the general crisis sentiment index: English, French, German, Italian, Norwegian, Portuguese and Spanish.

show that market-wide crisis sentiment is a powerful predictor of an insurer's stock performance during the period 2004 to 2012 regardless of an insurer's size. During the financial crisis, the stock performance of large insurers is not only negatively related to market-wide but also to idiosyncratic crisis sentiment. Stocks of insurers that retail investors perceived as particularly exposed to the banking crisis performed significantly worse than stocks of insurers which investors perceived to be more independent of the banking sector.

Our results imply that investors exited insurer stocks mainly due to irrational market-wide crisis sentiment. Conversely, retail investors and noise traders did indeed act on the sentiment of a general economic downturn rather than a differential assessment of the idiosyncratic exposure of insurers to the crisis. The effect of crisis sentiment on stock performance that we measure is large in magnitude and economically highly significant. Our analysis can thus be seen as an investigation into the importance of noise trading in stocks of financial institutions during the financial crisis.

Chapter 6

Depositor Sentiment

"Even sunspots could cause runs if everyone believed that they did."

Douglas W. Diamond, Economic Quarterly, Volume 93, Number 2, 2007, pp.189-200.

6.1 Introduction

The regulation of the banking sector and government interventions are often justified with the need to prevent bank runs in which depositors withdraw their deposits from a bank out of fear their deposits might be lost if the bank defaults. In case depositors start to run indiscriminately to banks that might not at all face financial distress, the ensuing contraints on banks' liquidity could cause severe damage to the entire financial system and the real economy.[61] Since the time of the Great Depression in the United States, governments have attempted to limit the risk of system-wide bank failures by introducing deposit insurance schemes that aim at preventing self-fulfilling runs by depositors. There now exists a large literature on the optimal design, the positive effects, but also the inherent agency problems of deposit insurance schemes.[62] Complementing

[61] The consequences and real economy costs of financial crises are discussed, e.g., by Bernanke (1983), Ongena et al. (2003), Calomiris and Mason (2003), Dell'Ariccia et al. (2008). Financial crises, however, can obviously be caused by other factors than depositor runs, too, as observed, e.g., by the "run on repo" during the recent financial crisis (see, e.g., Gorton and Metrick, 2012).

[62] One of the first empirical studies on this subject is due to Demirgüç-Kunt and Detragiache (2002) who find that the detrimental effects of deposit insurance on financial stability prevail. Subsequent analyses have focused on the adoption and design of deposit insurance schemes (see Demirgüç-Kunt et al., 2008) as well as the stabilizing effects of deposit insurance during times of financial crisis (see

this line of research, several studies have analyzed the behavior of depositors during financial crises and its effects on distressed and non-distressed banks. Evidence on the determinants of bank runs and the behavior of depositors, however, is still sparse, despite its obvious importance.

In this paper, we test whether household sentiment and attention for deposit insurance in the U.S. affect changes in bank deposits. Using two direct measures of depositors' aggregate level of sentiment and attention based on internet search volume data from Google, we find that depositor sentiment is significantly negatively related to changes in U.S. banks' demand and time deposits during the period of 2004-2013. In line with the hypothesis of depositors perceiving larger banks as safer due to too-big-to-fail guarantees, we find depositor sentiment to have a differential effect on small- and medium-sized banks and larger banks in our sample: while depositor sentiment decreases deposits at banks that are not systemically important, the opposite is true for larger banks. Conversely, the attention of households to deposit insurance as revealed by the volume of queries related to the Federal Deposit Insurance Corporation (FDIC) is significantly related to increases in bank deposits. Given our main findings, we then turn to the question whether depositor sentiment and attention can be used to explain the probability of a bank run from or to a given bank. Our key result in this analysis is that a higher level of information procurement by households on deposit insurance mitigates the probability of a bank run.

In addition to active information retrieval through internet searches on deposit insurance, depositors might also simply be exposed to news coverage of and by the FDIC. Therefore, we also shed light on the interplay of the presence of the FDIC in the media and the need of depositors to gather more information on the safety of their deposits. Interestingly, our analyses indicate a negative correlation of the number of press releases by the FDIC and the demand for more information by depositors as revealed on Google. As such, it appears as if media attention to the FDIC does not spur but rather substitutes depositors' demand for more information on the U.S. deposit insurance sys-

Anginer et al., 2014b).

tem. However, our analyses also reveal that depositors' active search for information on deposit insurance on the internet and passive exposure to news coverage on the topic both have a significant positive effect on changes in banks' demand and time deposits. Depositors thus appear to divert their attention to information sources on the internet via Google in case the presence of the FDIC in the media is low.

The results in our paper are closely related to the theoretical conclusions in Diamond and Dybvig (1983) who show that a deposit insurance scheme is the optimal strategy to hinder possible runs on banks in case depositors are perfectly informed and rational. In reality, however, the existence of perfectly informed depositors may not be given. Consequently, the subsequent theoretical literature includes numerous extensions of the Diamond-Dybvig-model in which these assumptions have been loosened (see, e.g., Chari and Jagannathan, 1988, Engineer, 1989, Goldstein and Pauzner, 2005, Azrieli and Peck, 2012). Our paper complements these papers empirically by highlighting the detrimental effect of depositor sentiment on bank deposits even in the presence of deposit insurance. To the best of our knowledge, both the direct measurement of depositor sentiment as well as the analysis into its relation to changes in bank deposits are new to the literature. The results we find are in line with recent findings in the literature that, so far, has tried to explain depositor behavior at the micro-level. For example, Brown et al. (2014) argue that the decision of depositors to withdraw money from their bank is driven by personal reasons and attitudes, rather than by the formal existence of deposit insurance schemes. Our results further support the notion that sentiment rather than fundamentals cause bank runs.[63]

Our paper is also related to several studies on the effectiveness of deposit insurance in preventing bank runs. First, Demirgüç-Kunt et al. (2008) find that the decision of

[63]The results of Osili and Paulson (2014) stress the finding that personal attitudes and experiences, rather than deposit insurance, influence depositor behavior. They show that persons that have encountered financial crises are less likely to use U.S. based banks to deposit their wealth. The hypothesis that individuals' perception and knowledge of a bank, and not fundamentals, determine changes in deposits is also supported by the work of Oliveira et al. (2014). They empirically assess the influence of depositors' perception of banks being "too-big-to-fail" on the changes in deposits during runs in 2008 in Brazil and conclude that extreme decreases cannot be explained by bank fundamentals (see also Pería and Schmukler, 2001, for a similar finding).

governments to introduce deposit insurance is often motivated by political rather than by economical reasons. For example, a country might introduce a deposit insurance scheme simply as an act of copying the structure of developed countries and not primarily to reduce the danger of possible bank runs. Nevertheless, Anginer et al. (2014b) argue that the use of explicit deposit insurance has a positive impact on the stability of the financial sector and reduces the default risk of banks during times of crisis, despite possible moral hazard. Similar to this study, Karas et al. (2013) investigate the impact of deposit insurance schemes on market discipline and find that the sensitivity of households towards the equity of banks during crises decreases significantly. Our study helps in understanding the factors that influence the effectiveness of deposit insurance. We find that an increased information retrieval on the deposit insurance scheme in place, and thus better informed depositors, decreases the likelihood of a bank run. Second, our paper complements the results of Iyer and Puri (2012) who make the case that depositors retrieve information from their local social network to decide whether to withdraw money from their bank account or not after the default of another independent bank nearby.[64] As our results suggest, depositor behavior is also significantly affected by information retrieval from sources outside the depositors' social network.

Finally, our paper also relates to the literature regarding the influence of investor sentiment on the economy. It has long been recognized that market-wide sentiment and fear influence the attitudes and decisions of investors and thus, determine the prices of assets such as stocks or bonds. As such, the question how investors' attention, attitudes, and sentiment can be quantified has been discussed extensively in the literature. In our study, we follow in the footsteps of Da et al. (2011) and Da et al. (2015) and use internet search volume data to directly measure depositor sentiment and depositor attention towards deposit insurance. While institutional investors and even noise traders may also use other sources of information for their financial decision making, we suspect internet search data to be particularly well suited for capturing the inter-

[64] In a follow-up study, Iyer et al. (2013) investigate which personal attributes of an individual contribute to the decision to withdraw money as a response to announcements of economic distress of a bank.

ests and attention of individual depositors. In doing so, our paper extends the quickly growing literature on the applications of search volume data from Google Trends (see also Ginsberg et al., 2009, Choi and Varian, 2009).

The remainder of this paper is structured as follows. First, we give an introduction to the topic of depositor sentiment and depositor attention as well as an overview of the previous literature on deposit insurance and bank runs in Section 6.2. In Section 6.3, we describe the data and variables used in our study and the construction of our main explanatory variables. Section 6.4 provides information on the empirical strategy of our analyses. Empirical results are presented in Section 6.5. Results of robustness checks are given in Section 6.6. Section 6.7 concludes.

6.2 Depositor sentiment and depositor attention

There now exists an extensive literature on the effects of limited information, investor sentiment, and heterogeneous investor attention on asset prices (see, e.g., Merton, 1987, Gervais et al., 2001, Sims, 2003, Hirshleifer and Teoh, 2003, Grullon et al., 2004, Seasholes and Wu, 2007, Tetlock, 2007, Barber and Odean, 2008, Hou et al., 2009). Similarly, limited information, bounded rationality, and irrationality could lead bank depositors to run even though their deposits are covered by a deposit insurance scheme. The empirical evidence by Pería and Schmukler (2001), Brown et al. (2014), Oliveira et al. (2014), and Osili and Paulson (2014) supports this hypothesis as deposit withdrawals appear to be driven by the personal attitudes and perceptions of depositors rather than by bank fundamentals.

Most theoretical models describing the decision of bank depositors to run usually make the assumption that agents can be divided into a group of patient depositors, and one group of impatient agents.[65] In the model of Diamond and Dybvig (1983), banks face the problem that panic-based runs can occur as a result of both patient and impatient depositors demanding early withdrawal at the same time, thereby forcing the

[65] See, e.g., Azrieli and Peck (2012) for a model with a continuum of agents characterized by their degree of impatience.

bank into default.[66] In fact, patient depositors could run due to bad expectations, i.e., the fear that others might run as well or the fear that the bank faces financial trouble. In this paper, we refer to the level of bad expectations on the part of households as depositor sentiment. For example, when depositors have bad expectations on the banks' financial soundness, the probability of a bank run might increase. This understanding is in line with most of the theoretical literature which assumes bank runs to be the result of pessimistic and noisy information of depositors about banks (see, e.g., Chen, 1999). However, it could even be the case that the sentiment of households caused by the fear of a general economic downturn could be sufficient to drive depositors to run. Consequently, the first hypothesis that we test predicts that higher levels of depositor sentiment are negatively related to bank deposits.

In addition to the expectations of agents, a critical assumption for the effectiveness of deposit insurance in these models is that depositors are informed about the existence of deposit insurance. While many theoretical models show that noisy information or misinterpretations about a bank's assets on the part of depositors can cause panic-based bank runs (see, e.g., Chari and Jagannathan, 1988, Chen, 1999), the question whether information on the existence of deposit insurance is also noisy is left unanswered in the literature. For a deposit insurance scheme to be effective in preventing bank runs, however, depositors need to be informed about its existence and its design.[67] The idea of imperfect information on deposit insurance affecting depositor behavior lies at the heart of the second hypothesis that we test in this paper. We measure the degree of uninformedness of depositors in the U.S. via the level of attention households pay to the FDIC and refer to the level of information retrieval on the FDIC as depositor attention.

[66] Complementing this view, some studies in this literature explain bank runs as a result of bank behavior, see Calomiris and Kahn (1991) and Diamond and Rajan (2001).

[67] Anecdotal evidence found by Goedde-Menke et al. (2014) for the German banking sector indeed suggests that depositors' knowledge of the deposit insurance schemes changed around the financial crisis.

6.3 Data

6.3.1 Google Trends

In this study, we use internet search data obtained from the analytics tool *Google Trends*, which gives us several advantages over other sentiment and attention measures. For example, internet search data delivers insights into honest information retrieval and interests of depositors since the search is anonymous.[68] Also, in contrast to other measures of sentiment, *Google Trends* data provides insights into the active information retrieval of depositors instead of passive information exposure through, e.g., news.[69][70] Measures derived from news or written publication in general may capture the sentiment of the market and thus influence the readers' investment decisions. Since news based measures of sentiment proxy passive attitudes of the market, we cannot extract the actual attention readers pay to the publications and its content.

With internet search data, however, we are able to gain insights on how depositors actively seek information on their topics of interest. Da et al. (2011) were among the first to apply internet search data to the field of academic finance. In their pioneering work, the authors investigate the usefulness of *Google Trends* data capturing the relative amount of searches for a specific stock ticker symbol to measure the attention of noise traders. They find that increased attention measured by internet search data predicts higher stock prices and price reversals in the near future. However, they specifically concentrate on attention of retail investors rather than on the household level. In their follow-up study, Da et al. (2015) construct a market-wide sentiment measure using internet search data on thirty economics-related search terms and show

[68] The information gained from the data is therefore not as biased as the one obtained from surveys, as survey participants may not be motivated or altruistic enough to give comprehensive and honest answers (see Singer, 2002). Additionally, the method of surveying delivers quite infrequent data.

[69] One approach to construct a sentiment measure based on news is given in the work of Tetlock (2007). The author constructs a sentiment measure via the fraction of negative words in the "Abreast of the Market column" in the Wall Street Journal.

[70] A more active way to obtain data on depositors' sentiment would be to analyze entries on financial message boards on the internet. One could possibly derive market sentiment from message boards by applying linguistic techniques, though it would be a quite indirect way of approximating mood on the internet (see Antweiler and Frank, 2004).

that it can be used to explain mutual fund flows and asset price reversals. In our study, we extend this idea to study the usefulness of search data on *deposit insurance* in the U.S. to explain phenomena in the real economy and predict depositors' behavior.

The search engine of Google is by far the most frequently used in the United States and thus, its wealth of data is a superior source for data on the attention of american households. Using the analytics tool *Google Trends*, we are able to download the *Google Search Volume Index* (GSVI) for specific terms or a list of words at a daily, weekly, or monthly frequency, depending on the requested time frame and search volume availability.[71] The GSVI of a search term measures the number of searches that occured in a specified time period, relative to the total amount of Google searches (and is scaled to a maximum of 100). The default setting of the *Google Trends* tool gives the user information on the relative attention towards a specific term worldwide and in the time frame from 2004 to the current day. For our purposes, we will restrict all queries on *Google Trends* to the time period of January 2004 to December 2013. If not stated otherwise, all queries are also performed for the search volume in the United States. Nevertheless, we will also obtain data on the search volume of terms restricted to a smaller geographical area, namely the 50 U.S. states and the District of Columbia. When entering a search phrase into *Google Trends*, we are also able to gain insights on related phrases, which are also displayed on the webpage. This will be helpful when we search and select appropriate phrases covering a specific theme. [72]

6.3.2 Depositor sentiment

In our analyses, we make use of the Financial and Economic Attitudes Revealed by Search (FEARS) index proposed by Da et al. (2015). This index combines the search

[71] If the user of *Google Trends* requests search volume data with a time frame of one quarter or less, one is able to retrieve daily search volume (in case the term is searched for often enough). If the GSVI is too low, only monthly or no data are provided.

[72] Another feature *Google Trends* provides is the comparison of up to five words simultaneously. When entering two ore more phrases, *Google Trends* shows bars that compare the average search volume in the specified time period, which is also reflected in the scale of the line graphs. A term that was searched for more often than others will determine the scale and thus the values of *Google Trends* data.

volume of thirty economics-related phrases such as “gold prices” or “bankruptcy”.[73] The FEARS index is calculated by taking the log changes of the words’ search volumes, winsorizing at the 5% level, regressing the time series on time dummies, and taking the residual to eliminate seasonality in the data. In contrast to Da et al. (2015), we download weekly search volume data for the list of thirty words and adjust the winsorized time series using month dummies. The thirty time series are then combined by averaging. FEARS represents the negative sentiment of households in the United States (higher values indicate a higher level of bad sentiment).

6.3.3 Depositor attention

We start by building a catalog of words associated with the topic of deposit insurance in the United States. When depositors are interested in the safety of their deposits it is, most of the time, clearly a sign of their attitude towards the current general economic situation and in specific the condition of their banking system. In particular, we intend to measure the attention of depositors towards the existing deposit insurance scheme and how it affects their behavior. For this purpose, we start the construction of our attention index by comparing the search volumes of the two phrases “FDIC”[74] and “deposit insurance”. If U.S. depositors want to retrieve information on the deposit insurance system of their country, they might simply type in the latter of the two search terms. However, they might also have heard of the institution providing deposit insurance before looking for further information. The output in *Google Trends* is shown in Figure 6.1.

