Interconnectedness in the Financial Sector: Three Essays on the Impact of the Financial Crisis and Banking Shocks on Insurance Firms

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Contents

List of Abbreviations

AIB	Allied Irish Banks
AIC	Akaike information criterion
AIG	American International Group
BaFin	Bundesanstalt für Finanzdienstleistungsaufsicht
BIC	Bayesian (Schwarz) information criterion
BLT	Bailout
CAR	Cumulated abnormal return
CEO	Chief executive officer
DAX	Deutscher Aktienindex
EC	European Community
ECB	European Central Bank
EEC	European Economic Community
e.g.	Exempli gratia
FAST	Financial Analysis Solvency Tools
FED	Federal Reserve
FOMC	Federal Open Market Committee
FRD	Fraud
FX	Foreign Exchange
G-SIFI	Global Systemically Important Financial Institution
GDP	Gross domestic product
GPW	Gross premiums written
LIBOR	London Interbank Offered Rate
LTCM	Long-Term Capital Management
NPW	Net premiums written

OLS	Ordinary least squares
PC	Property-casualty
Para.	Paragraph
QE	Quantitative easing
RBC	Risk-based capital
RBS	Royal Bank of Scotland
ROA	Return on assets
ROE	Return on equity
ROI	Return on investment
RAROA	Risk-adjusted return on assets
RAROE	Risk-adjusted return on equity
S&P	Standard & Poor's
sec.	Section
TARP	Troubled Asset Relief Program
VAG	Versicherungsaufsichtsgesetz
U.K.	United Kingdom
U.S.	United States (of America)
VIF	Variance inflation factor

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1 Introduction

This thesis consists of three essays on the interconnectedness between banks and insurance firms. The aim is to answer two important research questions: First, what is the impact of shocks from the banking sector, and the financial crisis of 2008 in particular, on the stock prices of insurance firms and the competitive environment in the insurance sector? Second, do regulatory authorities have the means to mitigate such crises, that is, does the regulatory framework to predict and counteract financial distress in the insurance sector work adequately during a severe financial crisis? The first essay analyzes the consequences of the financial crisis of 2008 on the competitive situation in the German insurance sector. In addition, it examines whether insurance groups' strategic group affiliation can affect the performance of their subsidiaries. The second essay questions how reliably regulators can forecast the financial strength of insurance firms during the financial crisis of 2008. The third essay examines the impact of policy interventions during the crisis on the stock prices of U.S. insurance firms. In addition, it analyzes the stock market response of insurers towards various shocks from the banking sector.

This section provides the motivation for the three essays and summarizes the main findings and contributions.

Strategic Group Performance and Dynamics under Different Economic Conditions

The first essay is entitled "Strategic Group Performance and Dynamics under Different Economic Conditions". This essay is based on a joint work with Dr. Muhammed Altuntas and Prof. Dr. Sabine Wende, both from University of Cologne. A previous version of this essay has been presented at the annual meeting of the *German Insurance Science Association (DVfVW)* in March 2015 and at the annual meeting of the *American Risk and Insurance Association (ARIA)* in August 2014. The paper is published in the April 2016 edition of *The Geneva Papers on Risk and Insurance – Issues and Practice*.

A *strategic group* represents a set of companies within one industry that are similar with respect to key strategic dimensions (Hunt, 1972; Porter, 1979). In this essay, we analyse strategic groups in the German insurance market by first subdividing the insurance groups into strategic groups. Furthermore, we examine if strategic group affiliation affects the performance of the insurance groups' subsidiaries in the German property-liability insurance sector. Finally, we examine the consequences of the financial crisis of 2008 on the strategic groups structure and examine whether changes in strategic group affiliation can be considered as a consequence of the financial crisis. For this analysis, company-level data of German insurance companies for the years 2004-2012 is examined using cluster analyses and regression analyses. The dataset comprises 829 firm-year observations including 50 holding companies.

Previous papers already tested if performance differences between firms can be explained by their strategic group affiliation. Our research contributes to the literature because these papers do not examine if these findings also hold for the subsidiaries of strategic group members. This provides valuable knowledge for performance analysis and benchmark purposes at the subsidiary level, because it extends available information on these firms given the potential influence of strategic group affiliation on its parent company and thus on its affiliate. In addition, we extend the literature on the impact of the financial crisis of 2008 on the insurance sector by analyzing the implications of the crisis for the business models of German insurance firms.

Solvency Prediction for Property-Liability Insurance Companies: Evidence from the Financial Crisis

The second essay is entitled "Solvency Prediction for Property-Liability Insurance Companies: Evidence from the Financial Crisis". This essay is based on a joint work with Prof. Dr. Sabine Wende from University of Cologne. A previous version of this essay has been presented at the *Roundtable on Insurance Regulation and Governance* at St. John's University in October 2012, at the annual meeting of the *Western Risk and Insurance Association (WRIA)* in January 2013 and at the annual meeting of the *German Insurance Science Association (DVfVW)* in March 2013. For this paper, I received the *Dorfman Doctoral Student Award 2013*. The paper is published in the January 2015 edition of *The Geneva Papers on Risk and Insurance – Issues and Practice*.

The solvency of insurance firms is tightly regulated in order to protect the policyholders by ensuring that the insurer will be able to meet its financial obligations in the future (Klein, 1995). To be able to intervene as early as possible and to minimize the potential costs associated with the financial distress of insurance firms, regulators aim to detect financially distressed companies at an early stage. Because macroeconomic factors can severely influence the solvency of insurance companies (Browne and Hoyt, 1995; Cheng and Weiss, 2012), it is of particular interest how reliably regulators can forecast their financial strength during the financial crisis. Against this background, we examine factors that predict the insurer's regulatory solvency ratio using regression analyses and company-level data of German property-liability insurers from 2004 through 2011.

This research contributes to the literature by showing that the current degree of solvency is a reliable indicator for the insurers' future financial strength even in times of financial crisis. This shows that a well calibrated prediction model allows German regulators to detect companies in distress early enough even during a severe financial crisis. Because previous papers focus on the prediction of insurer's financial strength in non-crisis times, our findings are highly relevant as we show that insurers in financial distress can be detected early enough to take appropriate action to protect policyholder's interests. In addition, the analysis indicates a high degree of financial stability within the German insurance industry, showing that the sector was able to bear the consequences of the financial crisis.

Policy Interventions and Banking Shocks: Evidence from the Insurance Sector

The third essay is entitled "Policy Interventions and Banking Shocks: Evidence from the Insurance Sector". This essay is based on a joint work with Prof. Dr. Martin F. Grace from Georgia State University and Prof. Dr. Sabine Wende from University of Cologne. A previous version of this essay has been presented at the annual meeting of the *American Risk and Insurance Association (ARIA)* in August 2013, at the annual meeting of the *European Finance Association (EFA)* in August 2013, at the annual meeting of the *German Insurance Science Association (DVfVW)* in March 2014, at the annual meeting of the *European Financial Management Association (FMA)* in June 2014 and at the *13th Symposium on Finance, Banking, and Insurance* in December 2014.

After analyzing the impact of the crisis on the competitive environment and the forecasting ability of regulators in the previous essays, this essay analyses the impact of policy interventions during the financial crisis on the stock prices of firms from the U.S. insurance sector which were designed to counteract the consequences of the crisis. Apart from "*conventional*" measures such as interest rate decreases, their interventions comprised a set of "*non-conventional*" measures such as monetary easing and liquidity provision. In addition, we examine the impact of banking-sector events (banking bailouts and trading frauds) on insurance firms. Using a database of 89 policy announcements and 10 banking sector events, we use an event study methodology and regression analyses to examine how such events affected U.S. insurance firms using a sample of 375 firm year observations for property-casualty insurers and 217 firm year observations for life insurers.

This research contributes to the literature by providing evidence for the effectiveness of policy measures regarding the stability of the insurance sector. Previous studies analyze the impact of policymakers' interventions on banks (Ricci, 2015), interbank risk premia (Aït-Sahalia et al., 2012) and aggregate markets (Fiordelisi, Galloppo and Ricci, 2014), but exclude insurance firms from their analyses. Given that the insurance sector has been strongly affected by the financial crisis that originated in the banking sector (Cummins and Weiss, 2014; Baluch, Mutenga and Parsons, 2011), knowledge on measures that can restore the stability in the insurance sector is valuable for regulators, managers and policyholders of insurance firms. In addition, given that the financial crisis was largely caused by a shock from the banking sector, we contribute to the literature by providing evidence on the exposure of insurance firms from shocks arising from the banking sector. While previous papers on the interconnectedness between banks and insurers (e.g. Billio et al., 2012; Chen et al., 2014) do not evaluate interconnectedness with respect to single, sector-specific events, we provide valuable knowledge for investors and regulators of insurance firms regarding the interconnectedness of the financial service sector.

2 Strategic Group Performance and Dynamics under Different Economic Conditions

Abstract

We analyse strategic groups in the German insurance market. We use cluster analysis to subdivide insurance groups into strategic groups. Furthermore, we analyse whether strategic group affiliation can affect the performance of the insurance groups' property-liability subsidiaries. In addition, we examine the consequences of the financial crisis of 2008 on the competitive situation in the German insurance sector and examine whether changes in strategic group affiliation can be considered as a consequence of the financial crisis. Using a dataset of 829 firm year observations for the years 2004 to 2012, our results indicate the existence of three strategic groups in the German insurance sector. In addition, we find that performance differences on subsidiary-level can be attributed to strategic group affiliation. Furthermore, we do not find evidence that the financial crisis induced changes in strategic group affiliation.

2.1 Introduction

The *strategic groups concept*[1,2] has been used in various research papers to analyse the different aspects of competitive strategy within an industry. A major purpose in examining this concept is to show that performance differences between firms can be attributed to strategic group affiliation (e.g. Mehra, 1996). Moreover, several papers (Mascarenhas, 1989; Fiegenbaum and Thomas, 1990) show that strategic group structures do not remain constant over time, but might change due to e.g. external, macroeconomic shifts such as financial crises. Knowledge of the competitive situation in the insurance industry with respect to the existence of strategic groups provides valuable knowledge for managers, shareholders and regulators of the respective industry, for example to evaluate the own company's situation, to analyse the competitive environment and profit opportunities or to assess the potential success of new strategies and market entries (Fiegenbaum, Hart and Schendel, 1996). However, to our best knowledge, no research exists so far on the existence of strategic groups in the German insurance industry and their relation to performance and the financial crisis of 2008.[3]

In our research, we analyse strategic groups in the German insurance market. We first subdivide the insurance groups into strategic groups using cluster analysis. Given that the German insurance industry is a highly regulated industry with several

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[1] A *strategic group* represents a set of companies within one industry that are similar with respect to key strategic dimensions (Hunt, 1972; Porter, 1979).

[2] For the purpose of this paper, it is essential to distinguish between the term strategic group as defined above and the term insurance group that refers to a holding company consisting of several insurance firms. Thus, strategic group refers to 'a group of firms pursuing similar strategies along strategic dimensions', while insurance group refers to 'a holding structure within the insurance sector'. Its subsidiaries are referred to as insurance companies or insurance subsidiaries. A strategic group member is an insurance group that is part of the respective strategic group. In some cases, a single insurance firm has no subsidiaries or a parent company. In these cases, we refer to these firms as insurance groups (holdings) as well.

[3] The existing literature on strategic groups in the insurance sector mainly focuses on the U.S. insurance industry (e.g. Ferguson, Deephouse and Ferguson, 2000; Fiegenbaum and Thomas, 1990, 1995). Berry-Stölzle and Altuntas (2010) examine strategic groups in the German pension funds industry as a part of the German insurance system, but not the insurance industry itself.

important differences in comparison to the U.S. insurance industry,[4] the results of previous studies might not be directly applicable in the German insurance sector.[5] Owing to the high degree of regulation, the firms should have comparable business models and firms from other sectors cannot directly compete in the German insurance market.[6] Hence, the sector is protected from outside competition of non-insurers and thus highly eligible for an analysis of strategic groups.

Additionally, we examine if strategic group affiliation affects the performance of the insurance groups' subsidiaries in the German property-liability insurance sector. Previous literature (Mehra, 1996) already examined if performance differences between firms can be explained by their strategic group affiliation. However, these papers do not examine if these findings also hold for their subsidiaries. Recent literature shows that conglomeration can affect firms by e.g. internal capital markets and transfer of know-how between holding members (Khanna and Rivkin, 2001). Hence, we know that holding structures can affect the subsidiaries' characteristics and performance. Given that strategic group affiliation can affect the strategic group members' performance and that holding affiliation can affect its subsidiaries' performance, we analyse if there is also a link between an insurance groups' strategic group affiliation and the performance of their subsidiaries.

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[4] Given the harmonization of regulatory frameworks for insurance firms in the European Union in recent years, regulation in the German insurance industry follows standards comparable to other European countries.

[5] The German insurance market is characterized by a large proportion of state-owned insurers, a low degree of capital market exposure and a very high level of stability and financial strength (Rauch and Wende, 2015) compared to the U.S. insurance sector. However, we are only aware of previous papers on strategic groups in the U.S. insurance industry.

[6] For example, a legal entity can only write life, health or property–liability business (Berry-Stölzle and Born, 2012). Non-insurance firms cannot offer insurance policies. Moreover, the insurers' investments are regulated by the *Insurance Regulatory Law* (*Versicherungsaufsichtsgesetz*) and the *Solvency Ordinance* (*Kapitalausstattungsverordnung*) regarding restrictions on investments in certain assets and diversification of assets. In addition, the regulatory authority can intervene in case of financial distress and demand changes in the insurer's business operations to re-establish a sufficient degree of solvency (Rauch and Wende, 2015). However, this only occurs in rare cases, so regulators do in general not interfere with the insurers' business strategies, thus allowing dynamics in the strategic groups structure.

Given that macroeconomic shifts like the financial crisis of 2008 were shown to affect an industry's strategic group structure (Mascarenhas, 1989), we analyse if changes in strategic group affiliation can be considered as consequences of the crisis. Even though the insurance industry has not been affected by the financial crisis as much as the banking sector (Harrington, 2009; Rauch and Wende, 2015), the crisis affected the insurance industry to a certain extent.[7] Even if the crisis might not have severely threatened the financial health of German insurance firms, it might have led to changes in the insurers' business strategies and consequently changes in strategic group affiliation. For insurance groups that changed strategic group affiliation after the financial crisis, we look for factors that might have induced movements between strategic groups. For example, insurance groups with a high capital market exposure in their asset portfolio might rethink their business model after the crisis and thus change strategic group affiliation.

For our analysis, we use company-level data of German insurance companies for the years 2004-2012. We employ a cluster analysis in order to subdivide insurance groups into strategic groups. We then use regression analyses to test if strategic group affiliation influences selected performance indicators of their subsidiaries from the property-liability sector. Our sample consists of 829 firm-year observations including 50 holding companies.

Our results indicate the existence of three strategic groups in the German insurance market. In addition, our analyses provide evidence that strategic group affiliation can affect the performance of the insurance groups' subsidiaries. Regarding the impact of the financial crisis of 2008 on strategic group dynamics, we find no evidence that factors related to the financial crisis affected changes in strategic group

[7] E.g. the crisis forced insurers to cut costs in order to maintain profitability; significant write-downs of financial assets; large losses in certain lines (e.g. credit insurance), thus evaluating strategic changes away to other, less risky business fields (Baluch, Mutenga and Parsons, 2011).

affiliation. This is consistent with previous literature and the general view that the crisis did not severely affect the German insurance industry.

Our results are valuable for regulators by evaluating the impact of financial crises on the competitive situation in the German insurance market. By subdividing the insurance groups into strategic groups, we provide relevant information for insurance executives, given that managers use members of the same strategic groups as reference points when they evaluate their own company's performance (Fiegenbaum and Thomas, 1995). Moreover, our analysis of the impact of the financial crisis on strategic group affiliation provides further insights on the consequences of the financial crisis of 2008 in the German insurance industry, given that we examine potential implications of the crisis for the insurers' business models. Last, by analysing whether strategic group affiliation affects the performance of the insurance groups' subsidiaries, we contribute to the literature on strategic groups as our research is, to our best knowledge, the first paper to analyse if strategic group affiliation not only affects the performance of strategic group members, but also their subsidiaries. We thereby provide important implications for performance analysis and benchmark purposes at the subsidiary level, as it extends available information on these firms given the potential influence of strategic group affiliation on its parent company and thus on its affiliate.