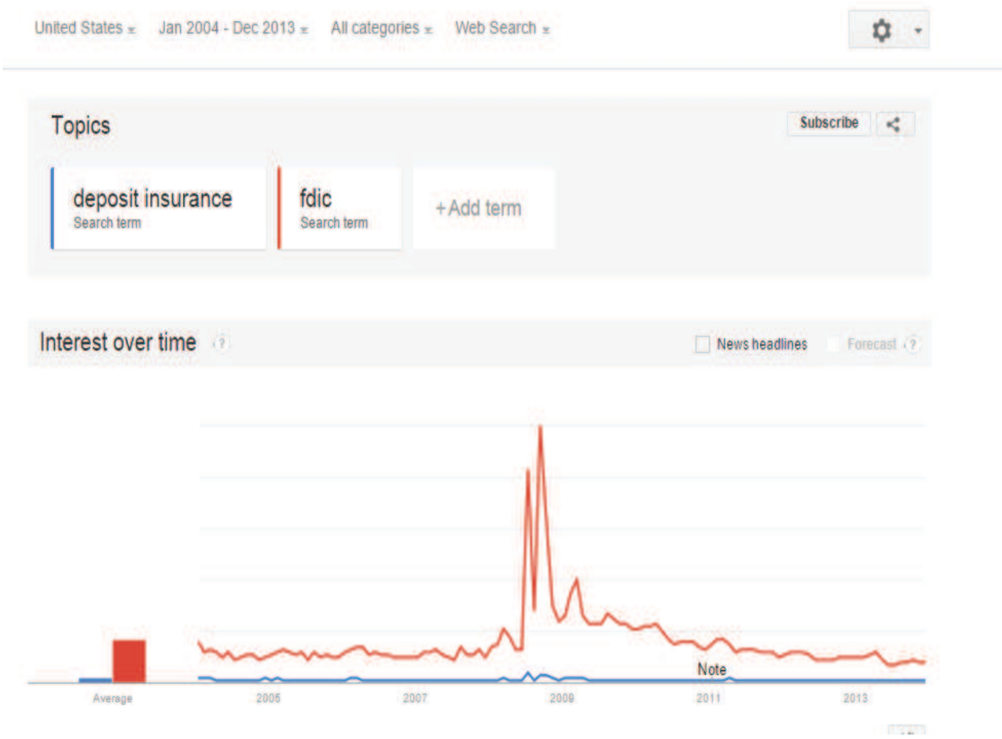
Obviously, the GSVI for “FDIC” dominates the GSVI of “deposit insurance” and peaks twice during the financial crisis, where the FDIC might have been relevant to depositors when deciding on their course of action. To obtain other relevant related search phrases, we type the two terms mentioned above into the *Google Trends* tool and

[73]The initial word list is derived using appropriate dictionaries. Phrases tagged as “economic” words with either “positive” or “negative” sentiment are retrieved and then ranked according to the strongest relations with market returns, which turn out to be negative relations.

[74]Note that *Google Trends* does not distinguish between upper or lower case letters.

Figure 6.1: Comparing the search terms "FDIC" and "deposit insurance" with Google Trends.

The figure represents the graphical output for a parallel Google Trends search on "FDIC" and "deposit insurance". Weekly search volumes scaled by the average search volume for "FDIC" (which has a higher average search volume than "deposit insurance") are plotted for the time period 2004 to 2013.



receive related search terms, e.g., variations of the terms or similar words. Afterwards, we compare each of the suggested terms with the GSVI of "FDIC" by using the specific search phrases and "FDIC" parallelly. By doing so, we are able to identify if a given search phrase has sufficient seach volume to be included in our analysis.[75] However, none of the related expressions is searched for nearly as often as the phrase "FDIC" itself. We thus conclude that in the quest for measuring depositors attention towards the deposit insurance scheme in the U.S., it is sufficient to restrict our list of words to

[75]The related search terms used are: *federal deposit insurance, deposit insurance corporation, car insurance deposit, bank deposit insurance, insurance no deposit, deposit insurance act, fdic insurance, deposit insurance scheme, fdic bank, fdic insurance, the fdic, fdic banks, fdic insured, fdic limits, fdic limit, fdic insurance limits, what is fdic* and *fdic coverage*.

this single search term.[76]

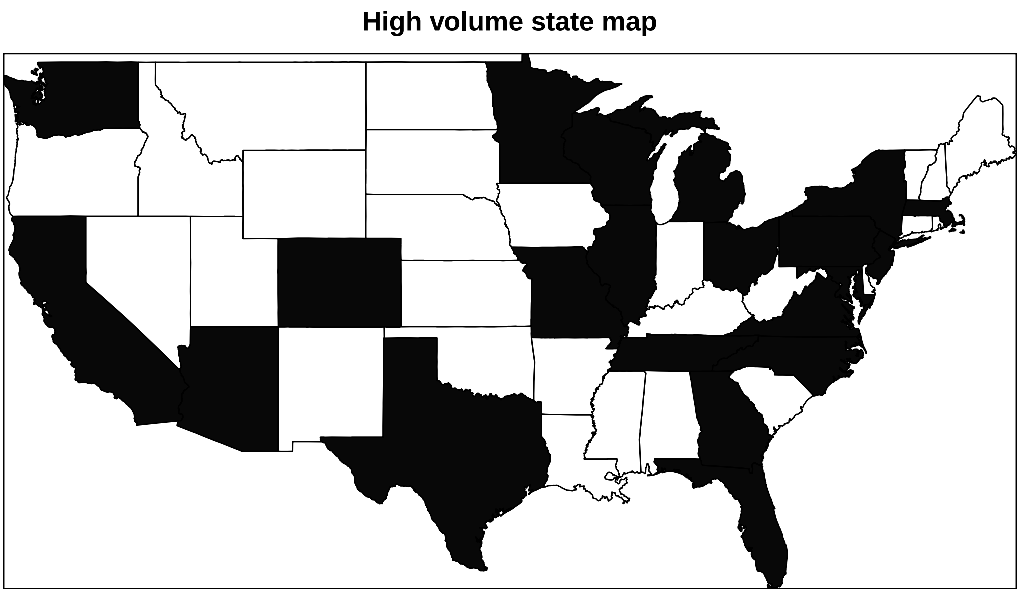
While the decision on the appropriate search term "FDIC" is based on the search volume for all states in the country, we expect both, the actual level of search volume and the time evolution of the GSVI to differ from state to state. Intuitively, the time evolution of interest in deposit insurance schemes in states with more internet usage (e.g., New York, Texas, or California) might differ from the time evolution of interest in deposit insurance in states with, e.g., a lower population density. We type "FDIC" into the *Google Trends* tool while restricting the search to specific states and download the weekly time series from 2004 to the end of 2013 for the 50 U.S. States and the District of Columbia. In case the search volume for "FDIC" is high enough, we are able to obtain weekly data on the SVI from 2004 to 2013. For some states, however, we are only able to retrieve monthly data (or no data in the case of the state of Wyoming), simply because the interest of the population measured with search data over this time frame is close to zero. We define states as "high volume" states if we are able to retrieve weekly search data on "FDIC" and "low volume" states otherwise. Figure 6.2 illustrates the geographical distribution of high and low search volume states in our sample.

From the map, we can see that most of the high volume states are located in the east of the United States. The other high-volume states are Arizona, California, Colorado, Texas, and Washington. With respect to the previous discussion of appropriate search terms, our main variable of interest is the $FDIC_t^j$-index, which is constructed by taking the weekly search volume of "FDIC" in state j winsorized at the 5% level, filtering out seasonality by regressing month-dummies on the index and using the residuals. Each time series is scaled by its standard deviation to minimize possible heteroskedasticity problems (see Da et al., 2011). Quarterly values are then obtained by taking the sum of weekly values for each quarter. Figure 6.3 shows the time evolution of the FDIC-index

[76] Another approach would be to aggregate the GSVI of several search terms into one time series, e.g. by averaging the values or performing a principal component analysis (see, e.g., Baker and Wurgler, 2006). Since the search volume for "FDIC" is way above the values of the other terms, we decide against a combination of GSVIs.

Figure 6.2: Distribution of states with high and low search volume.

The figure shows a heat map of the United States (excluding the low volume states Alaska and Hawai). A black area indicates a high search volume for the phrase “FDIC” on Google Trends (weekly search volume available) and a white area represents low or zero search volume.

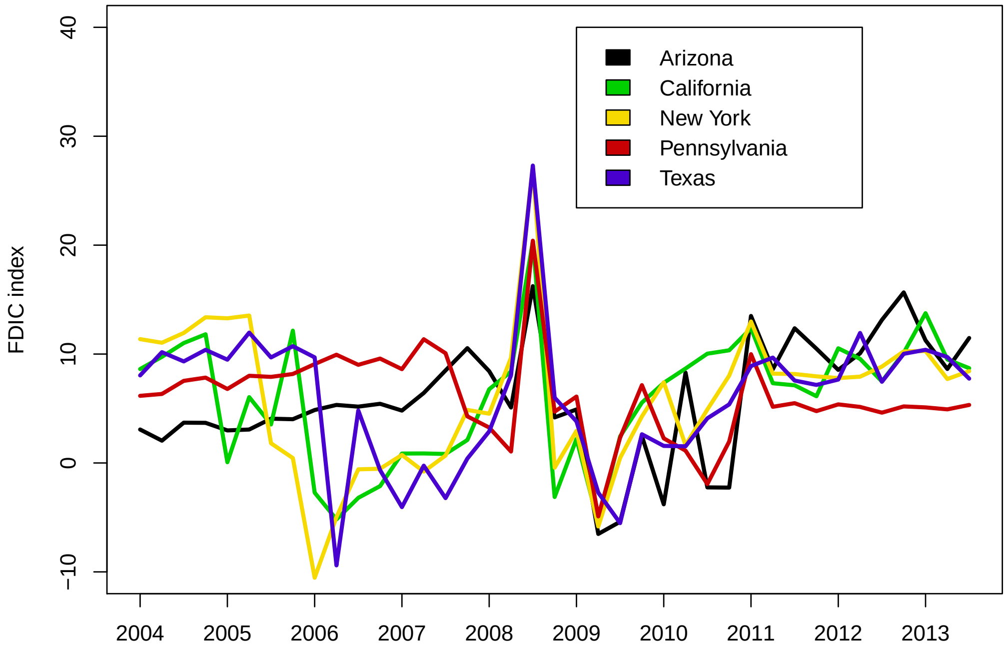


for five selected states.

In all states, attention to deposit insurance spikes in mid 2008 before the financial crisis and reaches a minimum level of attention at the beginning of 2009. Interestingly, depositor attention on “FDIC” in California, New York, and Texas is lowest around the beginning of 2006, while the values of the FDIC-index stay relatively constant from 2004 to 2008. After a few quarterly ups and downs in attention after the financial crisis, the search volume on “FDIC” in these states does not vary as significantly as before.

Figure 6.3: Time evolution of FDIC-index.

The figure shows the time evolution of the FDIC index for the states Arizona (black), California (green), New York (yellow), Pennsylvania (red), and Texas (blue). The FDIC-index is constructed as the search volume for "FDIC" from Google Trends in a given state for the time period 2004 to the end of 2013, winsorized at the 5% level, adjusted for seasonality, and scaled by its standard deviation. Higher values indicate a higher search volume on "FDIC".



6.3.4 Other data

In our analyses, we investigate the relation between U.S. depositor sentiment, depositor attention, and bank deposits. Therefore, we analyze bank deposits from U.S. banks that are insured by the FDIC. We obtain all FDIC call reports for the time period Q1 2004 to Q4 2013.[77] First, we include in our sample all banks that are located in one of the 50 U.S. states or the District of Columbia that have at least one listed quarter observation on demand and time deposits. Since we can only measure the effects of depositor attention on deposit insurance for high volume states, we omit all banks in

[77]The call reports are provided by the FDIC and can be downloaded at `www2.fdic.gov/sdi/download_large_list_outside.asp`.

the sample that are located in one of the low volume states and restrict ourselves to the high volume states. While this might seem a huge sacrifice of data on the first look, we still account for over 75.8% of all demand deposits and 72.2% of all time deposits (in Q1 2004). Our final sample includes 7,290 banks that report at least once in the given time frame.

6.4 Empirical strategy

Our goal is to empirically assess the interplay of depositors' knowledge of and attention towards deposit insurance and their resulting behavior. In theory, a perfectly informed, rational depositor is expected to acknowledge the existence and effectiveness of deposit insurance schemes and thus, the safety of his assets. Consequently, disastrous events such as bank runs and possible contagion effects should be very unlikely to occur if the assumptions for the depositors' level of information hold true.

In our analyses, we investigate the impact of depositor sentiment and attention on changes in bank deposits. As our dependent variables, we employ percental changes in demand and time deposits from 2004 to 2013. Demand deposits are widely considered as money and can be withdrawn at any given time by the banks' customers. They therefore bear the risk of creating spontaneous liquidity shortages at banks if depositors parallelly begin to withdraw their money. Changes in time deposits, on the other hand, reveal rather slow trends and long term depositor behavior. From 2004 to 2013 the amount of deposits of FDIC insured banks increased almost linearly, although the number of banks in the sample decreases. To adjust for inflation or the growth of money supply, which biases trends in deposits that are resulting from depositor behavior, we adjust the total values of demand and time deposits and the banks' total assets with the M2-index released by the Federal Reserve Board as a proxy for money supply [78].

[78] The index includes notes and coins in circulation (outside Federal Reserve Banks and the vaults of depository institutions), traveler checks of non-bank issuers, demand deposits, other checkable deposits (OCDs), which consist primarily of negotiable order of withdrawal (NOW) accounts at depository institutions and credit union share draft accounts, savings deposits, time deposits less than 100,000, and

Our two dependent variables are the change in demand deposits (ΔDemand) and the change in time deposits (ΔTime) in%. We winsorize the two variables at the 1% level to minimize the risk of outliers driving our results. As our main variable of interest in our regression analyses, we employ the FDIC-index introduced in Section 6.3.3. For our first analysis, we stimate the following model

$$\begin{aligned} \Delta\text{Deposits}_{i,t} &= \beta_1 \times \text{FDIC}_{i,t-1} + \beta_2 \times \Delta\text{Deposits}_{i,t-1} \\ &\quad + \Theta \times \text{CONTROLS}_{i,t-1} + \nu_t + \alpha_i + \varepsilon_{i,t}, \end{aligned}$$

where $\Delta\text{Deposits}_{i,t}$ is the change in demand or time deposits in one quarter and $\text{FDIC}_{i,t-1}$ is the lagged main independent variable of interest indicating the relative attention of depositors in the state of bank i towards deposit insurance. The control variables used are Return on assets (ROA) as a proxy for firm profitability, non-interest income relative to total interest income, a bank's equity ratio, the net interest margin, and also operating efficiency to control for preferences of depositors regarding bank fundamentals (see Oliveira et al., 2014). Additionally, we employ the size of a bank (natural logarithm of a bank's total assets at the end of a quarter) to check for differences in depositor behavior between smaller or larger banks, which could arise, e.g., because of possible too-big-to-fail guarantees. In our first set of regressions, we employ our full sample but also split our sample of banks into three samples, namely small, medium and large banks (measured by the 33.3%- and 66.7%-quantiles of the banks' size). Finally, we also include the FEARS-index introduced in Da et al. (2015) which consists of internet search volume data on thirty economics-related words. A higher value of FEARS indicates negative household sentiment on the current economy, which could not only affect stock returns, but also changes in deposits.

In general, our model could suffer from endogeneity problems since changes in deposits could induce higher levels of attention on deposit insurance and, of course, vice versa. We intend to solve this issue by employing the first lag of all indepen-

money-market deposit accounts for individuals. The index is constructed using Laspeyres' method and Q1 2004 as our basis.

dent variables. Since the call reports are published with a large time lag, the information on a bank's deposits should not affect depositors' behavior in that short time frame. In addition, depositors would need to inform themselves about the FDIC and their publicly available data and thus, should know about the deposit insurance in the first place. However, we estimate the dynamic panel model above with the (one-step) GMM-sys method (see Blundell and Bond, 1998) using the double lagged variables $\Delta \text{Deposits}_{i,t-2}$, $\text{FDIC}_{i,t-2}$, and $\text{NetInterestMargin}_{i,t-2}$ as instruments. Furthermore, we include bank-level fixed effects and quarter time-dummies to account for unobserved heterogeneity.

Beside the differentiation in bank size by depositors, we suspect the effects of several variables to differ during the crisis. For example, crisis sentiment of depositors could have induced decision-making that is not based on fundamental values and thus, could have caused significant drops in deposits. On the other hand, we know that no systematic runs on deposits occured during the recent crisis, which might indicate that depositors perceive bank deposits as a safer alternative in contrast to other investment classes. Also, depositors might seek additional information on the safety nets for their assets or deposits, but also the possible positive effects of financial knowledge could be counterbalanced by negative sentiment.

Since the interaction of crises times and depositor behavior is far from obvious, we further investigate the behavior of depositors with interaction terms of our main independent variables and a crisis dummy variable. We follow Oliveira et al. (2014) and declare the time frame of the financial crisis to be Q4 2008 and Q1 2009. Thus, we define our variable *Crisis* to be equal to one, if the bank observations is in Q4 2008 or Q1 2009 and zero otherwise. In our analyses, we particularly focus on the interaction of the variable *Crisis* with *FDIC* and *FEARS*. Finally, we employ the interaction of deposit insurance attention measured by *FDIC* and the household sentiment variable *FEARS*. Increased negative sentiment could lead to withdrawals of depositors' assets but also to intensified research on the safety options provided, which makes this interaction specifically interesting.

So far the empirical strategy intends to reveal the impact of deposit insurance awareness on the average trends of changes in deposits and thus, the behavior of U.S. depositors. As a next step, we want to shed light on the usefulness of internet search data to predict depositors' behavior. In particular, one might be interested in finding a reliable indicator of extreme withdrawals or, possibly, bank runs. Although the internet search data obtained from *Google Trends* is updated at a very high frequency (less than a week), its predicive power should be considered with caution. First of all, it is not clear which search terms could indicate the worries of depositors about possible bank runs or the distress of their (possibly local) bank. Second, worries about bank runs on specific banks are not only difficult to measure but bank runs also take place in a relatively short time frame and are therefore not captured at the quarterly frequency we have in our sample data. While we will not be able to forecast individual bank runs with internet search data on individual institutions, we will instead concentrate on the overall level of deposit insurance knowledge and attention, and the likelihood of extreme withdrawals of and gains in deposits.

We define large withdrawals as a percental decrease in demand deposits by the 20%-quantile of our whole sample observations. Similarly, we view a positive change in demand deposits over the 80%-quantile as a large gain in deposits. In theory, a higher level of awareness about deposit insurance should decrease the likelihood of large deposit withdrawals and could possibly increase the probability of significant positive changes in bank deposit levels and thus support the results in Diamond and Dybvig (1983) and subsequent work. We address this question by performing logistic panel regressions with bank- and time-fixed effects. In our setup, the dependent variables are $\text{Run}_{i,t}$, which is a dummy variable that takes on the value one if bank i experiences a drop in demand deposits by -9.8% (20%-quantile) in quarter t, and zero otherwise, and $\text{Gain}_{i,t}$, which is one if the increase in demand deposits is above +12.5% (80%-

quantile) and zero otherwise.[79] The estimated models are the following

$$\begin{aligned}\text{Run}_{i,t} \text{ or Gain}_{i,t} &= \beta_1 \times \text{FDIC}_{i,t-1} + \beta_2 \times \text{FEARS}_{t-1} \\ &\quad + \Theta \times \text{CONTROLS}_{i,t-1} + \nu_t + \alpha_i + \varepsilon_{i,t},\end{aligned}$$

where the controls are the first lag of control variables that are used in our previous analyses.

6.5 Empirical results

6.5.1 Changes in U.S. bank deposits

To get a first impression of the distribution of changes in deposits across the United States and to detect possible trends in deposits across U.S. states, we plot heat maps of changes in deposits. Figure 6.4 and 6.5 present heat maps indicating average changes in demand and time deposits in a given state for a pre-crisis, mid-crisis, and post-crisis quarter.

The average changes in demand deposits are mostly positive across the whole country in all three quarters. In Q4 2006, we see high increases in demand deposits in the center of the country (e.g. the mountain states). During the financial crisis, we still notice positive changes in demand deposits but to a smaller extent. After two years, in Q4 2010, the picture of changes in deposits still holds true.

For the 20%-quantile heat maps of changes in demand deposits, we see that the values seem to be rather negative across the whole country with the biggest drop of deposits in Q4 2006 happening in Arizona. Also, we can see that the number of extreme withdrawals increases during the crisis, before the landscape of extremely negative changes in deposits reverts to its normal state in 2010. Before, we saw that the average and 20%-quantile changes in time deposits were less extreme than in the case of demand deposits. In the mid-crisis quarter we notice less positive increases than in

[79] Our approach follows Iyer and Peydro (2011) who use similar quantiles to define large withdrawals.

Figure 6.4: Heat maps of changes in demand deposits.

The figure shows heat maps for percental changes in demand deposits for the fourth quarter in 2006, 2008, and 2010, respectively. The first row shows the maps for average values per state and the second row contains the 20%-quantiles of changes in demand deposits in each state. Percental changes of -20% and below are shown in black and increases of over +20% are shown in white. Values in between are presented with respective shades of grey. Data on demand deposit changes are winsorized at the 1% level.

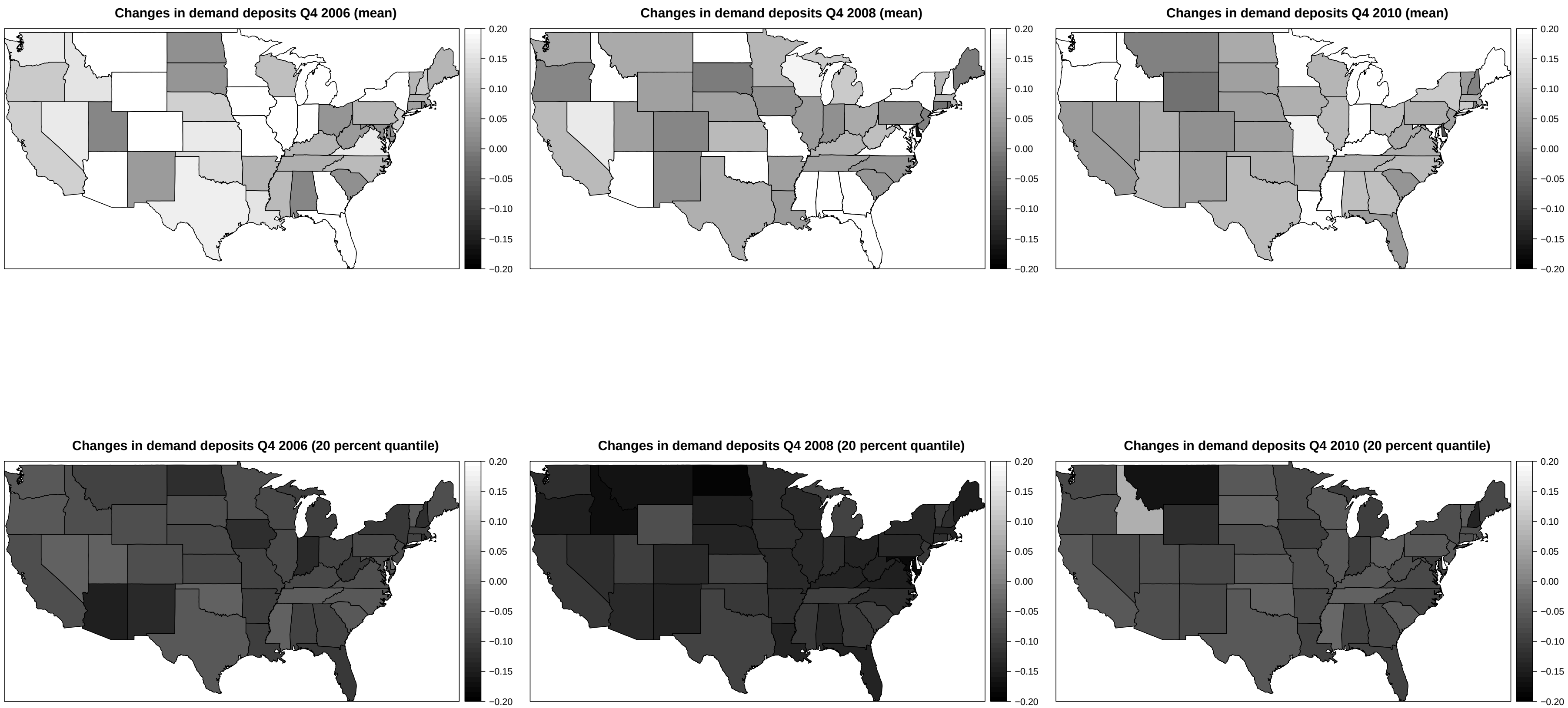
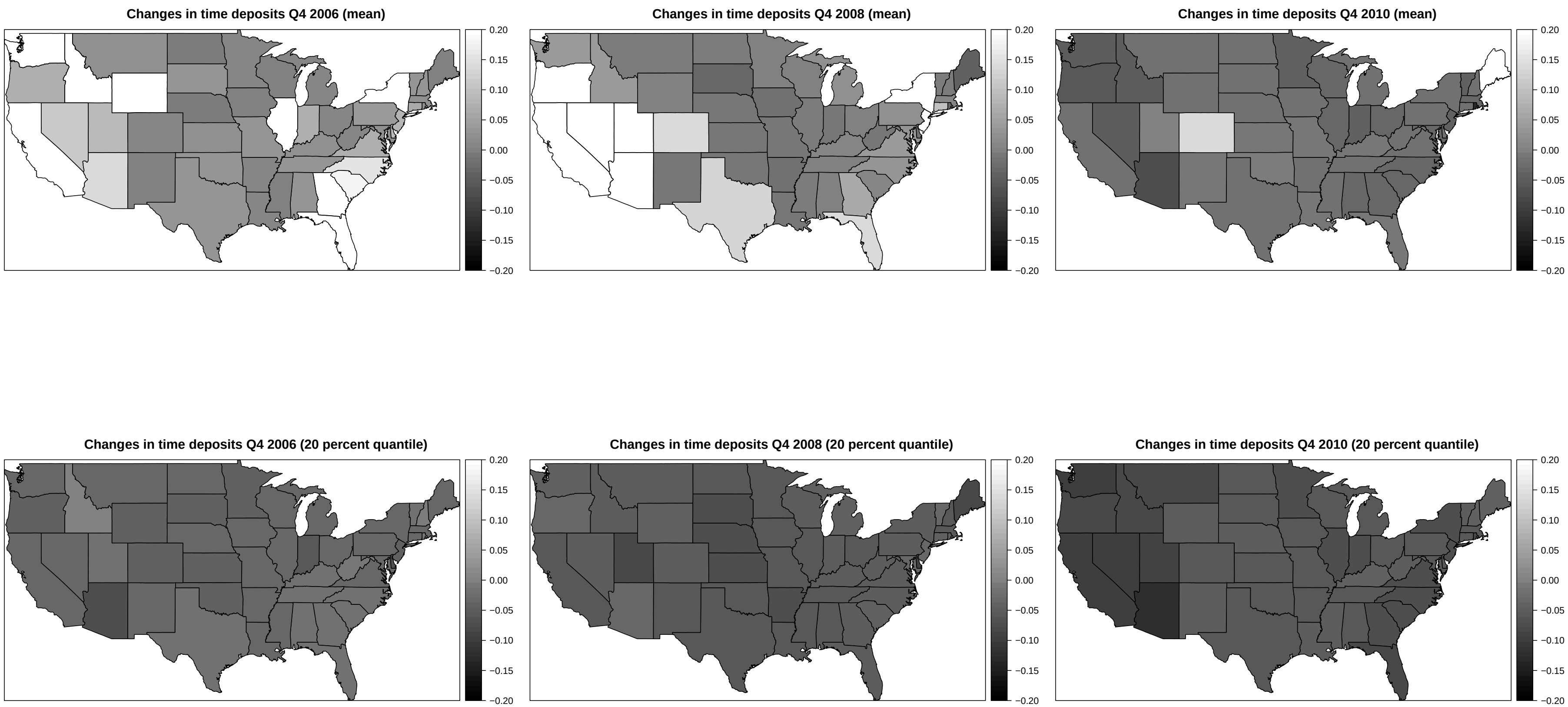


Figure 6.5: Heat maps of changes in time deposits.

The figure shows heat maps for percental changes in time deposits for the fourth quarter in 2006, 2008, and 2010, respectively. The first row shows the maps for average values per state and the second row contains the 20%-quantiles of changes in time deposits in each state. Percental changes of -20% and below are shown in black and increases of over +20% are shown in white. Values in between are presented with respective shades of grey. Data on time deposit changes are winsorized at the 1% level.



demand deposits but still extremely positive percental changes in time deposits in the western states of the U.S.

Changes in deposits may vary not only on the individual or state levels, but also over time. Figure 6.6 shows the time evolution of changes in demand and time deposits across our full sample for the time period Q2 2004 to Q4 2013. In addition to the time evolution of the mean values, the range of the values is expressed via the 20%- and 80%-quantiles. In the case of demand deposits, we see that extremely positive values peak twice (in Q4 2009 and Q4 2012) at around +20%. Extreme withdrawals (20%-quantile) in demand deposits, on the other hand, are lowest several times between 2006 to 2010 with about -15% decreases. However, average values of changes in deposits are positive for the whole sample period with several quarterly increases in demand deposits of +10% and with a maximum of approximately +20% in Q4 2012.

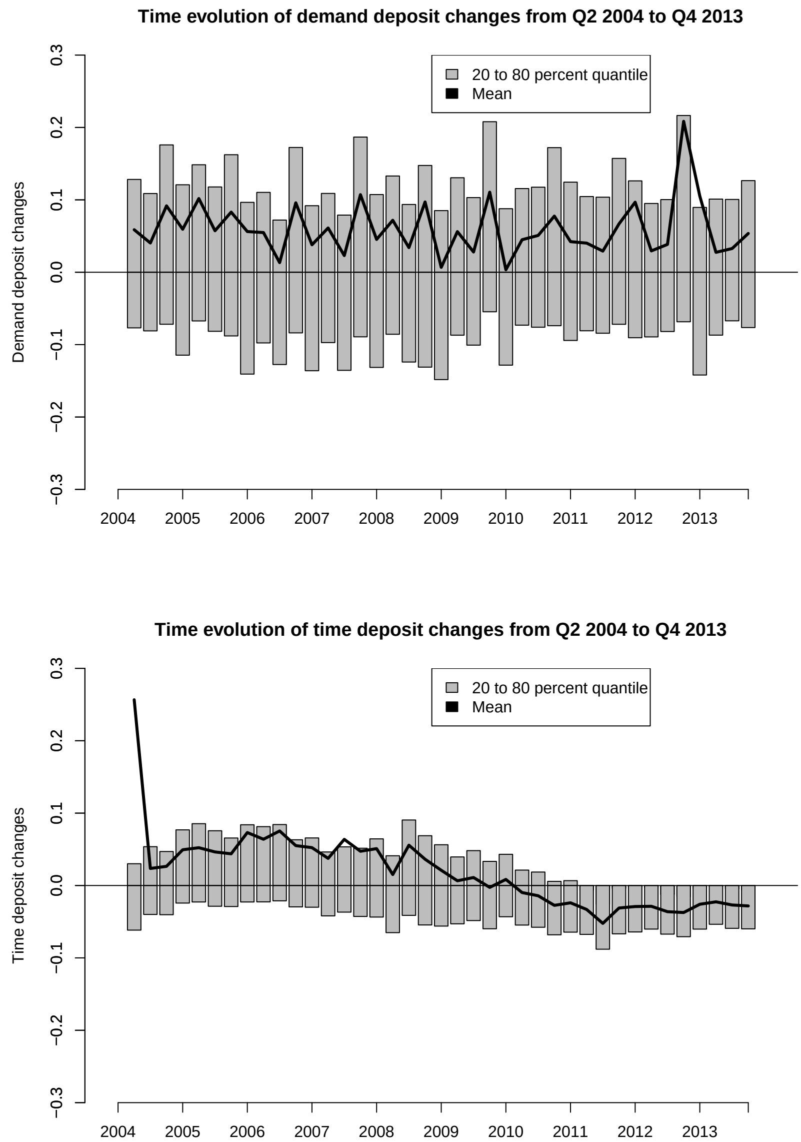
Turning to the changes in time deposits, we see a less volatile time evolution. Generally, changes in time deposits move within maximum increases of under 10% and minimum decreases over -10%. Interestingly, after the crisis, there is a strong negative trend in changes in time deposits where even the 80%-quantiles in changes seem to be negative. However, some extremely high values seem to bias the mean values in Q2 2004 and upcoming quarters until 2007. To address this issue, we rerun our main analyses on winsorized changes in time deposits but winsorize at the 5% and 10% level, respectively, in our robustness checks.

6.5.2 Depositor sentiment, depositor attention, and changes in deposits

Our main analyses are geared towards the effects of attention to deposit insurance and depositor sentiment on the movements in demand and time deposits. We investigate FDIC insured banks from 2004 to 2013 that are located in states with sufficient internet search volume on “FDIC”. Since we suspect depositor sentiment and depositor attention to have a differential effect on banks of different sizes, we run our regression

Figure 6.6: Time evolution of changes in deposits.

The figure shows barplots of quarterly changes in demand and time deposits (in percent) for the time period Q2 2004 to Q4 2013 for FDIC insured banks in high volume states. The top grey bars indicate the 80%-quantiles of changes in deposits each quarter and the bottom bars indicate the 20%-quantiles of changes in deposits. The black lines present the mean percental changes in deposits each quarter. Data on deposit changes are winsorized at the 1% level.



analyses for the whole sample and also separately for small, medium and large banks (by taking the 33.3%- and 66.7%-quantiles of size as cut-off values).

Table 6.1 presents summary statistics for the observations used in our panel regresions of changes in demand and time deposits.

Most strikingly, we see that average changes in demand and time deposits are positive across all samples. On average, demand deposits increased by 5.3% per quarter for all banks in the sample and time deposits increased by 1%. Surprisingly, demand deposits increase by almost 2% more for small banks than for medium or large sized banks. This also holds true for changes in time deposits. We observe that, on average, small banks also tend to be more efficient, have higher net interest margins and equity ratios but are also significantly less profitable. Therefore, we expect to find different factors to explain the movements in deposits for small banks in comparison to their larger counterparts.

We now turn to the description of our multivariate analyses on the impact of depositor sentiment and depositor attention on the trends in deposit changes. The results of our (one-step) GMM-sys regressions of ΔDemand and ΔTime on the FDIC-index, the FEARS-index, and our control variables are presented in Table 6.2.

We find two main results. First, we observe a positive relation of higher attention of depositors towards "FDIC" and changes in demand and time deposits. This is consistent with the theoretical basis in Diamond and Dybvig (1983) since increased attention to deposit insurance reveals depositors' knowledge of deposit insurance and thus implicates the effectiveness of such schemes. Empirically, this is also supported in the work of Brown et al. (2014), who report a significant influence of financial literacy on depositors' behavior. Second, we find that increased bad sentiment among depositors leads to systematic negative trends in changes in both demand and time deposits.

For the regressions with changes in demand deposits, we find a positive influence of depositors' attention to deposit insurance on the movements in demand deposits. The variable *FDIC* is statistically significant at the 1% level. On the other hand, we find the effects of household sentiment to significantly decrease the level of demand

Table 6.1: Summary Statistics.

The table shows mean values and standard deviations (in brackets) for the percental changes in demand and time deposits in a quarter and control variables that are used in the respective regression analyses. We report summary statistics for the regression analyses with the whole sample (all) and the split samples consisting of small, medium, and large banks (distinguished by the one third percentiles of total assets). Variable definitions and data sources are provided in Appendix E.1.