This paper proceeds as follows. In the next section, we discuss the theoretical background and provide the hypothesis development. In the third section, we describe our data and methodology. In the fourth section, we provide our empirical results. The final section concludes.

2.2 Theoretical Background and Hypothesis Development

The strategic groups concept was developed to understand differences within given industries and can thus be used to analyse the competitive context within industries. It has mainly been developed by Hunt (1972) and Porter (1979, 1980). Porter (1980) defines a strategic group as 'a group of firms pursuing similar strategies along strategic dimensions'. Prior to this, the companies within an industry were regarded as largely homogenous (Leask and Parker, 2007), except for differences in market share (Hall and Weiss, 1967; Marcus, 1969).

However, the introduction of the strategic groups concept led to a different perspective on the competitive environment within industries. Instead of viewing the firms as homogeneous competitors, firms within an industry might choose different approaches to serve the same customers. Thus, strategic groups can be regarded as sets of firms that compete for the industry's customers in different ways (Harrigan, 1985). The strategic groups concept provides valuable implications for the firms' management, given that it shapes the managers' understanding of the environment in which their firm operates (Reger and Palmer, 1996).

The existence of strategic groups in the literature is mainly justified by the presence of mobility barriers. Mobility barriers can be understood as structural or strategic factors, which protect a strategic group from the entry of potential rivals *within* the industry (Caves and Porter, 1977). In contrast to "external barriers" discussed in traditional economic theory which prevent *outside* firms to enter an industry, these barriers delineate strategic groups from competing with each other *within* a given industry (Harrigan, 1985).[8] Hence, firms are not able to move between strategic groups at will, given the presence of these barriers.

[8] In the context of the German insurance industry, "external barriers" refer to the regulatory framework that does not allow banks or other firms to directly write insurance policies in the German market, given

The strategic groups concept has mainly been used to explain performance differences within an industry in various studies. Given that most industries contain segments that are more profitable than others, a set of firms might persistently outperform its competitors (Porter 1979). For example, a firm that occupies a niche in a given industry might be prone to expand to other (more profitable) areas within the industry, but would be restricted to do so by the existence of mobility barriers. In addition, certain strategic groups might benefit from consumer preferences, e.g. due to group reputation, better promotion of products or other factors (Leask and Parker, 2007). Thus, firms within strategic groups that are protected by high mobility barriers face less competition and could therefore enjoy superior performance.

However, previous literature could not demonstrate an unambiguous relation between strategic group affiliation and performance differences within an industry. For example, Leask and Parker (2007) find performance differences between strategic groups in the U.K. pharmaceutical industry. In contrast, Cool and Schendel (1987) examine strategic groups in the U.S. pharmaceutical industry, finding no performance differences in this sector.[9]

These previous studies examine performance differences between holdings that built a strategic group, but not their subsidiaries. However, strategic group affiliation might not only affect the strategic group members on holding level (insurance groups, in our study), but also their subsidiaries because the subsidiaries usually follow a

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that a legal entity can only write life, health or property–liability business (Berry-Stölzle and Born, 2012). "Mobility barriers" in the insurance sector might arise due to building up a reputation in certain lines, which would protect these firms' market shares from other insurance firms. If several firms are for example specialized in writing legal protection insurance, an insurer who enters this market segment might not easily gain market share given its lack of reputation, even though the regulatory environment allows entering this market. This might hamper movements from one strategic group to another.

[9] Following related studies, we perform a Kruskal-Wallis one-way analysis of variance to analyse if performance differences between strategic groups exist in our analysis. Following Leask and Parker (2007) and Fiegenbaum and Thomas (1990), we test weather alternative measures of performance (profitability, risk, market share and efficiency) are significantly different between strategic groups in the German insurance market. Our results indicate significant performance differences regarding all performance indicators. The results are available upon request.

holding strategy and transfer their know-how within the holding. Therefore, we expect a close linkage between an insurance group (holding) and its subsidiary (Khanna and Rivkin, 2001) due to the adoption of strategic group-specific characteristics.[10] Hence, given the findings in previous studies, we know that holding (insurance group*)* structures can affect the subsidiaries' performance. Furthermore, given that strategic group affiliation can affect the strategic group members' performance and that holding affiliation can affect its subsidiaries' performance, we analyse whether there is a link between strategic group affiliation and the performance of the subsidiaries of the strategic group holdings. Therefore, we extend the existing literature on strategic groups and state:

> *H1: Performance differences between subsidiaries of members (insurance groups) of different strategic groups can be attributed to the parent companies' strategic group affiliation.*

Another important aspect of strategic group literature approaches *strategic group dynamics*: The composition of strategic groups can vary over time, i.e. firms might leave one strategic group and join another one. Basically, moving at will between strategic groups can be difficult due to the existence of mobility barriers, as discussed above. Consistent with that, several research papers found a low level of inter-industry movements and thus a low degree of strategic group dynamics (Oster, 1982; Mascarenhas, 1989). This might stem from the fact that companies within a strategic group resemble each other regarding their skills, capabilities and assumptions about the

[10] Following Leff (1978), strategic group members are "linked by relations of interpersonal trust on the basis of a similar personal, ethnic or commercial background". Moreover, capital transfers, the use of the parents companies' brand name and reputation (Khanna and Rivkin, 2001), and benefits from economies of scale and scope (Chang and Choi, 1988) can further enhance the link between a parent company and its subsidiary.

future. Hence, they should evolve similarly over time, given that they can anticipate each other's reaction very precisely (Porter, 1979).

However, depending on economic conditions, changes in business strategies might occur and thus may lead to changes in strategic group composition (Mascarenhas, 1989). Given that firms are adaptable and try to adapt to environmental changes (Meyer and Rowan, 1977), changes in economic conditions can lead to misalignments between a firm and its environment. Hence, the effectiveness of its current strategy can be reduced (Porter, 1980) and the firm might be prone to change its current strategy. This can lead to changes in strategic group affiliation. In particular, moving into a different strategic group can be facilitated in case of poor macroeconomic conditions (Hergert, 1983).

Mascarenhas (1989) examines strategic group dynamics over periods of economic stability, growth, and decline in international offshore oil-drilling. He finds a higher degree of strategic group dynamics in times of economic decline. Fiegenbaum and Thomas (1995) use strategic groups that act as reference points for others to explain strategic group dynamics in the U.S. insurance sector.[11] However, we are not aware of any study that examines strategic group dynamics with respect to the financial crisis of 2008 and its implication on strategic group affiliation.

On the one hand, even though the insurance industry has not been affected by the financial crisis as strongly as the banking sector (Harrington, 2009; Rauch and Wende, 2015), the crisis affected the insurance industry to a certain extent, for example significant write-downs of financial assets and large losses in certain lines like credit insurance (Baluch, Mutenga and Parsons, 2011). Hence, insurers with a large capital market exposure (e.g. due to a large proportion of stocks in their investments) had an incentive to rethink their investment strategy and their corporate strategy. Similarly,

[11] See Fiegenbaum and Thomas (1995) for additional studies on the topic of strategic group dynamics.

companies that experienced earning shocks during the crisis might have shifted away from risky businesses and tried to change their business model. Hence, the crisis may lead to a change in strategic group affiliation.

On the other hand, changes in strategic group affiliation might be completely unrelated to the financial crisis, given that these changes also occur under conditions of economic stability (Mascarenhas, 1989) and given the crisis' low impact on the insurance industry. Hence, they might rather be the result of ordinary processes of restructuring and strategic changes, because of the appointment of a new CEO, as a consequence of continuous underperformances or a large natural catastrophe. Summarising, our second hypothesis states:

> *H2: Strategic group dynamics in the aftermath of the financial crisis of 2008 can be attributed to factors that are related to the riskiness of the firm's business strategy.*

2.3 Data and Methodology

2.3.1 Data

We use company (subsidiary)-level data from the annual reports of German insurance companies for the years 2004 to 2012. We drop insurer-year observations with negative or zero surplus, investments, and total assets (Liebenberg and Sommer, 2008) and winsorize the data at the 1st and 99th percentile.[12] All variables are inflation-adjusted using 2005 as base year. Our final sample consists of 829 firm-year observations from 2004 through 2012.