	Demand deposits				Time deposits			
Sample:	All	Small	Medium	Large	All	Small	Medium	Large
ΔDeposits	0.053	0.065	0.045	0.048	0.010	0.023	0.003	0.002
	(0.45)	(0.45)	(0.41)	(0.47)	(0.16)	(0.22)	(0.12)	(0.12)
FDIC	0.631	0.816	0.785	0.268	0.604	0.758	0.776	0.250
	(12.17)	(12.14)	(12.10)	(12.24)	(12.17)	(12.15)	(12.10)	(12.24)
Net interest margin	3.871	3.962	3.911	3.740	3.871	3.950	3.914	3.749
	(1.04)	(1.00)	(0.96)	(1.12)	(1.08)	(1.03)	(1.02)	(1.15)
FEARS	0.003	0.002	0.003	0.004	0.003	0.002	0.003	0.004
	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)
Size	5.145	4.570	5.079	5.778	5.140	4.564	5.079	5.780
	(0.58)	(0.23)	(0.12)	(0.49)	(0.59)	(0.23)	(0.12)	(0.49)
ROA	0.589	0.396	0.668	0.701	0.596	0.447	0.636	0.714
	(2.68)	(2.65)	(3.12)	(1.61)	(2.09)	(2.88)	(1.58)	(1.45)
Non-interest income	0.620	0.956	0.420	0.433	2.130	4.680	1.310	0.433
	(24.66)	(35.04)	(21.29)	(10.68)	(170.77)	(263.53)	(141.68)	(11.22)
Operating efficiency	76.921	88.210	75.327	68.230	76.807	87.882	75.278	68.056
	(251.38)	(164.62)	(100.67)	(43.27)	(250.86)	(167.39)	(100.28)	(43.31)
Equity	0.113	0.129	0.106	0.103	0.114	0.132	0.107	0.103
	(0.06)	(0.08)	(0.04)	(0.04)	(0.07)	(0.09)	(0.05)	(0.04)
Observations	181,141	58,093	59,025	59,637	183,409	59,537	59,530	59,924

Table 6.2: GMM-sys regressions of changes in deposits.

The table shows the results of the (one-step) GMM-sys estimation of ΔDemand and ΔTime on *FDIC* and control variables. The dependent variables are the quarterly percental changes in demand deposits and time deposits. The main variable of interest is *FDIC* which is the Google Search Volume Index of the phrase "FDIC" from Google Trends, adjusted for seasonality, winsorized at the 5% level, and scaled by its standard deviation. Other regressors are defined in Appendix E.1. All independent variables are lagged by one quarter and the lagged dependent variable is included in the regressions. We employ double-lagged values of the dependent variables, *FDIC*, and *Net interest margin* as instruments. P-values are given in parentheses and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable:	ΔDemand				ΔTime			
Sample:	All	Small	Medium	Large	All	Small	Medium	Large
FDIC	0.0009***	0.0003	0.0006	0.0014**	0.0004***	0.0005**	0.0002*	0.0004***
	(0.007)	(0.636)	(0.297)	(0.036)	(0.000)	(0.016)	(0.064)	(0.005)
FEARS	-1.9332***	-7.4680***	-13.7430***	6.3370***	-3.5460***	-8.4343***	-14.1875***	4.3576***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size	-0.1923***	-0.7278***	-1.2295***	-0.5747***	-0.3551***	-0.8817***	-1.2494***	-0.3824***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ROA	-0.0126***	0.0023	-0.0138***	-0.0215***	-0.0074***	-0.0052***	0.0010	-0.0005
	(0.000)	(0.364)	(0.000)	(0.000)	(0.000)	(0.000)	(0.155)	(0.508)
Net interest margin	-0.0300***	-0.0460***	-0.0237***	0.0083	0.0105***	0.0222***	-0.0005	0.0075***
	(0.000)	(0.000)	(0.004)	(0.137)	(0.000)	(0.000)	(0.810)	(0.000)
Non-interest income	0.0003	-0.0002	0.0008	0.0020***	0.0000	0.0000	0.0000	0.0001
	(0.165)	(0.531)	(0.229)	(0.001)	(0.868)	(0.834)	(0.785)	(0.538)
Operating efficiency	0.0000***	0.0000	0.0002***	0.0001	0.0000	0.0000**	0.0000	0.0000
	(0.000)	(0.488)	(0.000)	(0.369)	(0.547)	(0.013)	(0.395)	(0.524)
Equity ratio	2.7338***	2.2196***	2.7438***	2.7521***	1.5459***	1.6299***	0.3034***	0.5475***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ΔDeposits$_{t-1}$	-0.1233***	-0.1154***	-0.1262***	-0.1397***	0.0115***	0.0323***	0.0058**	0.0015*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)	(0.092)
Bank-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	181,141	58,093	59,025	59,637	183,409	59,537	59,530	59,924
Wald	9,436.82	4,141.79	2,837.53	3,060.35	35,701.78	19,358.02	6,693.83	5,625.09
Wald (p-value)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001

deposits. However, the economic significance of these two contradicting forces differs drastically. An increase of one standard deviation in *FDIC* results in an average increase of demand deposits by 1.1% (0.0009×12.17) whereas the negative effects of depositor sentiment induce changes in demand deposits of -42.5% (-1.9322×0.22). For small- and medium-sized banks, we do not find a significant influence of depositor attention on demand deposits. Large banks, however, gain +1.7% (0.0014×12.24) in demand deposits from a one standard deviation increase in *FDIC*. Comparing the results of small- and medium-sized banks with the results for large banks, we notice that the influence of depositor sentiment is the exact opposite. While we find that FEARS has a strong negative influence on changes in deposits of smaller banks, the deposits of large banks are more likely to significantly rise with higher depositor sentiment. This picture is also revealed for the changes in time deposits. In this case, we also find weak significance of increased attention to the *FDIC* on time deposits. The results for these two variables show that the impact of depositor sentiment can influence the decisions of depositors concerning their assets. Since negative sentiment seems to increase the level of deposits for large banks, one could be tempted to use possible too-big-to-fail or bailout guarantees to explain this trend, which is consistent with previous results from, e.g., Oliveira et al. (2014). Therefore, we also include bank fundamentals to control for depositors' preferences for specific banks.

A higher equity ratio is associated with decreases in deposits, and a one standard deviation higher equity ratio has an economically large impact of +16.4% (2.7338×0.06) across our full sample, which is even higher for small banks' demand deposits (+17.8% = 2.2196×0.08 in comparison to +11.0% = 2.7521×0.04 for large banks). The efficiency of a bank seems to be a significant factor for increasing deposits at medium-sized banks, but less important for the largest banks. In contrast to the differences in the effects of depositor sentiment on small and medium-sized versus larger banks' deposits, we consistently find our variable size to influence depositors' preferences. Our results suggest that depositors choose small rather than large banks to deposit their money in the form of demand and time deposits. The factor size determines economically significantly large decreases in demand deposits of -16.7% (small), -14.8% (medium), and -28.2% (large), and similar values for time deposits.

Overall, our results suggest that both depositor sentiment and attention influence depositor behavior. To further investigate the relation of our main variables of interest with changes in deposits, we employ various interaction terms. Table 6.3 shows the respective results of additional (one-step) GMM-sys estimations of changes in deposits on control variables and interaction terms using the full sample.

The first two colums include a crisis dummy in addition to other control variables to check for possible differences that occured during the turmoil of the recent financial crisis. First, we interact *FDIC* with the crisis dummy to differentiate between the effects of *FDIC* during and outside the crisis. For the regression of ΔDemand, we find strong evidence for a positive relation of depositor attention and changes in demand deposits outside of the crisis period. The coefficient of the crisis dummy is positive and statistically significant at the 1% level, which is consistent with Oliveira et al. (2014) who document that depositors in Brazil used systemically important banks to allocate their money in the form of deposits. However, we find no evidence of a significant influence of the interaction term. Thus, we cannot conclude that increased attention to deposit insurance was the driver of the positive change in demand deposits during the two crisis quarters. In the regression of ΔTime, the crisis dummy is omitted due to collinearity.

Another regression employing the interaction of the crisis dummy and *FEARS* suggests that the effect of *FEARS* is independent of crisis times. A higher level of negative depositor sentiment leads to a significant decrease in both demand and time deposits. Again, we see that bank customers use deposit accounts for their wealth during crisis times, which is suggested by the significant positive relation between the crisis dummy and ΔDeposits.

Finally, we observe a strong interaction of depositor attention and depositor sentiment. The negative sign of the interaction term's coefficient indicates the following relation: Increased negative sentiment is associated with less attention to deposit in-

Table 6.3: GMM-sys regressions on changes in deposits with interaction terms.

The table shows the results of the (one-step) GMM-sys estimation of ΔDemand and ΔTime on *FDIC*, control variables and interaction terms. The dependent variables are the quarterly percental changes in demand deposits and time deposits. The main variable of interest is *FDIC* which is the Google Search Volume Index of the phrase "FDIC" from Google Trends, adjusted for seasonality, winsorized at the 5% level, and scaled by its standard deviation. Other regressors are defined in Appendix E.1. All independent variables are lagged by one quarter and the lagged dependent variable is included in the regressions. We employ double-lagged values of the dependent variables, *FDIC*, and *Net interest margin* as instruments. P-values are given in parentheses and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable:	ΔDemand			ΔTime		
Interaction:	Crisis x FDIC	Crisis x FEARS	FDIC x FEARS	Crisis x FDIC	Crisis x FEARS	FDIC x FEARS
FDIC	0.0009***	0.0009***	0.0009***	0.0004***	0.0004***	0.0004***
	(0.009)	(0.007)	(0.007)	(0.001)	(0.000)	(0.000)
FEARS	-1.9312***	-1.9332***	-2.3162***	-3.5450***	-3.5460***	-4.3390***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size	-0.1922***	-0.1923***	-0.1923***	-0.3550***	-0.3551***	-0.3551***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Crisis	0.9999***	1.1149***		omitted	2.1397***	
	(0.000)	(0.000)		-	(0.000)	
Crisis x FDIC	-0.0001			-0.0001		
	(0.925)			(0.729)		
Crisis x FEARS		omitted			omitted	
		-			-	
FDIC x FEARS			-0.0301***			-0.0623***
			(0.000)			(0.000)
Control variables:	Yes	Yes	Yes	Yes	Yes	Yes
Bank-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	181,141	181,141	181,141	183,409	183,409	183,409
Wald	9,438.76	9,436.82	9,436.82	35,708.90	35,701.78	35,701.78
Wald (p-value)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001

surance, which suggests that the irrational component of depositors' behavior overwhelmes the search for information on safety options for their assets. In reverse, a higher value of *FDIC* over time seems to mitigate depositor sentiment and thus, at least partly, lowers the likelihood of runs on deposits. The statistical significance of the main effects of *FDIC* and *FEARS* remains unchanged.

6.5.3 Does deposit insurance attention prevent bank runs?

So far we have examined the importance of depositor sentiment and depositor attention for average trends in demand and time deposits, but little is known about the factors explaining extreme events such as bank runs. In the context of our study, the following question arises: does negative sentiment or attention of depositors increase or decrease their propensity to withdraw large parts of their deposits? While this question has been addressed on the micro-level for single banks (see, e.g., Iyer and Puri, 2012, Brown et al., 2014), we investigate this issue on a macro-level. To do so, we estimate logit panel regression with fixed effects on the bank-level and time dummies of which the results are presented in Table 6.4. The first three regressions in Table 6.4 make use of the dummy variable *Run,* which takes on the value of one if ΔDemand is below -9.8% (20%-quantile), and zero otherwise. From the literature, we know that individual perception and knowledge of depositors can play a major role in the financial decision making process and can cause depositors to run, despite of promising bank fundamentals (see, e.g. Osili and Paulson, 2014). We therefore would expect that knowledge about the FDIC lowers the propensity of depositors to withdraw large parts of their assets.

In the baseline regression, we see that the variable *FDIC* is statistically significant at the 10% level (p-value of 0.05). It appears that at times of higher depositor attention to deposit insurance, the likelihood of large withdrawals is lower. This effect of depositor attention on extreme withdrawals holds also true when including the crisis dummy and its interaction with *FDIC*. None of the latter two variables seem to influ-

Table 6.4: Panel logistic regression of large withdrawals and gains in demand deposits.

The table shows the results of panel logistic regressions on large withdrawals and gains of deposits. The dependent variables are the dummy variables *Run*, which takes on the value one if a bank experiences changes in demand deposits below the 20%-quantile of ΔDemand deposits and zero otherwise, and *Gain*, which is equal to one if the changes in deposits are above the 80%-quantile and zero otherwise. The main variable of interest is *FDIC* which is the Google Search Volume Index of the phrase "FDIC" from Google Trends, adjusted for seasonality, winsorized at the 5% level, and scaled by its standard deviation. Other regressors are defined in Appendix E.1. All independent variables are lagged by one quarter. P-values are given in parentheses and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable:	Run			Gain		
FDIC	-0.0026*	-0.0030**	-0.0026*	0.0026*	0.0023	0.0026*
	(0.050)	(0.029)	(0.050)	(0.063)	(0.110)	(0.061)
FEARS	0.2065	0.1840	0.1689	1.6063***	1.5860***	0.3557
	(0.590)	(0.631)	(0.714)	(0.000)	(0.000)	(0.427)
Size	0.6932***	0.6925***	0.6928***	-0.7965***	-0.7971***	-0.8054***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Crisis		-0.1344			-1.0786***	
		(0.552)			(0.000)	
Crisis x FDIC		0.0089			0.0088	
		(0.175)			(0.231)	
Size x FDIC			0.0001			0.0040***
			(0.883)			(0.000)
Control variables:	Yes	Yes	Yes	Yes	Yes	Yes
Bank-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	186,026	186,026	186,026	184,041	184,041	184,041
Likelihood ratio	3,320.32	3,322.15	3,320.32	4,507.12	4,508.56	4,528.02
Likelihood ratio (p-value)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001

ence the probability of large withdrawals in demand deposits. The interaction term of the variable size and *FDIC* is included in the third column, but the results suggest that this interaction neither mitigates nor intensifies the likelihood of bank runs.

We notice two more important relations: Our results suggest that the size of a bank is a significant driver of the probability of large withdrawals. Large banks are more likely to suffer from large withdrawals in demand deposits than smaller ones. This could be due to the fact that large banks are also more likely to be present in the media and thus also to bad rumors and sentiment. Interestingly, depositor sentiment fails to explain large withdrawals, although we are able to explain average trends with the *FEARS* variable in our previous analyses.

Next, we turn to the three regressions concerning the opposite situation of a bank run, namely large gains in demand deposits. The dummy variable *Gain* is defined to take on the value of one if demand deposits increase by +12.5% (80%-quantile) in one quarter, and zero otherwise. For the size of a bank, we see a very similar relation with *Gain* to the one with with large withdrawals. The larger a bank is, the less likely it is to experience extreme percental increases in demand deposits. The variable *FDIC* itself is only slightly statistically significant but, nevertheless, increases the chances of large gains in deposits.

For large gains, we also see that during the crisis, depositors were less likely to induce large gains in deposits, although we did see a positive trend on average during the crisis. Also, even though depositor sentiment explains negative trends in deposits, the likelihood of large gains in deposits increases with bad sentiment. An explanation is that depositors favor bank deposits over other investment opportunities to allocate their wealth.

6.5.4 Why do depositors search for FDIC?

Our results this far show that depositors' attention and sentiment influence their decision whether to use bank deposits or not. In parts, depositors' attention to deposit insurance helps to explain the positive trends in deposits over time. Internet search data is a way of measuring the active knowledge information retrieval of depositors in several states. However, we cannot conclude that the actual level of knowledge about deposit insurance is higher or lower, when the variable *FDIC* is low. It could also be that the interest in “FDIC” in Google is low since most of the depositors use alternative information sources to learn more about deposit insurance. On the other hand, the search volume of “FDIC” could be high, simply because media coverage spreads the word about the respective institution. To address this question, we perform further analyses involving a proxy for the news coverage by the FDIC. To do this, we regress the state-specific volumes of “FDIC” on contemporary control variables. We estimate models of the following form

$$\mathrm{FDIC}_{j,t} = \beta_1 \times \mathrm{Press}_t + \beta_2 \times \mathrm{GIF}_t + \beta_3 \times \mathrm{GDP}_{j,t} + \nu_t + \alpha_j + \varepsilon_{j,t},$$

where $\mathrm{FDIC}_{j,t}$ is the FDIC-index of state j, Press_t is the number of press releases by the FDIC in quarter t, GIF_t is an index on the general interest in finance topics on the internet, $\mathrm{GDP}_{j,t}$ is the GDP growth of state j in quarter t and α_j and ν_t express state-level- and time-fixed effects. The results of our OLS-regressions are reported in Table 6.5.

Our first regression includes only the number of press releases by the FDIC as well as state- and time-fixed effects. We observe a negative relation of the number of press releases and contemporary search volume on FDIC, which could be interpreted as if more news coverage by the FDIC indicates that there is less need for additional information retrieval by depositors on the internet. However, we do not know whether depositors actually process the news by the FDIC since it is a passive measure of attention. Next, we include the GDP growth of a state as a control variable, which does not change the results. Another aspect we need to control for is whether the level of depositor attention is simply determined by trends in general interest in finance topics. Thus, we include in our regressions a General Interest in Finance (GIF) index, which

Table 6.5: Why do depositors search for deposit insurance?

The table shows the results of OLS panel regressions of the variable $FDIC_{j,t}$ on the number of press releases by the Federal Deposit Insurance Corporation per quarter, GDP growth per state, general interest in finance, and the interaction term of press releases and General interest in finance. All regressions are performed with state- and time-fixed effects in the period of 2004 to 2013. P-values are given in parentheses and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Adj. R^2 is adjusted R^2.

Dependent variable:	FDIC			
Press	-0.1130**	-0.1152***	-0.0733*	-0.0755*
	(0.010)	(0.009)	(0.068)	(0.064)
GDP growth		0.1206***	0.1167***	0.1202***
		(0.007)	(0.006)	(0.005)
GIF			-0.2708***	-0.1044
			(0.001)	(0.557)
Press x GIF				-0.0033
				(0.455)
State-fixed effects	Yes	Yes	Yes	Yes
Time-dummies	Yes	Yes	Yes	Yes
Observations	858	748	748	748
Adj. R^2	0.4153	0.4293	0.480	0.482

is provided by *Google Trends* when entering no search term but restricting the search category to “finance”. The index describes the relative changes in search volumes on search terms tagged in the finance category, where higher values indicate increasing interest. Running a regression using this variable, we do not find different results for the previous factors. Furthermore, GIF shows a negative relation with attention to FDIC. Finally, we use the interaction term of the variables *Press* and *GIF* to check whether press releases influence depositor attention, independent of the general level of interest in finance. This analysis is not successful as the coefficient of the interaction term is not statistically significant.