[12] Due to strong outliers, our measure of *Return on equity*, its standard deviation and *Risk-adjusted return on equity* are winsorized at the 5th and 95th percentile, while all other variables are winsorized at the 1st and 99th percentile. However, our results are consistent if they are also winsorized at the 1st and 99th percentile.

For our analysis, we form our strategic groups on holding (insurance group)-level, as strategic decision making rather takes place at the top of the holding structure than on subsidiary-level. Thus, following for example Leask and Parker (2007), we use holding-level data in a first step and cluster our insurance groups into strategic groups.[13] In a second step, we use company-level data to examine if strategic group affiliation affects the performance of the insurance groups' subsidiaries in the German insurance sector.[14] Given the strongly different business models, we do not include life or health insurance companies in this part of our analysis. Thus, for the analysis on subsidiary-level, we focus on the property-liability insurance subsidiaries of the insurance groups only, while the analyses on insurance group-level also include information on the insurance groups' activities in life and health business.[15]

[13] Given that our database does not include holding-level data, we aggregate affiliated insurers, controlling for potential double counting of intra-group shareholding (Liebenberg and Sommer, 2008; Altuntas and Gößmann, 2015). For unaffiliated insurance companies, each single company was accounted as its own pseudo group. Our database accounts for more than 90% of the overall premium volume of the German property-liability insurance industry.

[14] Forming strategic groups on holding (insurance group)-level ignores that strategies might be set by the parent but can still vary across subsidiaries, as some of them might follow different business models than other subsidiaries because they serve different market segments. However, most related papers cluster strategic groups on holding-level for the above mentioned reasons (e.g. Leask and Parker 2007; Mehra 1996). For the purpose of our study, forming strategic groups on holding (insurance group)-level is required for several reasons. First, our research question particularly aims to analyse the relation between strategic group affiliation on holding level and performance on the subsidiary-level. While in certain cases clustering on subsidiary-level can be more appropriate, our research approach requires grouping on holding-level as this relationship could not be examined if grouping was done on subsidiary-level. Grouping on subsidiary-level and comparing performance differences between these strategic groups would just repeat the research in previous papers. Moreover, using only subsidiary information for the clustering would neglect important information: Even though subsidiaries might follow different strategies than set by their parents, there might still be a strong impact of the parent on each subsidiary (Khanna and Rivkin, 2001). In addition, even though their strategies differ, they are still affected from being members of the group, e.g. due to the parent's reputation and capital transfer, internal transfer of knowledge and managers, company-specific guidelines and capital transfers. Hence, clustering on subsidiary-level would ignore these effects.

[15] Including life and health business related information while forming strategic groups is necessary given that while single firms are restricted to write either life, health or property-liability business, holding companies consist of separate legal entities that write different types of business. In our dataset, a few holdings purely write property-liability business, while no holding in the sample is focused on life/health insurance business only. Also, the firms' degree of diversification regarding life/health and property-liability business is considered as a major strategic factor for clustering strategic groups (Johnson, Ranigan and Weisbart, 1981).

2.3.2 Methodology

2.3.2.1 Strategic Groups in the German Insurance Sector

Following related studies, we employ cluster analysis to identify strategic groups at the insurance group-level.[16] Following these studies, we cluster firms into strategic groups based on two sets of factors that are thought to be associated with the acquisition of competitive advantage: (1) factors that capture the *scope commitment* of the firms' operation and (2) factors that deal with the firm's *resource commitment*. The *scope commitment* factors include e.g. variables related to the firm's product diversity, market segments targeted and the firm's size. The *resource commitment* factors include information on the firm's resource deployment, e.g. distribution methods and investment or financing strategies. We follow Fiegenbaum and Thomas (1990, 1995) and Ferguson, Deephouse and Ferguson (2000) and use the following set of insurance business-specific variables for our cluster analysis.

Scope commitment variables

We use the insurance group's property-liability business market share in the German insurance market to measure its positioning in the German insurance sector (*Group PC%*), given that the share of property-liability business can significantly affect the firm's return on scale (Johnson, Ranigan and Weisbart, 1981) and thus the firm's performance.

A high degree of diversification might reduce the insurer's risk, but also its performance (Liebenberg and Sommer, 2008). We use a Herfindahl index based on

[16] See Harrigan (1985) for details on cluster analyses.

gross premiums earned in the respective line of business to capture the business segments covered by the insurer (*Herfindahl*).[17]

Larger firms might enjoy economies of scale and thus better performance (Scherer, 1980). Moreover, size can affect the firm's market power, flexibility and strategic response to environmental challenges. We include an indicator of insurer size, measured by the natural logarithm of its total assets (*Ln(total assets)*).

Furthermore, we include the insurer's age in years (*Age*).[18] Given that insurance business requires a high degree of trust, reputation is an important asset for the insurer's strategy and its success. The insurer's age is highly correlated with its reputation to provide reliable coverage and its survival probability (Anderson and Formisano, 1988).

The firm's ownership form can strongly affect its strategy, given that it provides different incentives for the firm's managers. For example, stock firms might be more profit-oriented (Mayers and Smith, 1981) and thus show a better performance. We include a dummy variable that equals one if the insurer is a mutual insurer (*Mutual*).[19]

Resource commitment variables

Following Ferguson, Deephouse and Ferguson (2000) we include a dummy variable equal to one if the firm mainly writes policies using a single distribution channel (*Distribution channel*).[20] There are various benefits which can result from the

[17] The lines-of-business are: personal accident, personal liability, total auto, legal expenses, fire, homeowners' personal property, residential and commercial building damage, transportation, credit insurance and other miscellaneous business.

[18] Ferguson, Deephouse and Ferguson (2000) measure age as the year of their analysis (1996) minus the insurer's year of incorporation, which leads to a constant measure of age over the observation period. For robustness, we perform another cluster analysis using their definition of age but receive identical results.

[19] Another ownership form in the German insurance sector are public insurers. These are founded as non-profit, state-owned organizations with the purpose to serve a certain region or administrative district (For further information, see Berry-Stölzle, Koissi and Shapiro, 2010). However, given their different regulation and ownership structures, we exclude them from our analysis.

[20] To measure the firms' strategic scope regarding its customers, Fiegenbaum and Thomas (1990) include a measure of the firms' premiums written in commercial lines vs. the premiums written in personal lines.

use of multiple channels: First, insurance firms can reach an extended coverage of the market by employing various distribution channels (Coelho and Easingwood, 2004). Further, knowledge and information about customers can be shared by different channels (Easingwood and Coelho, 2003). An insurer which uses different channels is also able to target different customer segments or to reach new customer segments by this way. Moreover, the use of multi-channel distribution may be suitable to meet the needs of existing customers in a better way (Tsay and Agrawal, 2004). Hence, the choice of whether to use single or multi-channel distribution has significant strategic implications regarding relative managerial control over product marketing and degree of potential market penetration, as well as overall cost effectiveness, among other competitive factors (Barrese and Nelson, 1992).

Reinsurance can affect the firm's strategy and performance in several ways, for example the reduction of the insurer's risk and the stabilization of its profits (Ferguson, Deephouse and Ferguson, 2000). Furthermore, the reinsurer pays the "reinsurance commission" to the primary insurer as a mutually agreed price as a compensation for the administrative expenses incurred by the insurer in generating the business and settling loss claims (Meier and Outreville, 2006). Since the use of more reinsurance increases an insurer's underwriting capacity and generates reinsurance commissions as income, we argue that reinsurance can accelerate new competitive opportunities (Mayers and Smith, 1990). Thus, we use the ratio of GPW (gross premiums written) minus direct GPW to direct GPW to measure the firm's degree of reinsurance (*Reinsurance*).

The firm's operational leverage affects its performance ratios and the insurer's risk (Fiegenbaum and Thomas, 1990). To measure the insurer's financing strategy, we

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This data is not available in our dataset, because German accounting standards do not require that insurance companies make this distinction.

use the insurer's operational leverage (*Op. leverage*), measured as the ratio of NPW (net written premiums) to the firm's book equity.[21]

Finally, we include the ratio of stocks and real estate to total investments to measure the firm's investment strategy (*Asset risk*). A high proportion of stocks and real estate should increase the firm's profitability, but also its risk (Fiegenbaum and Thomas, 1990).

Given that cluster analysis groups the firms into clusters regarding their degree of similarity using a set of factors, the results might be skewed by the relative scale of the factors used as cluster variables (Leask and Parker, 2007). Thus, the clustering results can be affected by the scale and unit of measurement of variables (Kim and Mc Intosh, 1999). Hence, we use z-scores to transform all variables to a common scale prior to our cluster analysis.

We employ two cluster analyses in order to examine whether strategic group affiliation changed in the aftermath of the financial crisis of 2008. First, we cluster the firms for the years 2004-2008 (*pre-crisis period*). Second, we employ an additional cluster analysis using the years 2009-2012 (*post-crisis period*). This approach follows related papers that analyse the effects of events that lead to environmental changes on firm strategy, thereby dividing the observation period into two sub-periods that include all years of the analysis (Kim and McIntosh, 1999; Cho and Hambrick, 2006).[22] We use

[21] A more precise measure of equity would include full risk capital that includes other forms of capital to back losses than just book equity. However, such data is not available at the insurance group-level.

[22] We classify the year 2009 as post-crisis year because previous research indicates that the crisis affected the German insurance sector only weakly, and the effects are mostly limited to the year 2008 while the industry has already strongly recovered in 2009 (Rauch and Wende, 2015), given that performance indicators and solvency capital of German insurance firms almost returned to pre-crisis levels already in 2009. For robustness, we did several cluster analyses to validate our clustering results. First, we exclude the years 2008 and 2009 from our clustering procedure, as the restructuring process could take place in these years. In another cluster analysis, we use the years 2004 till 2006 as our pre-crisis period and the years 2010 till 2012 as post-crisis period, hence excluding the years 2007-2009. Our results are almost unaffected by these approaches and can be requested upon demand. However, these clusterings are associated with a large loss of data and hence valuable information is lost. Therefore, we follow Kim and McIntosh (1999) and Cho and Hambrick (2006) and include all years in our analysis without excluding any year that captures an environmental change.

the years 2009 to 2012 giving the firms time to adapt their strategies to the new market environment after the crisis, as strategic changes might take years to unfold (Kim and Mc Intosh, 1999). To be able to examine strategic group dynamics, i.e. movements between strategic groups between these periods, we only include insurance groups that are contained in our dataset during the pre-crisis period and the post-crisis period, i.e. they must have at least one observation during 2004-2008 and at least one observation during 2009-2012.

2.3.2.2 The Effect of Strategic Group Affiliation on the Insurance Groups' Subsidiaries

To examine the effect of strategic group affiliation on the insurance groups' subsidiaries' performance, we estimate the following regression model on company-level for the years 2004-2012:[23]

$$Performance_{i,t} = f(Strategic\ group\ affiliation_{i,t},\ Firm\text{-}specific\ factors_{i,t}) \qquad (1)$$

We use different measures of performance for our analysis to validate our findings. First, we use *Return on assets* and *Return on equity* as dependent variables ($Performance_{i,t}$) in our regressions. Given that higher returns might just be a consequence of higher risk taking, we use *Risk-adjusted return on assets* and *Risk-adjusted return on equity* as dependent variables in our regressions as alternative measures of performance. *Risk-adjusted return on assets (equity)* is the firm's *Return on assets (equity)* divided by its standard deviation of the previous 5 years.[24]

[23] Given that our dataset indicates a panel structure, standard errors are clustered on firm-level and include year-fixed effects. We use clustered standard errors because Petersen (2009) writes that "Cluster standard errors are robust to heteroscedasticity" (p. 438) and standard errors clustered by firm "are robust to any form of within-cluster correlation" (p.459). We do not include firm-fixed effects due to the binary and time-invariant nature of our main variables of interest (*Dummy strategic group 1-3*), *Subsidiary* and *Mutual*.

[24] In addition, to control for risk-taking in our regressions using non-adjusted performance measures (ROA and ROE), we include the performance measure's standard deviation of the previous 5 years as a

To measure the subsidiaries strategic group affiliation, we include a dummy variable (*Dummy strategic group 1-3*) for each strategic group equal to one if the subsidiaries' parent company is part of the respective strategic group. Hence, we include two dummy variables for the three strategic groups in our regression (the third dummy is omitted). *Firm-specific factors* denote a vector of control variables associated with insurer performance in previous research. We include *Size*, measured by the natural logarithm of total assets. Given that, all else equal, larger insurers have a lower risk of insolvency, they can charge higher prices and thus show a higher performance (Sommer, 1996). In addition, larger firms might have market power and thus a higher degree of performance (Cummins and Nini, 2002). We control for the firm's operational leverage by including *Op. leverage*, the ratio of NPW to the firm's regulatory equity capital.[25] Because safer insurers might charge higher prices, a high degree of leverage might indicate a low degree of safety and thus lower performance (Sommer, 1996). Moreover, we control for insurers' business mix by adding a *Herfindhal* index based on gross premiums earned in the respective line of business, as diversification might affect performance positively by scope economies, larger internal capital markets, and risk reduction (Liebenberg and Sommer, 2008).[26] In addition, we control for the insurer's ownership form by including a dummy variable equal to one if the firm is a mutual insurer (*Mutual*). Owner–policyholder conflicts are less relevant for mutual insurers, but stock insurers might benefit from better corporate control mechanisms (Liebenberg and Sommer, 2008). Finally, we include *Subsidiary*, a dummy variable equal to one if the

control variable for risk-taking in our model (Liebenberg and Sommer, 2008). Alternative approaches to capture firm risk are market-based indicators of risk. However, these measures are not available in our dataset. Our regressions include further measures of risk (asset risk and operational leverage) that capture additional aspects of the firm's risk. By including these measures, we capture most factors relevant to the firms' risk.

[25] This measure of capital includes e.g. paid-in capital stock and parts of the firms' subordinate debt. See Rauch and Wende (2015) for additional details.

[26] For robustness, we include the percentages of premiums written in each line of business to measure diversification. The main results remain unaffected. The regression outputs are available upon request.

subsidiary is part of a holding (insurance group) structure. A subsidiary might receive benefits (capital transfer and know-how) from its holding company, hence showing a higher level of performance. The parent company might withdraw funds from its subsidiary, hence negatively affecting its performance. In addition, we include the amount of subsidiaries in the group to control for the size of the insurance group (*Number of subsidiaries*).[27]

2.3.2.3 The Consequences of the Financial Crisis for Strategic Group Affiliation

To examine the consequences of the financial crisis of 2008 regarding strategic group dynamics, we examine changes between pre-crisis period strategic groups affiliation and post-crisis period strategic groups affiliation. Hence, we estimate the following logit-Model:

$$\begin{aligned} \Delta SG\ affiliation_{i,post\text{-}crisis} = {} & \alpha + \beta_1\, ROA_{i,2008} + \beta_2\, ROA\ shock_{i,2008} + \beta_3\, Herfindahl_{i,2008} \\ & + \beta_4\, Size_{i,2008} + \beta_5\, Number\ of\ subsidiaries_{i,2008} + \beta_6\, Op.\ leverage_{i,2008} \\ & + \beta_7\, Asset\ risk_{i,2008} + \beta_8\, Premium\ growth_{i,2008} \end{aligned} \tag{2}$$

$\Delta SG\ affiliation_{i,post\text{-}crisis}$ is a dummy variable equal to one if an insurance group - has moved from one strategic group to another one within the post-crisis period and zero if it remains in the same strategic group as during the pre-crisis period.[28]

For this part of the analysis, we examine the transition from the pre-crisis period to the post-crisis period.[29] We analyse if changes between strategic groups that occur

[27] We use variance inflation factors (VIFs) to test for multicollinearity among the independent variables in our analysis. The mean VIF is well below the benchmark level of 10. This indicates that multicollinearity between our explanatory variables does not appear to be a concern (Belsley et al., 2005; Chatterjee and Hadi, 2013).