6.6 Robustness and further analyses

To verify the robustness of our results, we perform several tests and further analyses.[80] As a first robustness check, we include in our baseline GMM-sys regressions the GDP growth of a state in which a bank is located. Depositor behavior could simply by determined by the economic environment the depositors are in, but our regressions reveal that the GDP growth neither is a reliable factor to explain changes in deposits, nor does it change the impact of depositor attention and depositor sentiment.

Next, we control for the general interest in finance by employing the GIF index introduced before. In doing so, we control for the possibility that depositors simply search for "FDIC" or other economics related subjects because the general level of interest in financial topics has an upward trend. Including GIF in additional GMM-sys regressions with ΔDemand and ΔTime, however, does not change our main findings. In section 6.5.4, we show that the presence of the FDIC in press releases was related to the need of depositors to gain more information on deposit insurance and related topics. Therefore, we substitute our variable FDIC by the number of press releases per quarter while having in mind that due to the limited geographical variation of this variable, we are not able to capture differences on the state- or bank-level. However, including this variable shows that a higher presence in the media through press releases leads to upwards trends in both demand and time deposits. The negative impact of depositor sentiment is still valid. Also, we control for the ratio of retail deposits and total deposits of a bank to control for the fraction of household depositors' assets among a bank's total deposits, but find no changes in our inferences.

Further, we consider the possibility that the interest in the Federal Deposit Insurance Corporation increases due to changes in the CD rates offered by banks. We therefore investigate the impact of the 3-month CD rate (published by the Federal Reserve Bank of St. Louis) on changes in deposits. Changing CD rates might in fact be highly

[80] The tables containing the results of our further analyses and robustness checks as well as additional information on our data set can be found in Appendix E.

correlated with depositors' attention to deposits and deposit insurance, which, however, does not change the effect of depositors' financial knowledge on their behavior. To measure the isolated influence of the level of CD rates on depositor behavior, we regress the quarterly average of the CD rates on the contemporary FDIC index and include the residual as an additional variable in our regressions. We find that our inferences do not change and that the sole impact of the CD rates' level is not significant in determining changes in deposits.

In the midst of the financial crisis, the Emergency Economic Stabilization Act was introduced as a way of bailing out troubled (financial) institutions with the aim of stabilizing the financial system in the United States.[81] At its core, the act contained the so-called Trouble Asset Relief Program ("TARP" in short) which allowed the U.S. Department of Treasury to buy up assets and equity of troubled financial institutions to strengthen financial stability. Several studies find that investors perceive banks that are associated with "too-big-to-fail" or bailout guarantees differently than non-systemic banks (see, e.g., Oliveira et al., 2014, Gandhi and Lustig, 2015). To control for differences in changes in the deposits at banks that did or did not receive government support through TARP, we include in our regressions a dummy variable *TARP* that is one if a bank or its holding received government support and zero before Q3 2008 or if the bank did not receive TARP support. We estimate GMM-sys regressions for changes in demand and time deposits that include the dummy variable and also its interaction with *FDIC*. For demand deposits, we find that the coefficients of TARP and the interaction term are statistically insignificant. On the other hand, TARP seems to have a positive effect on changes in time deposits. The coefficient of the interaction of *FDIC* and *TARP* is negative and statistically significant. We therefore conclude that the introduction of TARP has in fact decreased the interest in the FDIC.[82] Our main

[81] In addition, the deposit insurance coverage limit was increased from $100,000 to $250,000 per depositor and bank to strengthen the confidence of depositors and mitigate the possibility of depositors frantically withdrawing their assets from banks. Lambert et al. (2014) empirically address the effect of this increase of the coverage limit and show that banks affected by this change in regulation engaged in riskier investments (e.g., risky commercial real estate loans) due to moral hazard.

[82] Comparing the search volumes for "TARP" and "FDIC" with Google Trends, however, reveals that "FDIC" was still the more prominent search term of the two.

inferences regarding depositor attention and depositor sentiment are the same.

In a further analysis, we split our sample of banks according to their average ratio of non-performing loans to total assets and also according to the average ratio of insured deposits to total deposits. We estimate (one-step) GMM-sys and logistic panel regressions for banks in the bottom and top quartiles of these two additional variables. The results show that the *FDIC* variable fails to explain the extreme withdrawals or gains in demand deposits in those specific categories of banks. For the changes in demand deposits, we find a statistically significant positive relation with depositor attention for banks in the bottom quartile of the insured deposits ratio. This also holds true for the changes in time deposits. While we find a consistently negative influence of depositor sentiment on the changes in demand deposits for all categories, we find that depositors appear to differentiate between banks with high and low non-performing loans ratios when looking at the changes in time deposits. We see that depositor sentiment is positively related to changes in time deposits for banks with a low non-performing loans to total assets ratio. For banks with a higher ratio, we find a negative relation between the *FEARS*-index and changes in time deposits. Thus, our results support the notion of depositors withdrawing their money from troubled banks with bad loans and running to banks perceived as financially healthier when depositor sentiment increases. For banks in the bottom and top quartile of insured deposits ratio, we do not find such a differential effect, although one could expect it, since banks with less insured deposits do not have the full effect of deposit insurance coverage and could thus, more likely experience extreme withdrawals of deposits.

Although we split our sample according to the banks' total assets to further account for size effects and also include size as an independent variable in our regressions, our approach could still be criticized for not capturing the contemporary changes in a bank's size (e.g., a bank could exhibit a relative decrease in its demand deposit ratio that is simply caused by an increase in bank size and not by withdrawals by customers). To further investigate this aspect, we perform additional regressions with the dependent variable ΔRatio which is the relative quarterly change in a bank's demand deposit ratio. As independent variables, we include the contemporary changes in a bank's size (ΔSize), the lagged values of *FDIC*, *FEARS*, and *Net Interest Margin*. We estimate static and dynamic panels with simple OLS and also with (one-step) GMM-sys (and use double-lagged values of *FDIC*, *Net interest margin*, and the dependent variable as instruments). Our results reveal that the influence of depositor attention and sentiment we find in our main analysis is also valid for changes in demand deposit ratios.[83]

Also, we re-estimate our baseline models with different specifications. Instead of employing the GMM-sys estimators, we perform pooled OLS regressions with time-fixed effects and also estimate models with state-fixed effects, as well as robust standard errors adjusting for clustering on the bank level. Our main inferences remain the same. Also, instead of winsorizing our changes in deposits at the 1% level, we repeat our GMM-sys regressions with winsorized changes at the more conservative 5% and 10% level, respectively, but find no different results. As another set of robustness tests, we re-run our GMM-sys baseline regressions using double lagged values of all independent variables created with balance-sheet data to further mitigate concerns of endogeneity in our analysis. Also, we use the mean of the weekly values of the FDIC-index as a way of aggregating the search volume data to a quarter and employ this average in our main analyses. In both of the tests, our main results remain the same as before.

One possible concern could be the selection bias through the restriction of our data sample to high volume states, although our sample covers over 70% of all deposits in the United States. Therefore, we employ a Heckman two-stage selection procedure to detect effects of a selection bias. For the selection model, we use the lagged control variables size, return on assets, non-interest income, equity ratio, and operating efficiency as well as the average GDP growth per state, the states' population density, one lag of changes in deposits, and time dummies. However, we find no significant effect of the non-random sample selection on our main results in any of the regressions.

[83]Using simple OLS yields a significant negative influence of ΔSize on changes in demand deposit ratios, but employing GMM-sys shows that the changes in the deposit ratios are not due to changes in a bank's size.

Turning to our logistic panel regressions, we repeat the baseline regressions with a different definition for the Run and Gain dummy variables. We try to explain even more extreme withdrawals and gains by employing dummy variables that take on the value one if the changes in demand deposits are below (above) the 5%-, 10%-, or 15%-quantile (85%-, 90%-, or 95%-quantile) of the full sample, and zero otherwise. For extremely large withdrawal, we see that *FDIC* is no good predictor but depositor sentiment increases the likelihood of such extreme events at a statistically significant level. For the other regressions, we find depositor attention and depositor sentiment to increase the probability of large gains in demand deposits, although average trends in deposits are negatively affected by bad sentiment. As a further analysis, we estimate the baseline logistic panel regression using a different aggregation of the weekly values of the FDIC-index. First, we take the average instead of the sum to obtain quarterly values. The second approach we take is to use the maximum value in a quarter to proxy peaks in attention to the FDIC. Finally, we use the maximum of the weekly differences of the FDIC-index in a quarter to measure rapid changes in depositor attention. When investigating large withdrawals, however, the variables consistently fail to explain these extreme events. For large gains in demand deposits, we find that the maximum value and the maximum in differences have more predictive power than simply the mean and the sum of the FDIC-index values.

6.7 Conclusion

This paper constitutes the first analysis of the effects of depositor sentiment and depositor attention on changes in bank deposits in the U.S. during the period of 2004-2013. Using two direct measures of depositors' aggregate level of sentiment and attention based on internet search volume data from Google, we find that depositor sentiment is significantly negatively related to changes in U.S. banks' demand and time deposits. Conversely, a higher level of depositor attention to deposit insurance correlates positively with changes in bank deposits.

Our results suggest that personal attitudes and sentiment rather than bank fundamentals play a vital role in explaining the behavior of depositors. We also find further empirical evidence that depositor behavior is affected by the perception of a too-big-to-fail policy. More precisely, depositor sentiment has a differential effect on small and large banks: while depositor sentiment decreases deposits for small- and medium-sized banks, both demand and time deposits increase for larger banks when depositor sentiment is high.

Our findings have important implications for policy-makers and regulators: First, our findings document that deposit insurance helps in mitigating the risk of panic-based bank runs - but only if the existence of an explicit deposit insurance scheme is known among depositors. Our key result here is that a higher level of information procurement by households on deposit insurance mitigates the probability of a bank run. Interestingly, we find the media presence of the FDIC to substitute depositors' demand for more information on the U.S. deposit insurance system, with depositor attention being diverted to information sources on the internet via Google in case the presence of the FDIC in the media is low. The most important finding for policy-makers in this respect, however, is that the attention of households to deposit insurance in general exerts a mitigating effect on deposit outflows.

Finally, an important question that has not been addressed in this study (nor in the previous literature) is whether depositor attention and sentiment also possess such a significant impact on depositor behavior in case deposits are not covered by an explicit deposit insurance scheme. In particular, it would be interesting to analyze the differential effect of depositors' sentiment and attention on deposit outflows across different countries with differently designed deposit insurance schemes and different institutional environments. We intend to address this question in future research.

Appendix A

Supplementary Material for Chapter 2

A.1 Sample insurance companies

Table A.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 A.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	

A.2 Variable definitions and data sources

Table A.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 (2014), 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 (2012). 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 A.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 pro-rated 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 B

Supplementary Material for Chapter 3

B.1 Variable definitions and data sources

Table B.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 (2014), 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 B.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 C

Supplementary Material for Chapter 4

C.1 Variable definitions and data sources

Table C.1: 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 bank characteristics were retrieved from the *Thomson Reuters Financial Datastream* and *Thomson Worldscope* databases. The country control variables are taken from the World Bank's World Development Indicator (WDI) database. Data on the banks' regulatory environment are taken from Barth et al. (2006) and Barth et al. (2013a).

Variable name	*Definition*	*Data source*
Dependent variables		
Buy-and-hold return	Log annual buy-and-hold stock returns computed from the first and last trading day in a year.	Datastream, own. calc.
Bank characteristics		
Beta	Beta of a stock calculated as the ratio of the covariance of the stock's return and the MSCI World Index return and the variance of the stock's returns in one year.	Datastream, own calc.
MES	Annual Marginal Expected Shortfall as defined by Acharya et al. (2010) as the average return on an individual bank's stock on the days the *World Datastream Bank* index experienced its 5% worst outcomes.	Datastream, own calc.
ΔCoVaR	Unconditional ΔCoVaR as defined by Adrian and Brunnermeier (2014), 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.
Total assets	Natural logarithm of a bank's total assets at fiscal year end.	Worldscope (WC02999).
Market-to-book	Market value of common equity divided by book value of common equity.	Worldscope (WC07210 and WC03501).
Leverage	Book value of assets minus book value of equity plus market value of equity, divided by market value of equity (see Acharya et al., 2010).	Worldscope (WC02999, WC03501, WC08001), own calc.
Non-interest income	Non-interest income divided by total interest income.	Worldscope (WC01021 and WC01016).
Loans	Ratio of total loans to total assets.	Worldscope (WC02271 and WC02999).
Loan loss provisions	Natural logarithm of expenses set aside as an allowance for uncollectable or troubled loans divided by total loans.	Worldscope (WC01271 and WC02271).
Debt maturity	Total long-term debt (due in more than one year) divided by total debt.	Worldscope (WC03251 and WC03255).
Deposits	Total deposits divided by total liabilities.	Worldscope (WC03019 and WC03351).
Return on assets	Pre-tax return of the insurer on its total assets.	Worldscope (WC08326).
Tier-1-capital	Ratio of Tier 1 Capital to total risk-weighted assets.	Worldscope (WC18157).
Systemic size	Ratio of a bank's total liabilities to national GDP.	Worldscope (WC03351), WDI database.
Liquidity	Mean value of the Amihud measure of an individual stock's illiquidity adjusted following the procedure proposed by Karolyi et al. (2012). The adjusted Amihud measure is defined as $-\ln\left(1+\frac{\lvert R_{i,t}\rvert}{P_{i,t}VO_{i,t}}\right)$ where $R_{i,t}$ is the return, $P_{i,t}$ is the price, and $VO_{i,t}$ is the trading volume of stock i on day t.	Datastream, own calc.

Table C.1: Variable definitions and data sources (continued).

Variable name	*Definition*	*Data source*
Interconnectedness	Number of in- and outgoing granger causalities as introduced in Billio et al. (2012).	own calc.
Capital Requirement Deviation	Captures to which degree a banking firm's capital deviates from group average.	own calc.
Regulatory environment		
Capital Regulatory Index	Index of the stringency of capital regulations in the banking system, capturing whether the capital requirement reflects certain risk elements and deducts certain market value losses from capital before minimum capital adequacy is determined. Index ranges from 0 to 10. Higher values denote greater stringency.	Barth et al. (2006, 2013a).
Official Supervisory Power	Index of the extent to which supervisory authorities have the authority to discipline banks by taking specific actions to prevent and correct problems. Index ranges from 0 to 14. Higher scores denote greater power.	Barth et al. (2006, 2013a).
Diversification index	Index of the guidelines for asset diversification. Index ranges from 0 to 2. Higher scores denote more diversification.	Barth et al. (2006, 2013a).
Entry requirements	Index of the legal requirements that need to be fulfilled before issuance of the banking license. Index ranges from 0 to 8. Higher scores denote greater stringency.	Barth et al. (2006, 2013a).
Private monitoring index	Index of the incentives and capabilities provided by regulatory and supervisory authorities to encourage the private monitoring of banks. Index ranges from 0 to 12. Higher scores indicate greater regulatory empowerment of the monitoring of banks by private investors.	Barth et al. (2006, 2013a).
Corporate governance	Consolidated index of the six Worldwide Governance Indicators by averaging.	World Bank, own calc.
Corporate governance (pca)	Consolidated index of the six Worldwide Governance Indicators by using principal component analysis.	World Bank, own calc.
Country characteristics		
GDP growth	Annual real GDP growth rate (in %).	WDI database.
Inflation	Log of the annual change of the GDP deflator.	WDI database
HHI	Herfindahl-Hirschman Index computed as the sum of the squared market shares of a country's domestic and foreign banks.	WDI database.
Crisis dummy	Dummy variable that equals one if a financial crisis is identified by Laeven and Valencia (2012) in a country for a given year, and zero otherwise.	Laeven and Valencia (2012).

Appendix D

Supplementary Material for Chapter 5

D.1 Additional figures

Figure D.1: International bank and insurer stock prices 2006-2013.

The figure shows plots of the Datastream World Life Insurance, World Non-Life Insurance and World Bank indexes as well as the MSCI World Index. The data are taken from the *Thomson Reuters Financial Datastream* database and cover the period from 01/02/2006 to 10/11/2013. The business cycle contraction during and after the financial crisis as defined by the National Bureau of Economic Research (NBER) is highlighted by the area shaded in grey. All data series of stock prices are normalized to 100 at the start of 2006.

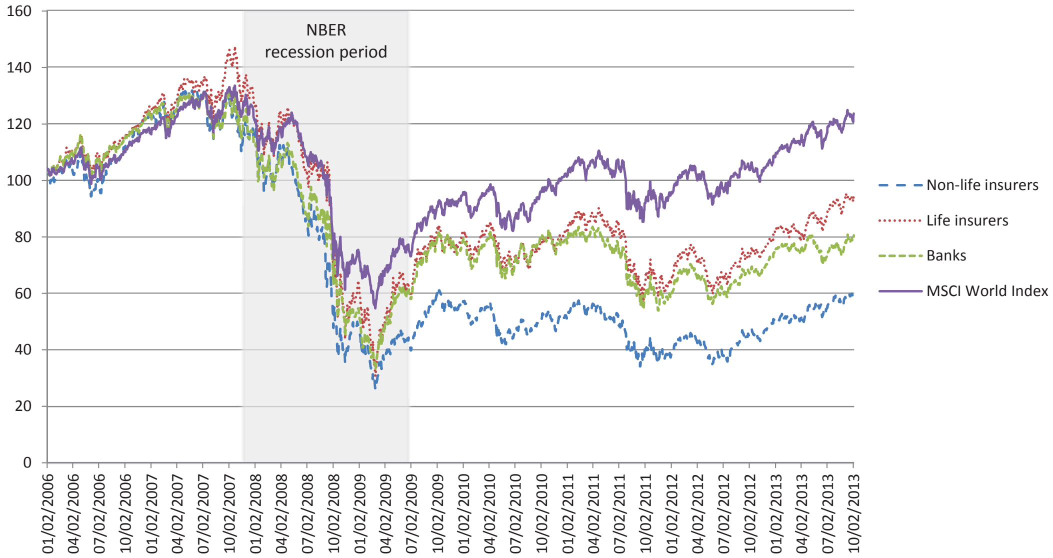


Figure D.2: Illustration of Google Trends search.