[28] This analysis is conducted on insurance group-level only, given that we formed strategic groups on insurance group-level, even though the crisis might have also induced changes in business strategy on subsidiary-level. However, following our definition of insurance groups, it also contains single insurance firms that have no subsidiaries or a parent company.

between these periods (i.e. if an insurance group changes strategic group affiliation and becomes member of another strategic group) can be explained by firm-specific factors in the year 2008.[30] This would indicate that insurers react to the crisis regarding their risk exposure and potentially change their business strategy. Furthermore, including the years 2009-2012 as post-crisis period allows us to analyse strategic changes that might occur over a longer time horizon, as such changes might take place directly after the crisis in the year 2009 or in later years. We include factors that mostly represent the riskiness of the insurers' business strategy. Given that the crisis might induce insurers to rethink their business models, these factors might be associated with changes in strategic group affiliation as a consequence of the crisis.

We include the firm's return on assets (*ROA*) of the year 2008, because a large loss in the year of the crisis (2008) might indicate weaknesses of the insurer's current strategy. Moreover, we analyse if the firm experienced a shock to earnings (*ROA shock)*, measured by the percentage change of its ROA between the years 2007 and 2008, as a major, relative loss in the crisis year might induce managers to change the strategy towards a safer strategy in order to prevent financial problems in future turmoil.

Given that previous literature showed that focused insurers outperform diversified insurers (Liebenberg and Sommer, 2008), diversified insurers have an incentive to change towards a rather focused strategy. *Herfindahl* indicates a Herfindahl index based on gross premiums earned in the respective line of business.

All else equal, larger insurers have a lower risk of insolvency (Sommer, 1996). Hence, we include *Size*, measured by the natural logarithm of total assets. In addition, we include a measure of the total number of subsidiaries in the insurance group

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[29] The post-crisis period lasts from 2009 to 2012, hence changes in strategy might happen in one of these years or even happen as a slow process over several years in this period.

[30] For robustness, we repeat the regression analysis using independent variables from 2007. The results remain consistent.

(*Number of subsidiaries*), as its ability to change strategic group affiliation might be restricted by the size and complexity of the insurance group.

Firms with a higher degree of riskiness might rather be induced to change their strategic group affiliation in the aftermath of the crisis. *Op. leverage* and *Asset risk* refer to operational leverage (ratio of NPW to the firm's equity) and asset risk (ratio of stocks and real estate to total investments),[31] indicating the riskiness of its financing and investment strategy.

Finally, we include the recent growth rate (*Premium growth*) of NPW (from 2007 to 2008), as premium growth is associated with an increase in the company's risk, in particular in times of economic downturn (Chen and Wong 2004). [32]

2.4 Results

2.4.1 Descriptive Statistics

Table 1-3 show descriptive statistics for all variables used in our analysis. The number of observations and the mean for variables on subsidiary-level (Table 1) and insurance group-level (Table 2 and Table 3) are presented.

Table 1 shows summary statistics for the company (subsidiary)-level variables used in our regression analysis (Hypothesis 1). The results show a relatively high amount of risky assets (22.82%), which appears relatively high for a sector that is known for a high degree of solvency and the absence of insurer failures (Rauch and Wende, 2015). Moreover, the table shows that the majority of firms are affiliated in a holding structure: 93% of the firms in our sample are subsidiaries of an insurance

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[31] For robustness, we analyze if measures of asset risk relative to the insurers' liabilities change the results, given that the level of risk is relative to the underlying liabilities and hence potentially different for insurers with large shares of life insurance activities. Our results remain unaffected when using these measures.

[32] We also compare the insurers' premiums written in each line of business and its asset composition before and after the crisis. The unreported results do not indicate significant changes in the firms' business composition.

group.[33] In addition, the table indicates that about 52% of the single companies belong to *Strategic group 3*, which is the largest strategic group in our sample. Consistent with previous findings for the insurance sector during the financial crisis, the results show that the German property-liability insurance industry has been relatively profitable on average during the observation period, indicated by all performance measures.

Table 1 Summary Statistics at Subsidiary-Level

Variable	Obs	Mean	Std. Dev.	Min	Max
ROA (%)	829	4.13	4.58	-12.56	17.93
ROE (%)	829	22.06	20.40	-16.25	63.39
RAROA	829	2.74	3.02	-2.73	15.68
RAROE	829	2.66	2.60	-1.03	8.96
Size	829	5.93	1.40	3.33	9.03
Op. leverage	829	2.88	1.63	0.20	19.17
Asset risk (%)	829	22.82	16.11	0.00	73.94
Herfindahl (%)	829	54.68	30.94	15.94	100.00
Mutual (%)	829	50.06	50.03	0.00	100.00
Subsidiary (%)	829	93.12	25.32	0.00	100.00
Number of subsidiaries	829	7.15	4.63	1.00	24.00
Standard deviation ROA (%)	829	2.53	2.11	0.16	11.18
Standard deviation ROE (%)	829	13.23	10.50	2.15	40.33
Dummy strategic group 1 (%)	829	25.33	43.52	0.00	100.00
Dummy strategic group 2 (%)	829	22.32	41.66	0.00	100.00
Dummy strategic group 3 (%)	829	52.35	49.97	0.00	100.00

Note: This table shows the summary statistics for insurers at subsidiary-level for the years 2004-2012. *ROA* is the ratio of net income to total assets. *ROE* is the ratio of net income to total equity. *RAROA* is the ratio of ROA to the standard deviation of its ROA of the last five years. *RAROE* is the ratio of ROE to the standard deviation of its ROE of the last five years. *Size* is the natural logarithm of the firm's total assets in million €. *Op. leverage* is the ratio of NPW to equity. *Asset risk* is the amount of stocks and real estate divided by total investments. *Herfindahl* denotes a Herfindahl index based on gross premiums earned in different lines of the firm's property-liability business. *Mutual* is a dummy variable equal to one if the firm is a mutual insurer. *Subsidiary* is a dummy variable equal to one if the firm is member of an insurance group. *Number of subsidiaries* denotes total number of subsidiaries in the insurance group. *Standard deviation ROA* is the standard deviation of its ROA of the last five years. *Standard deviation ROE* is the standard deviation of its ROE of the last five years. *Dummy strategic group 1-3* denote dummy variables equal to one if the firm's parent company is part of the respective strategic group based on our cluster analysis.

[33] Among the 50 insurance groups in our sample, 7 are single unaffiliated firms while 43 are holding companies that consist of more than one insurance firm.

Table 2 presents the summary statistics of the holding (insurance group)-level cluster variables that we use to identify strategic groups. It can be seen that 54.40% of our insurance groups are classified as *Mutual* insurance groups. Comparable to the findings on subsidiary-level, the table indicates a relatively high proportion of risky assets (26.14%). In addition, it can be seen that property-liability business accounts for the largest share of revenue of German insurance groups (55.11%).

Table 2 Summary Statistics Strategic Clustering Variables (Insurance Group-Level)

Variable	Obs	Mean	Std. Dev.	Min	Max
Scope commitment variables					
Group PC% (%)	443	55.11	33.98	5.09	100.00
Herfindahl (%)	443	43.57	26.88	15.18	100.00
Ln(total assets)	443	6.36	1.64	3.49	10.43
Total assets	443	2,127.43	4,341.35	32.69	33,911.80
Mutual (%)	443	54.40	49.86	0.00	100.00
Age	443	114.84	46.96	18.00	215.00
Resource commitment variables					
Distribution channel (%)	443	51.92	50.02	0.00	100.00
Reinsurance (%)	443	5.12	9.75	0.00	74.85
Op. leverage	443	2.37	1.10	0.45	7.49
Asset risk (%)	443	26.14	15.84	0.00	81.50

Note: This table shows the summary statistics for cluster variables to form strategic groups for the years 2004-2012. *Group PC%* denotes the proportion of gross premiums earned in property-liability business by the group's overall gross premiums earned. *Herfindahl* denotes a Herfindahl index based on gross premiums earned in different lines of the group's property-liability business. *Ln(total assets)* is the natural logarithm of the group's total assets in million €. *Total assets* is the group's total assets. *Mutual* is a dummy variable equal to one if the group's legal form is a mutual insurer. *Age* denotes the age of the group. *Distribution channel* is a dummy variable equal to one if the group's distribution system is concentrated on one channel. *Reinsurance* denotes the proportion of reinsurance ceded to a reinsurer. *Op. leverage* is net written premiums divided by the firm's equity. *Asset risk* is the amount of stocks and real estate divided by total investments.

Moreover, Table 3 shows the summary statistics of a set of variables that proxy for the firms' risk on holding (insurance group)-level to examine the consequences of the financial crisis of 2008 on strategic group affiliation (Hypothesis 2). It can be seen that 22% of the firms changed strategic group affiliation in the aftermath of the crisis (*ΔSG affiliation*). Hence, 11 insurance groups changed their affiliation. Moreover, as indicated by a positive *ROA*, it can be seen that the average insurance group was profitable even during the peak of the financial crisis. However, as indicated by *ROA Shock*, the table indicates that average profitability strongly decreased during the year 2008, on average by 24.32%. Moreover, the industry was still able to increase its premium revenue by 1.4% on average during the economic downturn in 2008, indicating that the financial crisis did not lead to strong decreases in insurance demand.

Table 3 Crisis Impact Summary Statistics (Insurance Group-Level)

Variable	Obs	Mean	Std. Dev.	Min	Max
ΔSG affiliation (%)	50	22	41.85	0.00	100.00
ROA_{2008} (%)	50	4.24	4.26	-7.96	15.40
ROA $shock_{2008}$ (%)	50	-24.32	123.50	-660.05	386.46
$Herfindahl_{2008}$ (%)	50	43.13	27.20	15.23	100.00
$Size_{2008}$	50	6.35	1.68	3.74	10.25
Number of $subsidiaries_{2008}$	50	4.66	3.69	1.00	17.00
Op. $leverage_{2008}$	50	2.35	1.05	0.61	5.62
Asset $risk_{2008}$ (%)	50	25.43	15.37	0.00	73.07
Premium $growth_{2008}$ (%)	50	1.40	6.66	-24.97	23.49

Note: This table shows the summary statistics for each insurer at holding-level. *ΔSG affiliation* is a dummy variable equal to one if the insurer changes from one strategic group to another one after the crisis and zero if it remains in the same strategic group. *ROA* is the firm's lagged return on assets. *ROA shock* is the percentage change of its ROA. *Herfindahl* indicates a Herfindahl index based on gross premiums earned in the respective line of business. *Size* is the natural logarithm of the *Insurance Group's* total assets in million €. *Op. leverage* is the ratio of NPW to the firm's equity. *Asset risk* is the ratio of stocks and real estate by total investments. *Premium growth* is the growth rate of NPW. All independent variables are from the year 2008. *Number of subsidiaries* denotes total number of subsidiaries in the insurance group.

2.4.2 Strategic Group Classification Results

Our cluster analysis identifies three strategic groups in the German insurance market.[34] The finding is similar to Ferguson, Deephouse and Ferguson (2000) and Fiegenbaum and Thomas (1990) who identify, depending on the period, around three main strategic groups in the U.S. insurance industry. To validate the classification results of our cluster analysis, we use several confirmatory techniques. This is an

[34] An earlier version of our analysis included public insurers in the clustering process. Not surprisingly, these firms have been assigned to their own, fourth, group. However, as discussed earlier, we decided to exclude these firms from our analysis given their different business models. The results of this clustering process are available upon request.

important step in determining strategic groups for empirical analyses, as groupings might otherwise rather be statistical artifacts than meaningful classifications of the industry's firms (Leask and Parker, 2007). First, we validate our findings visually by using dendograms.[35] Second, we compare our results to another classification using a k-means algorithm to subdivide the firms into strategic groups (Dess and Davis, 1984)[36] Our classification results are robust against both confirmatory techniques, hence providing further evidence on the existence of three strategic groups in the German insurance market.[37]

Our analysis yields the following strategic groups:[38] Table 4 shows that group 1 ("Small, specialized insurers") contains relatively small insurers that focus on one or only a few lines of business (e.g. credit insurers or legal expense insurers like *Coface Kredit* or *Roland*). This is indicated by a Herfindahl of 63.86% in pre-crisis times and 69.25% in post-crisis times. Mainly, they are involved in property-liability business, indicated by a share of 85.98% of gross premiums earned in property-liability business by the group's overall gross premiums earned in pre-crisis times (86.32% in post-crisis times). This group mostly contains relatively small insurers, in particular in the post-crisis period (indicated by €327.28 million of *Total assets*). Given that most of these firms are focused in certain lines of business that suffered from severe losses during the financial crisis (e.g. credit insurance), it is not surprising to see that the number of firms in this strategic group severely decreased after the crisis.

[35] Dendograms "are visual depictions of the sequence of convergence among clusters as the level of similarity within clusters decreases" (Ketchen, Thomas and Snow, 1993). See Aldenderfer and Blashfield (1984) for further information.

[36] The k-means algorithm "assigns the cluster membership of each observation to the cluster with the nearest centroid" (Ketchen, Thomas and Snow, 1993). See Aldenderfer and Blashfield (1984) for further information.

[37] Results are available upon request.

[38] A list of insurance groups included in each strategic group is available upon request.

Group 2 ("Focus on life/health business") consists of insurers that are mainly focused on life/health insurance business like *Barmenia* or *Debeka*. They are relatively risk averse regarding their low level of *Asset risk* (15.65% and 24.35%, respectively) and hence require much lower levels of reinsurance than firms in other strategic groups (1.31% and 1.05%). This strategic group contains only mutual insurers. Compared to the first group, this group is characterized by a relatively high degree of diversification (represented by a *Herfindahl* of 28.87% and 35.80%).

Group 3 ("Big, diversified insurers") consists of major companies like *Allianz* or *HUK Coburg*, i.e. large firms with a long tradition in the German insurance market. Also, major foreign players with substantial business in the German insurance industry are members of this strategic group, like *AXA*, *Zurich* or *Generali*. Given their size (indicated by €5,224.24 and €5,918.25 million of *Total assets*, respectively), it is not surprising that these firms are also strongly diversified and active in many different lines of insurance business (*Herfindahl* of 26.72% and 28.18%, respectively). Their investment strategy is based on a relatively high degree of risky assets (indicated by *Asset risk* of 27.09% and 28.63%). Moreover, the Group mostly consists of large, international insurers that can be considered as financial conglomerates, given their larger shares of financial activities and bancassurance. Thus, analyzing this strategic group can provide valuable insights given that the financial crisis may affect those financial conglomerates stronger than pure insurance companies.