The figure illustrates the graphical output of the weekly aggregated search volume index (SVI) from Google Trends (http://www.google.com/trends/). The figure shows the plotted SVI for the the search query “financial crisis” and the SVI is scaled by the maximum over the time period 2004 to 2013.

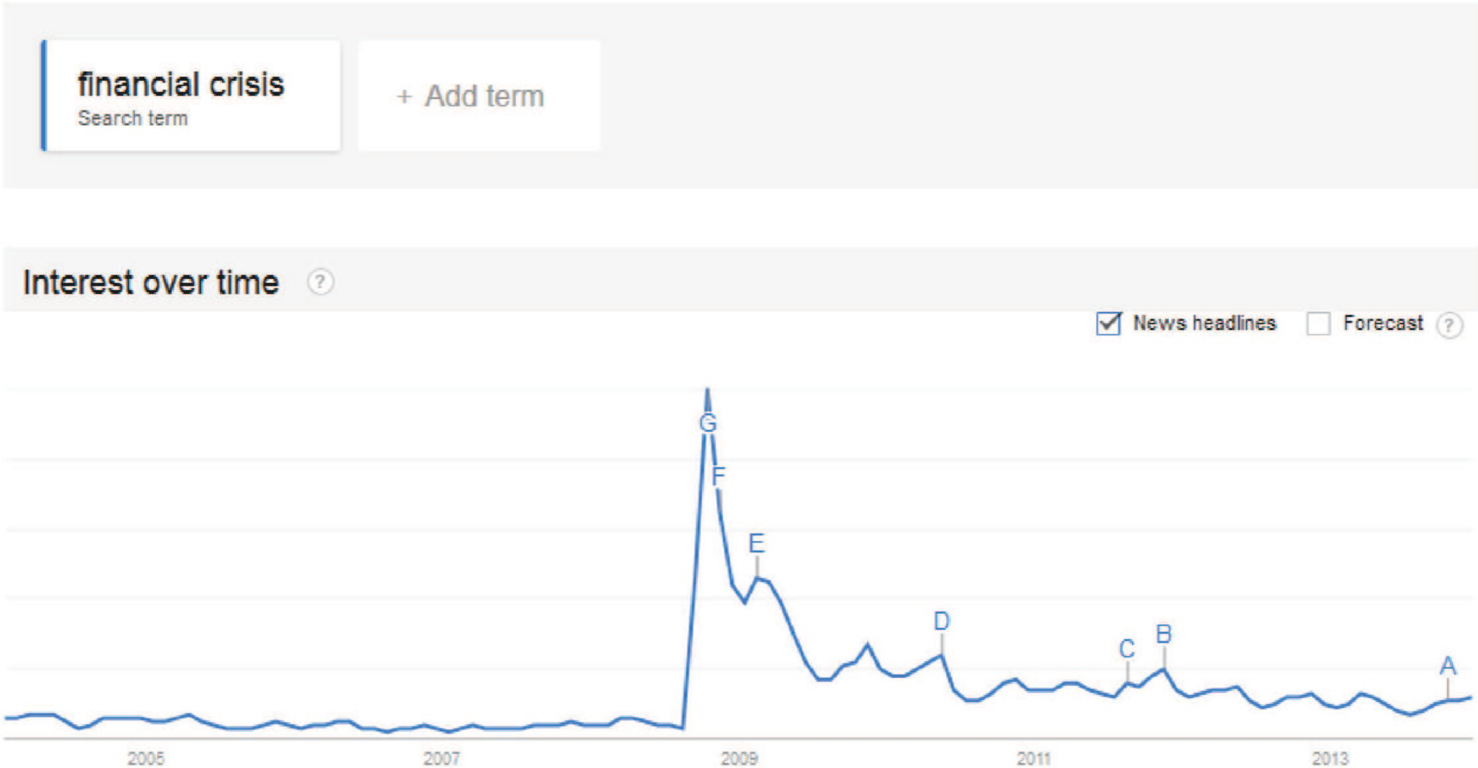
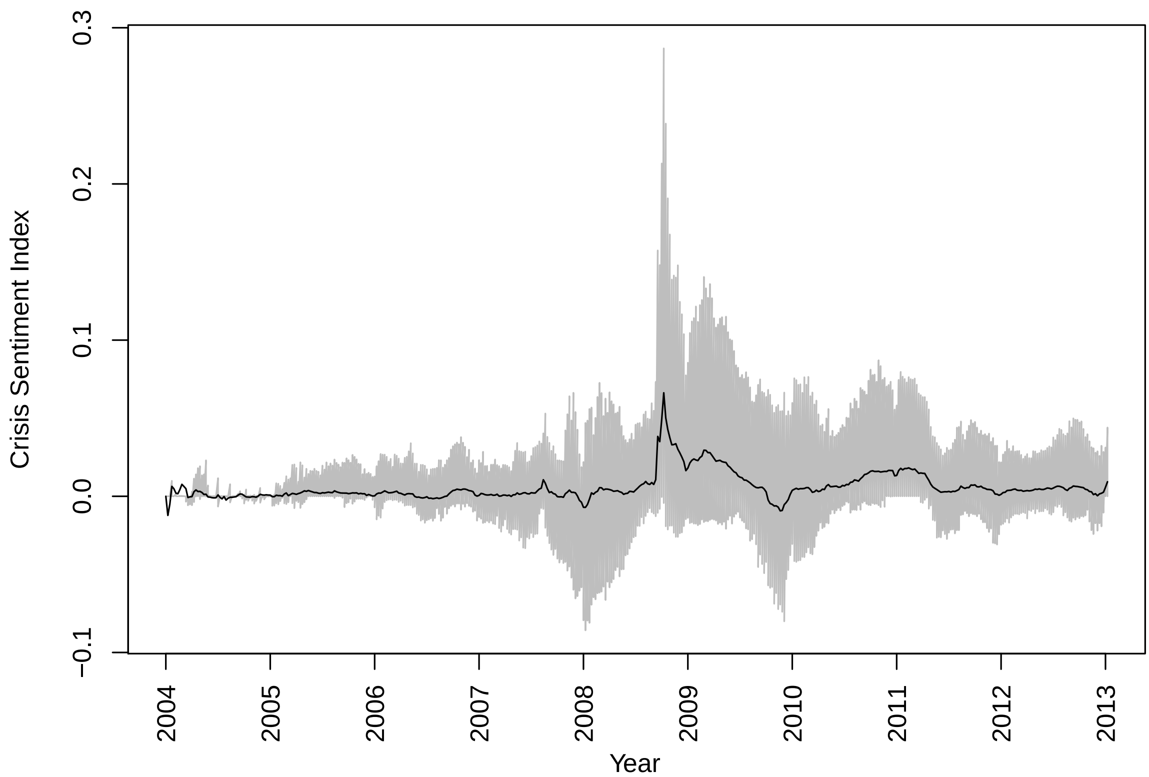


Figure D.3: Time evolution of the Crisis Sentiment Index.

The figure shows a plot of the time evolution of the Crisis Sentiment Index (CSI) during our full sample period 01/01/2004 to 12/31/2012 across our full sample of 253 international insurers. The Crisis Sentiment Index is computed using data from *Google Trends* via $CSI_t^i := \left(\frac{GSVI_t^i + Z_t}{200}\right) \cdot \rho_t^i$. where Z_t is the first principal component of the Google Search Volume Indices (GSVI) for several crisis-related search query terms, $GSVI_t^i$ is the GSVI for insurer *i*th ticker symbol (or company name in case of a numeric ticker symbol) and ρ_t^i is the (dynamic) correlation between Z_t and $GSVI_t^i$. The cross-sectional mean values of the CSI are shown as a black line while the range between the 10%- and 90%-quantiles of CSI values in the cross-section are highlighted by the shaded area in grey.



D.2 Variable definitions and data sources

Table D.1: 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.

Variable name	*Definition*	*Data source*
Dependent variable and main explanatory variables of interest		
Buy-and-hold returns	Quarterly buy-and-hold return on an insurer's stock.	Datastream, own calc.
General crisis sentiment	First principal component of the four GSVIs of the search terms "financial crisis", "credit crisis", "subprime crisis" and "bank crisis", calculated using a rolling window enlarged by one week after each estimation, starting with a window of 52 weeks for the first year. For each quarter, the Crisis-GSVI is the average of the weekly first principal components in that quarter.	Google Trends, own calc.
CSI	Value of the Crisis Sentiment Index lagged by one quarter. The Crisis Sentiment Index is computed using data from *Google Trends* via $CSI_t^i := \left(\frac{GSVI_t^i+Z_t}{200}\right) \cdot \rho_t^i$. where Z_t is the first principal component of the Google Search Volume Indices (GSVI) for several crisis-related search query terms, $GSVI_t^i$ is the GSVI for insurer ith ticker symbol (or company name in case of a numeric ticker symbol) and ρ_t^i is the (dynamic) correlation between Z_t and $GSVI_t^i$.	Datastream, Google Trends, own calc.
Control variables		
Return on assets	An insurer's return on assets defined as pre-tax return of the insurer on its total assets.	Worldscope (WC08326).
Return on equity	An insurer's earnings per share during the last 12 months.	Worldscope (WC08372).
MES	Marginal Expected Shortfall as defined in 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.
Total assets	Natural logarithm of an insurer's total assets.	Worldscope (WC02999).
Market-to-book ratio	Market value of common equity divided by book value of common equity.	Worldscope (WC07210, WC03501).
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).
Investment activity	Ratio of the insurer's absolute investment income to the sum of absolute investment income and absolute earned premiums.	Worldscope (WC01002, WC01006),own calc.
Investment success	Ratio of the insurer's investment income to net revenues.	Worldscope (WC01001, WC01006), own calc.

Table D.1: Variable definitions and data sources (continued).

Variable name	*Definition*	*Data source*
Control variables		
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).
Loss ratio	Claim and loss expense plus long term insurance reserves divided by premiums earned.	Worldscope (WC15549).
Debt Maturity	Total long-term debt divided by total debt.	Worldscope (WC03251), own calc.
Board size	Natural logarithm of the number of directors on an insurer's board.	ESG ASSET 4 (CGBSDP060).
Board independence	Percentage of independent outside directors on the board of directors.	ESG ASSET 4 (CGBSO07S).
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	Ratio of annual trading volume to shares outstanding.	WDI database (World Bank).
Internet use	Number of people with access to the internet in the insurer's home country per 100.	WDI database (World Bank).

D.3 Sample insurance companies

Table D.2: 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 Worldscope*. 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 D.2: 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	

Appendix E

Supplementary Material for Chapter 6

E.1 Variable definitions and data sources

Table E.1: Variable definitions and data sources.

The table presents variable definitions and data sources for all dependent variables, bank characteristics, and macroeconomic control variables.

Variable name	Variable definition	Data source
Dependent variable		
ΔDemand	Change in a bank's demand deposits per quarter (in percent).	FDIC call reports.
ΔTime	Change in a bank's time deposits per quarter (in percent).	FDIC call reports.
ΔRatio	Change in a bank's ratio of demand deposits to total deposits per quarter (in percent).	FDIC call reports.
Main variables of interest:		
FDIC	Sum of the winsorized weekly search volume of the term "FDIC" per state (in quarter), adjusted for seasonality and scaled by its standard deviation.	Google Trends.
FEARS	Quarterly average of the weekly FEARS-index introduced in Da et al. (2015).	Google Trends.
Bank characteristics:		
Size	Natural logarithm of a bank's total assets at the end of a quarter.	FDIC call reports.
Return on assets	Net income after taxes and extraordinary items (annualized) as a percent of average total assets.	FDIC call reports.
Non-interest income	Non-interest income divided by total interest income.	FDIC call reports.
Net interest margin	Total interest income less total interest expense (annualized) as a percent of average earning assets.	FDIC call reports.
Operating Efficiency	Non-interest expense, less the amortization expense of intangible assets, as a percent of the sum of net interest income and non-interest income.	FDIC call reports.
Equity ratio	Ratio of a bank's total equity and total assets.	FDIC call reports.
Crisis	Dummy variables that takes on the value one if the bank observation is in Q4 2008 or Q1 2009 (see Oliveira et al., 2014).	Own calc.
Retail deposit ratio	Ratio of a bank's retail deposits and total deposits.	FDIC call reports.
Non-performing loans	Sum of total assets past due 30-90 days and still accruing interest, total assets past due 90 or more days and still accruing interest, and total assets which are no longer accruing interest divided by total assets.	FDIC call reports.
Insured deposits	Ratio of a bank's insured deposits and total deposits.	FDIC call reports.
Macroeconomic controls:		
GDP growth	GDP growth by state per year.	U.S. Bureau of Economic Analysis.
General interest in finance (GIF)	Quarterly average of the winsorized weekly changes in interest for financial topics via Google searches per state, adjusted for seasonality and scaled by its standard deviation.	Google Trends.
CD rate	Average 3-month CD rate per quarter.	Federal Reserve Bank of St. Louis.
Press releases	Number of press releases by the FDIC per quarter.	FDIC.

E.2 Institutional details on the Federal Deposit Insurance Corporation

The Federal Deposit Insurance Corporation (FDIC) was founded in 1933 as a consequence of a series of bank failures during the 1920s. It is designed as a regulation and monitoring vehicle for banks and thrifts in the United States and is supposed to strengthen the stability of the financial system by currently insuring over 9 trillion dollars of deposits. The current coverage limit is 250,000 $ per depositor per bank for each account category (checking and saving accounts, CDs and money market accounts). As of 2013, over 6,500 institutions are insured via the FDIC. These banks include state-chartered banks that are not participating in the Federal Reserve System.[84] Insured banks need to fulfill liquidity and reserve requirements and are obliged to send quarterly call reports to the FDIC which include data on the banks' balance sheets.[85] Call reports are published on the FDIC's wesbite a few months after the reports were sent in. We obtain the aggregated call reports from the website of the FDIC for the time period from 2004 to 2013. [86] In our main analyses, we include only banks from states with sufficient search volume for "FDIC", which account for approximately 75.8 % of all demand deposits and 72.2 % of all time deposits (in Q1 2004). All banks with a minimum of one quarter of data on deposits are included in the sample.

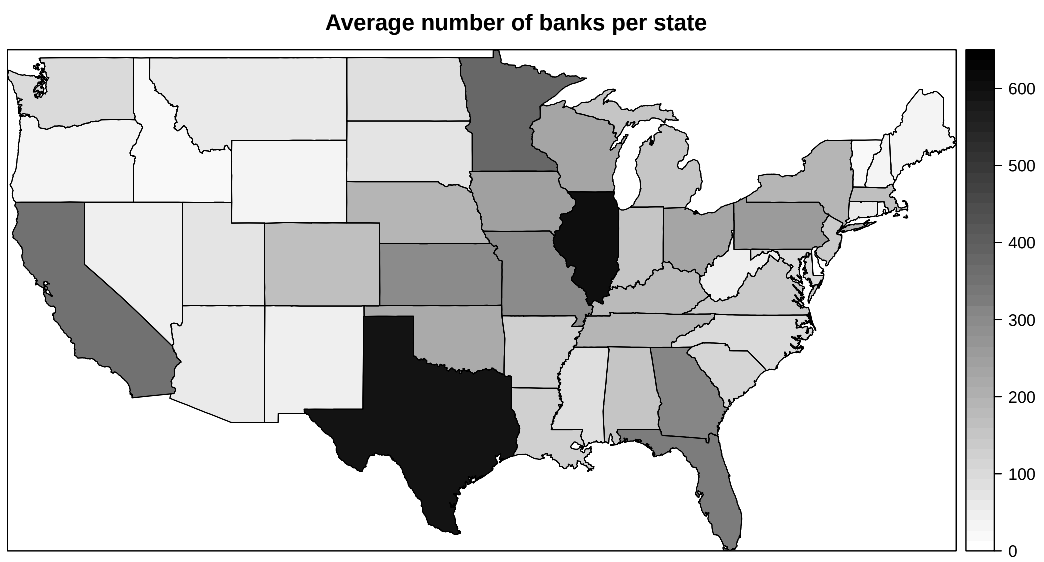
[84]The deposit insurance system applies to individual banks in a state, and not necesseraliy on the holding level. Thus, the data set includes several banks with the same company name but in a different state.
[85]Call reports have to be sent in at latest 30 days after the end of the corresponding quarter.
[86]Note that we use the reports for all banks of the fifty states and District of Columbia but exclude banks from Guam, American Samoa, Puerto Rico and Virgin Islands.

E.3 Further description of the sample

Our sample includes 7,290 of 11,126 FDIC insured banks that reported at least once from Q1 2004 to Q4 2013. Figure E.1 shows a heat map of the average number of FDIC insured banks for United States that reported during the given time period (excluding Alaska and Hawai). Clearly, the states of Illinois and Texas have the highest number of

Figure E.1: Number of banks per state.

The figure shows a heat map of the number of FDIC insured banks in the United States (excluding the low volume states Alaska and Hawai). A darker shade of grey indicates a higher number of FDIC insured banks in a state.

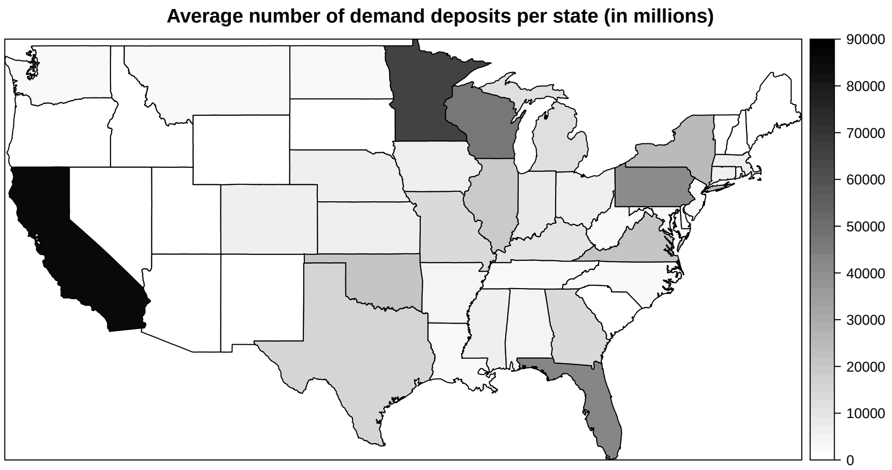


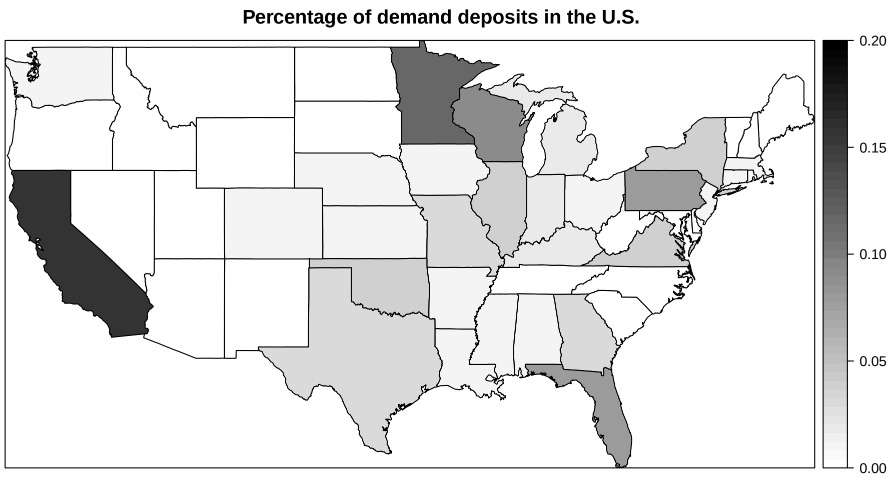
FDIC insured banks in our sample with over 800 and 700 banks reporting per quarter, respectively. These two states are followed by Minnesota (over 500) and California (over 450).[87] In terms of size, however, we do not have the same distribution. Figure E.2 shows two heat maps of the United States that indicate the level of demand deposits and the percentage of all demand deposits in the United States.

[87]Note that all of the four states are "high-volume states" and are included in our main analyses.

Figure E.2: Distribution of demand deposits across the United States

The figure shows heat maps of demand deposits across the United States (excluding the low volume states Alaska and Hawai). A darker area in the upper plot represents a higher value of the sum of all demand deposits (in million $ US) in a state (average from 2004 to 2013), whereas a darker area in the lower plot represents a higher percentage of all demand deposits in the United States. From the two pictures, we can see that California holds by far the largest percentage of all demand deposits (around 20%). The state with the second largest percentage is Minnesota.





E.4 Further analyses

In Section 6.6, we described the results of additional GMM-sys regressions of changes in deposits on *FDIC*, *FEARS*, and various control variables. Table E.2 shows the results of these additional analyses.

We control for a general interest in finance (GIF), residuals of a regression of *FDIC* on the 3-month CD rate, a state's GDP growth, and the ratio of a bank's retail deposits and total deposits. Also, we exchange the variable *FDIC* with the number of press releases by the Federal Deposit Insurance Corporation and include it in our regressions.

During the recent financial crisis, the Emergency Economic Stabilization Act was introduced and contained several programs (e.g., the Troubled Asset Relief Program "TARP") to strengthen the stability of the financial system in the United States. When receiving government support, bank managers could be tempted to change their risk-taking behavior and thus, possibly creating moral hazard. On the other hand, depositor behavior could be influenced by possible "too-big-to-fail" perceptions or bailout guarantees. As a further analysis, we investigate the impact of the introduction of TARP on a bank's changes in deposits. Table E.3 shows the results of (one-step) GMM-sys regressions that include the dummy variable *TARP* that is one if a bank or its holding received government support and zero before Q3 2008 or if the bank did not receive TARP support. Our additional results suggest that TARP did not affect the changes in demand deposits but had a statistically significant impact on changes in time deposits. Also, the interaction term of depositor attention and TARP shows that the introduction of TARP decreased the interest in the FDIC.

Naturally, we would expect that troubled banks (e.g., banks that hold a higher percentage of non-performing loans) are more vulnerable to deposit withdrawals than their financially healthier counterparts. For the purpose of analyzing the impact of depositor attention and depositor sentiment on specific subsets of banks, we split our sample of banks into bottom and top quartiles of the average ratio of non-performing loans and total assets. Additionally, we investigate differences in changes in deposits for a group

Table E.2: Additional GMM-sys regressions of changes in deposits.

The table shows the results of the (one-step) GMM-sys estimation of ΔDemand and ΔTime on *FDIC* and control variables. The dependent variables are the percental changes in demand deposits and time deposits. The main variable of interest is *FDIC* which is the Google Search Volume Index of the phrase “FDIC” from Google Trends, adjusted for seasonality, winsorized at the 5% level, and scaled by its standard deviation. Additionally, we include the variables General interest in finance (GIF), which is an index obtained from Google Trends indicating the changes in search interest for finance topics for each state, the residuals of the linear regression of the 3-month cd rate on the FDIC-index, the GDP growth per state, and the ratio of a bank’s retail deposits to total deposits. Other regressors are defined in Table E.1. All independent variables are lagged by one quarter and the lagged dependent variable is included in the regressions. We employ double-lagged values of the dependent variables, *FDIC* and *Net interest margin* as instruments. P-values are given in parentheses and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable:	ΔDemand					ΔTime				
FDIC	0.0012***	0.0009**		0.0010***	0.0010***	0.0004***	0.0003***		0.0002**	0.0003***
	(0.001)	(0.013)		(0.006)	(0.005)	(0.000)	(0.001)		(0.041)	(0.002)
FEARS	-1.9364***	-1.9598***	-2.2807***	-2.4203***	-3.1660***	-3.5428***	-3.5288***	-4.1531***	-4.1494***	-2.2557***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GIF	-0.0016***					-0.0004***				
	(0.000)					(0.000)				
CD rate residual		-0.0003					-0.0001			
		(0.246)					(0.285)			
Press			0.0255***					0.0465***		
			(0.000)					(0.000)		
GDP growth				-0.0003					0.0002	
				(0.400)					(0.121)	
Retail deposit ratio					-0.4460***					0.4735***
					(0.000)					(0.000)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	181,141	176,808	181,141	159,816	181,119	183,409	178,978	183,409	161,724	183,409
Wald	9,450.26	9,085.00	8,513.22	8,035.81	9,662.37	35,714.36	35,550.39	36,683.07	31,334.29	39,849.36
Wald (p-value)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001

Table E.3: GMM-sys regressions of changes in deposits (TARP).

The table shows the results of the (one-step) GMM-sys estimation of ΔDemand and ΔTime on FDIC and control variables. The dependent variables are the quarterly percental changes in demand deposits and time deposits winsorized at the 1% level. The main variable of interest is FDIC which is the Google Search Volume Index of the phrase "FDIC" from Google Trends, adjusted for seasonality, winsorized at the 5% level, and scaled by its standard deviation. A dummy variable TARP is included which is one if the bank observation is in Q3 2008 or later and the bank or its holding has received government support through the TARP program. Other regressors are defined in Appendix E.1. All independent variables are lagged by one quarter and the lagged dependent variable is included in the regressions. We employ double-lagged values of the dependent variables, FDIC, and Net interest margin as instruments. P-values are given in parentheses and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable:	ΔDemand		ΔTime	
FDIC	0.0009***	0.0009***	0.0004***	0.0005***
	(0.007)	(0.009)	(0.000)	(0.000)
FEARS	-1.9196***	-1.9179***	-3.5658***	-3.5883***
	(0.000)	(0.000)	(0.000)	(0.000)
TARP	-0.0218	-0.0246	0.0326***	0.0751***
	(0.437)	(0.495)	(0.000)	(0.000)
FDIC × TARP		0.0001		-0.0023***
		(0.957)		(0.000)
Other controls	Yes	Yes	Yes	Yes
Bank-fixed effects	Yes	Yes	Yes	Yes
Time-dummies	Yes	Yes	Yes	Yes
Observations	181,141	181,141	183,409	183,409
Wald	9,437.07	9,437.08	35,721.72	35,762.33
Wald (p-value)	< 0.001	< 0.001	< 0.001	< 0.001

of banks with a lower and a higher ratio of insured deposits to total deposits. Intuitively, we would expect that a bank that has less insured deposits is also more susceptible to deposit withdrawals, since not all of its deposits are covered by the FDIC. Table E.4 and E.5 show the results of the baseline GMM-sys and logistic panel regressions for these subsamples.

As our main results, we find that depositor attention to the FDIC has a statistically significant positive impact on changes in deposits for banks that have lower ratios of insured deposits to total deposits. For changes in time deposits, we also observe a positive effect for banks in the top quartile of non-performing loans ratio which is particlarly interesting, since, although this subsample of banks holds more bad loans in their portfolio, attention to the FDIC partly prevents depositors from withdrawing their assets. The variable *FEARS* is almost always significant with a negative sign of the coefficient except for changes in time deposits of banks with little non-performing loans. We conclude that depositor sentiment has different effects on changes in time deposits for banks with less troubled assets (positive) and those with more (negative). This result suggests that depositors appear to rationally distinguish between financially heatlthier banks and banks with a higher proportion of bad loans.

In our main analyses, we focus on the winsorized changes in (absolute) demand and time deposits as our dependent variables. This approach could be criticized for not adequately capturing the relevant changes in deposits, since a relative change in absolute deposits has different magnitudes when comparing smaller with larger banks. As an alternative to relative changes in (absolute) demand deposits, we employ the changes in a bank's demand deposit ratios as our dependent variable for additional panel regressions. Our main variables of interest are, again, depositors' sentiment and depositors' attention to the FDIC. However, demand deposit ratios could also change simply because a bank's size is increasing or decreasing while the amount of demand deposits remains the same. Therefore, we include in these regressions the contemporary changes in a bank's size as another independent variable. The results for static and dynamic panel OLS and GMM-sys regressions of changes in demand deposit ra-

Table E.4: GMM-sys regressions of changes in deposits for banks in quartiles of non-performing loans ratio and insured deposits ratio.

The table shows the results of the (one-step) GMM-sys estimation of ΔDemand and ΔTime on *FDIC* and control variables. The full sample is split into the bottom and top quartile of the variables *Non-performing loans*, which is the sum of total assets past due 30-90 days and still accruing interest, total assets past due 90 or more days and still accruing interest, and total assets which are no longer accruing interest divided by total assets, and the ratio of insured deposits to total deposits (the bank sample is split according to their average value of these variables over the sample period). The dependent variables are the quarterly percental changes in demand deposits and time deposits winsorized at the 1% level. The main variable of interest is *FDIC* which is the Google Search Volume Index of the phrase "FDIC" from Google Trends, adjusted for seasonality, winsorized at the 5% level, and scaled by its standard deviation. Other regressors are defined in Appendix E.1. All independent variables are lagged by one quarter and the lagged dependent variable is included in the regressions. We employ double-lagged values of the dependent variables, *FDIC*, and *Net interest margin* as instruments. P-values are given in parentheses and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable:	ΔDemand				ΔTime			
	Non-performing loans		Insured		Non-performing loans		Insured	
	< 25%	> 75%	< 25%	> 75%	< 25%	> 75%	< 25%	> 75%
FDIC	0.0013	-0.0002	0.0033***	0.0005	0.0004	0.0005**	0.0011***	0.0001
	(0.122)	(0.748)	(0.000)	(0.449)	(0.199)	(0.026)	(0.006)	(0.290)
FEARS	-1.5857***	-0.6443	-2.2356***	-0.9762**	1.8580***	-5.6289***	-4.0613***	-2.6126***
	(0.000)	(0.175)	(0.000)	(0.014)	(0.000)	(0.000)	(0.000)	(0.000)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,266	49,704	37,789	47,250	33,717	50,486	37,868	49,147
Wald	2,664.24	2,198.28	3,107.08	1,865.36	5,469.87	11,794.93	7,220.76	7,509.19
Wald (p-value)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001

Table E.5: Panel logistic regression of large withdrawals and gains in demand deposits for banks in quartiles of non-performing loans ratio and insured deposits ratio.

The table shows the results of panel logistic regressions on large withdrawals and gains of deposits. The full sample is split into the bottom and top quartile of the variables *Non-performing loans*, which is the sum of total assets past due 30-90 days and still accruing interest, total assets past due 90 or more days and still accruing interest, and total assets which are no longer accruing interest divided by total assets, and the ratio of insured deposits to total deposits (the bank sample is split according to their average value of these variables over the sample period). The dependent variables are the dummy variables Run, which takes on the value one if a bank experiences changes in demand deposits below the 20%-quantile of ΔDemand deposits and zero otherwise, and *Gain*, which is equal to one if the changes in deposits are above the 80%-quantile and zero otherwise. The main variable of interest is FDIC which is the Google Search Volume Index of the phrase "FDIC" from Google Trends, adjusted for seasonality, winsorized at the 5% level, and scaled by its standard deviation. Other regressors are defined in Appendix E.1. All independent variables are lagged by one quarter. P-values are given in parentheses and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable:	Run				Gain			
	Non-performing loans		Insured		Non-performing loans		Insured	
	< 25%	> 75%	< 25%	> 75%	< 25%	> 75%	< 25%	> 75%
FDIC	-0.0029	-0.0009	0.0005	-0.0038	0.0034	-0.0011	-0.0004	0.0044
	(0.391)	(0.724)	(0.858)	(0.162)	(0.293)	(0.679)	(0.876)	(0.131)
FEARS	1.6854**	-1.8171**	0.5299	0.8159	1.5693**	3.6641***	3.5315***	0.4692
	(0.047)	(0.013)	(0.531)	(0.262)	(0.045)	(0.000)	(0.000)	(0.498)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,731	51,978	39,278	48,795	33,901	50,887	39,297	47,921
Likelihood ratio	534.33	909.4	661.62	918.13	1,022.47	1,048.33	1,164.81	1,279.95
Likelihood ratio (p-value)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001

tios on *FDIC, FEARS, Net interest margin*, and changes in a bank's size are presented in Table E.6. As in the baseline GMM-sys regressions of changes in demand and time deposits, we find that depositor attention to the FDIC is positively related to changes in demand deposit ratios and that depositor sentiment has a strong negative influence. Interestingly, in our GMM-sys regressions, we find no evidence that these changes in demand deposit ratios are due to simple changes in a bank's size.

E.5 Robustness checks

In our main analyses, we winsorized all changes in deposits at the 1% level to remove extreme outliers in our sample. However, for the changes in time deposits, we see that there are still extreme changes from 2004 to 2006 that bias the mean changes in deposits. Therefore, we also run analyses that use changes winsorized at the 5% and 10% level, which is a more conservative approach. The time evolutions for the mean changes in demand and time deposits as well as 20%- and 80%-quantiles in each quarter with winsorization at the 10% level are shown in Figure E.3. The time evolution of mean changes in demand deposits show an almost identical pattern as in our main analyses, but only at a lower level. In some quarters, we even have negative mean changes in deposits. For the evolution of ΔTime, we notice that the extreme outliers do not bias the mean changes in time deposits with an extreme magnitude anymore. Also, we see the same time trends as before.

Additionally, we rerun our baseline GMM-sys regressions from Table 6.2 of our main analyses with the dependent variables ΔDemand and ΔTime winsorized at the 5% and 10% level. The regression results for the 5% winsorized dependent variables are given in Table E.7.

Overall, the results remain qualitatively unchanged. However, this time we find a slight significance for depositor attention on changes in demand deposits for medium-sized banks and for changes in time deposits for small-sized banks. The other important inferences are still valid.

Table E.6: GMM-sys regressions of changes in demand deposit ratios.

The table shows the results of OLS and (one-step) GMM-sys panel regressions of the changes in demand deposit ratios (ΔRatio) on *FDIC*, *FEARS*, changes in bank size, and control variables. The dependent variable is the quarterly percental changes in demand deposit ratios winsorized at the 1% level. The main variable of interest is *FDIC* which is the Google Search Volume Index of the phrase "FDIC" from Google Trends, adjusted for seasonality, winsorized at the 5% level, and scaled by its standard deviation. Other regressors are defined in Appendix E.1. All independent variables except for ΔSize are lagged by one quarter and the lagged dependent variable is included in the regressions. We employ double-lagged values of the dependent variables, *FDIC*, and *Net interest margin* as well as the lagged values of ΔSize as instruments. P-values are given in parentheses and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable:	ΔRatio						
Estimation:	OLS				GMM		
ΔRatio$_{t-1}$		-0.1897***	-0.1898***	-0.1897***	-0.1352***	-0.1352***	-0.1352***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FDIC$_{t-1}$	0.0005***	0.0006***	0.0006***	0.0006***	0.0007**	0.0006**	0.0007**
	(0.003)	(0.003)	(0.004)	(0.003)	(0.039)	(0.046)	(0.039)
ΔSize$_t$	-0.0060**	-0.0070***	-0.0070***	-0.0070***	-0.0064	-0.0064	-0.0064
	(0.010)	(0.005)	(0.005)	(0.005)	(0.140)	(0.140)	(0.140)
Net interest margin$_{t-1}$	-0.0233***	-0.0198***	-0.0198***	-0.0198***	-0.0143***	-0.0142***	-0.0143***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FEARS$_{t-1}$	-0.0389***	-0.0326***	-0.0328***	-0.0035	-0.2581***	-0.2576***	-0.2616***
	(0.001)	(0.004)	(0.004)	(0.766)	(0.000)	(0.000)	(0.000)
Crisis			omitted			omitted	
			-			-	
Crisis × FDIC			0.0003			-0.0005	
			(0.699)			(0.671)	
FEARS × FDIC				0.0026***			-0.0003
				(0.000)			(0.804)
Bank-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	187,882	180,834	180,834	180,834	180,834	180,834	180,834
F/Wald	32.39	83.85	81.89	83.85	6,947.11	6,947.28	6,947.11
F/Wald (p-value)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
R^2	0.0099	0.0463	0.0463	0.0463	-	-	-

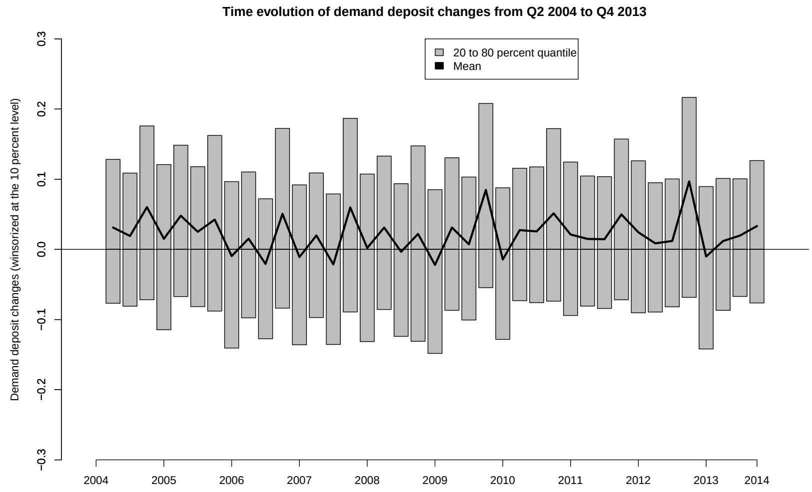
Table E.7: GMM-sys regressions of changes in deposits (5% winsorization).

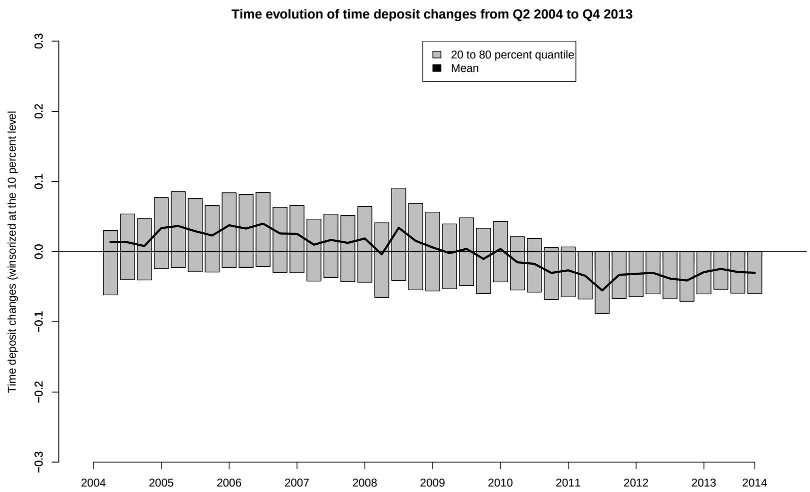
The table shows the results of the (one-step) GMM-sys estimation of ΔDemand and ΔTime on *FDIC* and control variables. The dependent variables are the quarterly percental changes in demand deposits and time deposits winsorized at the 5% level. The main variable of interest is *FDIC* which is the Google Search Volume Index of the phrase "FDIC" from Google Trends, adjusted for seasonality, winsorized at the 5% level, and scaled by its standard deviation. Other regressors are defined in Appendix E.1. All independent variables are lagged by one quarter and the lagged dependent variable is included in the regressions. We employ double-lagged values of the dependent variables, *FDIC*, and *Net interest margin* as instruments. P-values are given in parentheses and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable:	ΔDemand				ΔTime			
Sample:	All	Small	Medium	Large	All	Small	Medium	Large
FDIC	0.0006***	0.0005	0.0005*	0.0005*	0.0003***	0.0002**	0.0001	0.0002**
	(0.000)	(0.101)	(0.051)	(0.090)	(0.000)	(0.021)	(0.107)	(0.027)
Net interest margin	0.0013	0.0034	-0.0017	0.0052*	0.0075***	0.0148***	0.0028**	0.0048***
	(0.518)	(0.325)	(0.679)	(0.056)	(0.000)	(0.000)	(0.041)	(0.000)
FEARS	-1.7267***	-5.4672***	-13.9715***	4.3284***	-1.5158***	-4.0040***	-10.8637***	2.7091***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size	-0.1668***	-0.5473***	-1.2285***	-0.3776***	-0.1558***	-0.4186***	-0.9602***	-0.2393***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ROA	-0.0048***	0.0005	-0.0036***	-0.0062***	-0.0027***	-0.0030***	0.0013***	0.0006
	(0.000)	(0.671)	(0.008)	(0.000)	(0.000)	(0.000)	(0.006)	(0.215)
Non-interest income	0.0001	0.0000	0.0004	0.0007**	0.0000	0.0000	0.0000	0.0001
	(0.234)	(0.910)	(0.240)	(0.023)	(0.846)	(0.976)	(0.702)	(0.322)
Operating efficiency	0.0000	0.0000	0.0000***	0.0000	0.0000	0.0000	0.0000	0.0000*
	(0.167)	(0.317)	(0.000)	(0.724)	(0.372)	(0.101)	(0.524)	(0.093)
Equity ratio	1.1107***	1.0234***	0.8453***	0.8961***	0.5828***	0.5067***	0.2045***	0.3845***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ΔDeposits$_{t-1}$	-0.1969***	-0.2062***	-0.1981***	-0.1986***	0.0320***	0.0072**	0.0260***	0.0264***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.042)	(0.000)	(0.000)
Bank-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	181,141	58,093	59,025	59,637	183,409	59,537	59,530	59,924
Wald	17,880.80	8,122.73	6,034.73	5,644.76	37,069.86	15,700.97	10,416.10	9,129.92
Wald (p-value)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001

Figure E.3: Time evolution of changes in deposits (10% winsorization).

The figure shows barplots of quarterly changes in demand and time deposits (in percent) for the time period Q2 2004 to Q4 2013 for FDIC insured banks in high volume states. The top grey bars indicate the 80%-quantiles of changes in deposits each quarter and the bottom bars indicate the 20%-quantiles of changes in deposits. The black lines present the mean percental changes in deposits each quarter. Data on deposit changes are winsorized at the 10% level.





Next, we estimate our main model using pooled OLS instead of GMM-sys. We employ pooled OLS regression without bank fixed effects but with time dummies and robust standard errors accounting for clustering on the bank level but also on the state level. The results are shown in Table E.8. For both dependent variables, we still find a positive relation with *FDIC* and a negative relation with depositor sentiment. For demand deposits, however, we only find a statistical significance of *FEARS* on the 5% level when using clustered standard errors on the bank level and no state fixed effects.

Table E.8: Pooled OLS regression.

The table shows the results of OLS regressions of ΔDemand and ΔTime on the FDIC-index and control variables with clustered standard errors on the bank- and state-level. Regressors are defined in Appendix E.1. P-values are given in parentheses and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable:	ΔDemand		ΔTime	
FDIC	0.0007***	0.0007***	0.0004***	0.0004***
	(0.001)	(0.001)	(0.000)	(0.000)
FEARS	-0.4328**	-0.3455*	-0.5373***	-0.4406***
	(0.017)	(0.071)	(0.000)	(0.000)
Size	0.0080***	0.0075**	0.0001	-0.0003
	(0.007)	(0.012)	(0.951)	(0.766)
ROA	-0.0071**	-0.0072**	-0.0117***	-0.0116***
	(0.034)	(0.027)	(0.000)	(0.000)
Non-interest income	-0.0002***	-0.0002***	0.0000	0.0000
	(0.004)	(0.003)	(0.290)	(0.274)
Net interest margin	-0.0098***	-0.0096***	0.0054***	0.0054***
	(0.000)	(0.000)	(0.000)	(0.000)
Efficiency ratio	0.0000	0.0000	0.0000*	0.0000*
	(0.328)	(0.330)	(0.078)	(0.078)
Equity ratio	0.9423***	0.9417***	0.5801***	0.5821***
	(0.000)	(0.000)	(0.000)	(0.000)
ΔDeposits$_{t-1}$	-0.1041***	-0.1048***	0.0490***	0.0488***
	(0.000)	(0.000)	(0.000)	(0.000)
Bank-fixed effects	No	No	No	No
Time-dummies	Yes	Yes	Yes	Yes
State-fixed effects	No	Yes	No	Yes
Cluster level	Bank	State	Bank	State
Observations	181,141	181,141	183,409	183,409
R^2	0.0464	0.0472	0.1351	0.1362

Accounting for clusters on the state level and also using state-fixed effects in the OLS specification yields only 10% statistical significance. Qualitatively, we find no changes for our main variables of interest.

As another robustness check, we reestimate our panel logistic regressions with bank- and time-fixed effects using a different definition for the binary dependent variables *Run* and *Gain*. For the baseline models, we report the regression results in Table E.9. It seems that in these extreme cases of large withdrawals, depositor attention does not play a role in mitigating the likelihood of large withdrawals. For large gains, however,

Table E.9: Panel logistic regression of large withdrawals and gains in demand deposits (other definitions).

The table shows the results of panel logistic regressions on large withdrawals and gains of deposits. The dependent variables are the dummy variables *Run*, which takes on the value one if a bank experiences changes in demand deposits below the 5%-, 10%-, or 15%-quantile of ΔDemand deposits and zero otherwise, and *Gain*, which is equal to one if the changes in deposits are above the 85%-, 90%-, or 95%-quantile and zero otherwise. The main variable of interest is *FDIC* which is the Google Search Volume Index of the phrase "FDIC" from Google Trends, adjusted for seasonality, winsorized at the 5% level, and scaled by its standard deviation. Other regressors are defined in Appendix E.1. All independent variables are lagged by one quarter. P-values are given in parentheses and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable:	Run			Gain		
	5%	10%	15%	85%	90%	95%
FDIC	0.0021	0.0018	-0.0013	0.0042***	0.0054***	0.0074***
	(0.388)	(0.321)	(0.376)	(0.008)	(0.005)	(0.005)
FEARS	1.3982*	1.1897**	0.7607*	1.2680***	0.8618*	0.5553
	(0.058)	(0.026)	(0.085)	(0.002)	(0.077)	(0.422)
Size	0.4650***	0.5590***	0.6013***	-0.8457***	-0.9387***	-0.9759***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	110,662	155,687	177,335	172,522	152,057	109,020
Likelihood ratio	843.33	1,836.31	2,622.31	4,078.79	3,779.83	3,021.42
Likelihood ratio (p-value)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001

we find a positive relation of *FDIC* and the probability of large gains in demand deposits. Again, we find a slightly significant influence of depositor sentiment on the likelihood of large gains in demand deposits, but also a modest significant influence on the probability of extremely large withdrawals by depositors.

Our results for depositor attention and its influence on changes in deposits could be biased due to the way we aggregate the weekly data to obtain quarterly values. Therefore, we also estimate our baseline GMM-sys regressions using the mean of the weekly values in a quarter for the FDIC-index. Also, we employ two additional measures of depositor attention that differ only in the way we aggregate the weekly FDIC-index to create the quarterly index. The results of these additional analyses can be found in Table E.10. From Table E.10 we see that our inferences do not change significantly (the main difference is that the coefficients of the FDIC-index show more statistical significance for small and medium-sized banks). The logit panel regressions reveal that depositor attention, again, slightly decreases the likelihood of extreme demand deposit withdrawals. While the maximum value of depositor attention and the maximum difference of the FDIC-index do not have enough predictive power to explain large withdrawals, we find that these two are statistically significant factors that increase the likelihood of large gains in deposits. This is interesting, since it shows that single peaks in depositor attention (instead of constant attention on a higher level) may also have influence on extreme movements in demand deposits. Similar to our findings in the main analysis, we observe that higher sentiment actually increases the chances of extreme gains in demand deposits.

Table E.10: GMM-sys regressions of changes in deposits (mean FDIC).

The table shows the results of the (one-step) GMM-sys estimation of ΔDemand and ΔTime on *FDIC* and control variables. The dependent variables are the quarterly percental changes in demand deposits and time deposits winsorized at the 1% level. The main variable of interest is $FDIC_{\text{mean}}$ which is the Google Search Volume Index of the phrase “FDIC” from Google Trends, adjusted for seasonality, winsorized at the 5% level, and scaled by its standard deviation. $FDIC_{\text{mean}}$ is the quarterly average of the weekly values. Other regressors are defined in Appendix E.1. All independent variables are lagged by one quarter and the lagged dependent variable is included in the regressions. We employ double-lagged values of the dependent variables, *FDIC*, and *Net interest margin* as instruments. P-values are given in parentheses and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable:	ΔDemand				ΔTime			
Sample:	All	Small	Medium	Large	All	Small	Medium	Large
$FDIC_{\mathbf{mean}}$	0.0196***	0.0130	0.0082	0.0290***	0.0097***	0.0082***	0.0039**	0.0092***
	(0.000)	(0.126)	(0.262)	(0.001)	(0.000)	(0.005)	(0.023)	(0.000)
FEARS	-1.8002***	-6.8534***	-13.5036***	6.1170***	-3.3502***	-8.4900***	-14.1289***	4.2161***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obervations	180,704	58,074	58,986	59,271	182,972	59,518	59,491	59,558
Wald	9,749.20	4,319.04	3,014.85	3,041.49	35,471.61	19,356.44	6,837.22	5,533.19
Wald (p-value)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001

Table E.11: Panel logistic regression of large withdrawals and gains in demand deposits (other FDIC).

The table shows the results of panel logistic regressions on large withdrawals and gains of deposits. The dependent variables are the dummy variables *Run*, which takes on the value one if a bank experiences changes in demand deposits below the 20%-quantile of ΔDemand deposits and zero otherwise, and *Gain*, which is equal to one if the changes in deposits are above the 80%-quantile and zero otherwise. The main variables of interest are variations of the FDIC-index which is the Google Search Volume Index of the phrase "FDIC" from Google Trends, adjusted for seasonality, winsorized at the 5% level, and scaled by its standard deviation. The columns with "Max" and "Mean" indicate that the maximum and the mean value of *FDIC* in a quarter is used to aggregate the weekly values of *FDIC*. The *FDIC* variable in "Diff" is the maximum of the weekly differences in the weekly FDIC-index. Other regressors are defined in Appendix E.1. All independent variables are lagged by one quarter. P-values are given in parentheses and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable:	Run			Gain		
	Max	Mean	Diff	Max	Mean	Diff
FDIC	-0.0117	-0.0578***	0.1000	0.0313***	0.0339*	0.3731**
	(0.298)	(0.001)	(0.489)	(0.007)	(0.056)	(0.011)
FEARS	0.2792	0.0740	0.3491	1.6105***	1.6077***	1.4868***
	(0.462)	(0.847)	(0.353)	(0.000)	(0.000)	(0.000)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	185,566	185,566	185,566	183,581	183,581	183,581
Likelihood ratio	3,321.23	3,331.01	3,320.63	4,511.83	4,508.24	4,510.99
Likelihood ratio (p-value)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001

E.6 Heckman two-stage selection procedure

One concern with our inference is that we restrict our data sample to banks that are in a high-volume state (where we find sufficient search volume for "FDIC" with *Google Trends*). Although our sample covers over 70% of all deposits in the United States, we investigate the impact of this non-random sample selection to mitigate concerns of a possible selection bias. To do so, we estimate Heckman two-stage selection models (see Heckman, 1979) in which the selection dummy is one if a bank is located in a high-volume state (and thus, is included in our sample), and zero otherwise. We use the first lag of the changes in deposits, bank fundamentals lagged by one quarter, time dummies, a state's GDP growth, and its population density as regressors in the selection model. The estimates for changes in demand deposits and changes in time deposits are shown in Table E.12. The estimates for the selection model suggest that banks in a state with a higher population density are more likely to be included in our sample. Interestingly, a state's GDP growth is negatively correlated with the selection variable high-volume dummy. Most importantly, the estimates for the Inverse Mills Ratio are not statistically significant on convential levels. Thus, we conclude that non-random sample attrition is not a problem in our analyses.

Table E.12: Heckman two-stage selection model.

The table shows the results of a Heckman two-stage procedure. The selection dummy is one if a bank is located in a high-volume state and zero otherwise. All explanatory variables are lagged by one quarter. The regressors are defined in Appendix E.1. P-values are given in parentheses and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable:	ΔDemand	ΔTime
FDIC	0.0008**	0.0008***
	(0.027)	(0.000)
FEARS	6.7658***	5.5123***
	(0.000)	(0.000)
Other controls	Yes	Yes
Time-dummies	Yes	Yes
Selection variable:	High-volume dummy	High-volume dummy
GDP growth	-0.0109***	-0.0110***
	(0.000)	(0.000)
Population density	0.0085***	0.0086***
	(0.000)	(0.000)
Size	-0.0998***	-0.0970***
	(0.000)	(0.000)
ROA	-0.0340***	-0.0276***
	(0.000)	(0.000)
Non-interest income	0.0095***	-0.0002*
	(0.000)	(0.071)
Equity ratio	-0.9309***	-1.0766***
	(0.000)	(0.000)
Operating efficiency	0.0000*	0.0000*
	(0.050)	(0.057)
ΔDeposits$_{t-1}$	0.0245***	0.3013***
	(0.001)	(0.000)
Inverse Mills ratio (lambda)	0.0047	-0.0030
	(0.435)	(0.231)
Observations	148,402	151,387
Wald	5,014.29	21,621.2
Wald (p-value)	< 0.001	< 0.001

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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.

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