Table 4 Summary Statistics Strategic Groups (Insurance Group-Level)

SG 1: Small, specialised insurers				
	Panel A: Pre-crisis (2004-2008)		Panel B: Post-crisis (2009-2012)	
Variable	Obs	Mean	Obs	Mean
Group PC% (%)	103	85.98	61	86.31
Herfindahl (%)	103	63.86	61	69.26
Ln(total assets)	103	5.60	61	5.27
Total assets	103	549.41	61	327.28
Mutual (%)	103	46.60	61	19.67
Age	103	81.45	61	77.08
Distribution channel (%)	103	71.84	61	54.10
Reinsurance (%)	103	4.21	61	10.05
Op. leverage	103	2.28	61	1.98
Asset risk (%)	103	32.02	61	24.56

SG 2: Focus on life/health business				
	Panel A: Pre-crisis (2004-2008)		Panel B: Post-crisis (2009-2012)	
Variable	Obs	Mean	Obs	Mean
Group PC% (%)	53	12.56	80	36.58
Herfindahl (%)	53	28.87	80	35.80
Ln(total Aassets)	53	5.47	80	5.79
Total assets	53	454.59	80	676.73
Mutual (%)	53	100.00	80	100.00
Age	53	121.26	80	125.50
Distribution channel (%)	53	90.57	80	90.00
Reinsurance (%)	53	1.31	80	1.04
Op. leverage	53	2.24	80	2.01
Asset risk (%)	53	15.64	80	24.35

SG 3: Big, diversified insurers				
	Panel A: Pre-crisis (2004-2008)		Panel B: Post-crisis (2009-2012)	
Variable	Obs	Mean	Obs	Mean
Group PC% (%)	85	47.49	58	45.08
Herfindahl (%)	85	26.72	58	28.18
Ln(total assets)	85	7.96	58	8.16
Total assets	85	5,224.24	58	5,918.25
Mutual (%)	85	29.41	58	34.48
Age	85	143.18	58	150.85
Distribution channel (%)	85	0.00	58	0.00
Reinsurance (%)	85	8.57	58	4.91
Op. leverage	85	2.72	58	2.99
Asset risk (%)	85	27.09	58	28.63

Note: Panel A shows the summary statistics for each strategic group for the years 2004-2008. Panel B shows the summary statistics for each strategic group for the years 2009-2012. SG 1-3 denotes the respective strategic groups for this period. See Table 2 for variable description.

2.4.3 The Effect of Strategic Group Affiliation on the Insurance Groups' Subsidiaries' Performance

Hypothesis 1 states that performance differences between subsidiaries of members of strategic groups can be attributed to the parent company's strategic group affiliation. Table 5 shows the regression results analyzing the relation between performance and the parent companies' strategic group affiliation. The results provide evidence for Hypothesis 1. We find significant relationships between performance and the parent companies' strategic group affiliation for subsidiaries of *Strategic group 2* and mostly for *Strategic group 3,* irrespective of the performance measure. Consistent with the literature, our results suggest that in general the parent companies' strategic group affiliation can affect the subsidiaries' performance. This finding might indicate that the subsidiaries of an insurance group are affected by the holdings' know-how (e.g. are more efficient due to transfers of knowledge from its holding) or benefit from its parent company's reputation and thus sell more insurance policies because the subsidiary appears to be more reliable to consumers. In addition, it supports the finding of prior papers (e.g. Liebenberg and Sommer, 2008) who find that focused insurers outperform diversified insurers: Both *Strategic groups 2* and *3* perform poorly relatively to *Strategic group 1*, which follows a focus strategy (as indicated by a Herfindahl of 63.86% in pre-crisis times and 69.25% in post-crisis times).

Table 5 Regression Results at Subsidiary-Level

	(1) (ROA)	(2) (ROE)	(3) (RAROA)	(4) (RAROE)
Size	-0.004	0.009	0.096	0.098
	(0.004)	(0.014)	(0.183)	(0.162)
Op. leverage	-0.005***	0.006	-0.215*	-0.132
	(0.002)	(0.011)	(0.111)	(0.103)
Asset risk	-0.010	0.016	1.714	1.188
	(0.031)	(0.119)	(1.615)	(1.485)
Herfindahl	-0.010	-0.037	0.275	0.493
	(0.012)	(0.060)	(0.667)	(0.637)
Mutual	-0.000	0.004	0.323	0.133
	(0.008)	(0.040)	(0.575)	(0.477)
Subsidiary	0.028	0.091	1.792	1.913*
	(0.020)	(0.083)	(1.207)	(1.072)
Number of subsidiaries	0.002**	0.011***	0.000	0.015
	(0.001)	(0.003)	(0.048)	(0.042)
Dummy strategic group 2	-0.019*	-0.081*	-1.333**	-1.150**
	(0.011)	(0.046)	(0.628)	(0.547)
Dummy strategic group 3	-0.025**	-0.095*	-0.980	-1.149*
	(0.011)	(0.050)	(0.662)	(0.616)
Standard deviation ROA	-0.295			
	(0.227)			
Standard deviation ROE		0.177		
		(0.159)		
Constant	0.067**	0.023	1.286	0.715
	(0.030)	(0.133)	(1.576)	(1.511)
R2	0.103	0.113	0.087	0.076
Adj. R2	0.083	0.093	0.068	0.056
Year Fixed Effects	Yes	Yes	Yes	Yes
Number of Observations	829	829	829	829

Note: This table shows the results of pooled OLS regressions using clustered standard errors at firm-level for the years 2004-2012 at subsidiary-level. Columns (1)-(4) denote the results of different regression analyses, using *ROA*, *ROE*, *RAROA* and *RAROE*, as dependant variables as denoted in the second line, respectively. ***, ** and * denotes significance at the 1%, 5% and 10% level. See Table 1 for variable description.

2.4.4 The Consequences of the Financial Crisis for Strategic Group Affiliation

Hypothesis 2 states that strategic group dynamics in the aftermath of the financial crisis of 2008 can be attributed to factors that are related to the riskiness of the firm's business strategy. Table 6 presents the results of a logit regression examining whether changes in strategic group affiliation can be attributed to factors related to the firms' risk and thus endanger the firm in times of crisis, providing evidence to rethink their business strategy.

Table 6 Regression Results at Insurance Group-Level

	(Logit)
ROA_{2008}	-1.896
	(10.596)
ROA $Shock_{2008}$	0.154
	(0.379)
$Herfindahl_{2008}$	-1.329
	(1.838)
$Size_{2008}$	-0.316
	(0.403)
Number of $Subsidiaries_{2008}$	-0.017
	(0.184)
Op. $Leverage_{2008}$	-0.541
	(0.437)
Asset $Risk_{2008}$	4.542^{*}
	(2.599)
Premium $Growth_{2008}$	-2.729
	(6.255)
Constant	1.479
	(2.714)
Number of Observations	50

Note: This table shows the results of a logistic regression for changes in strategic group affiliation between the pre-crisis period and the post-crisis period, using firm-specific variables from the crisis year 2008 as independent variables. The table shows the regression results at holding-level. ***, ** and * denotes significance at the 1%, 5% and 10% level. See Table 3 for variable description.

We find very limited evidence for Hypothesis 2, as only *Asset risk* is significant at the 10% level in our analysis, indicating that insurance groups with a riskier asset portfolio were more likely to change strategic group affiliation in the aftermath of the financial crisis. However, consistent with previous literature (Harrington, 2009; Rauch and Wende, 2015) we conclude that the impact of the financial crisis on the German insurance sector was low. Instead, changes in strategic group affiliation might rather be the result of ordinary processes of restructuring and strategic changes, e.g. due to the appointment of a new CEO or sector-specific events like natural catastrophes.[39] Moreover, our results indicate a relatively high degree of strategic group dynamics in the German insurance market: We find that 11 of the 50 insurance groups (22%) change their affiliation during the financial crisis. Even though these changes may not be attributed to the consequences of the financial crisis, this indicates relatively low

[39] For robustness, we compare the clustering variables of insurance groups that changed strategic group affiliation and those who remained in the same strategic group using t-tests. In addition, we compare the clustering variables of insurance groups that changed strategic group affiliation between the pre-crisis period and post-crisis period. For both analyses, we find almost no significant differences, providing further evidence for the low impact of the crisis on the German insurance sector. The results are available upon request.

mobility barriers in the German insurance market, given that insurance groups change their strategic group affiliation relatively frequently.[40]

2.5 Conclusion

This study aims to examine strategic groups in the German insurance sector. We cluster insurance groups into strategic groups and examine whether performance differences can be attributed to strategic group affiliation on subsidiary-level. Furthermore, we analyse whether changes in strategic group affiliation in the aftermath of the financial crisis of 2008 can be considered as a consequence of the financial crisis. Our results indicate that performance differences between subsidiaries of insurance groups can be attributed to the strategic group affiliation of their parent companies. Consistent with previous research, we find that the impact of the financial crisis on the German insurance sector was negligible and strategic group changes appear to be unrelated to the financial crisis of 2008.

Our research contributes to the literature in several ways. First, our study is, to our best knowledge, the first study that examines strategic groups in the German insurance sector. Second, we extend the existing literature on strategic groups by providing evidence that performance differences between firms' strategic group members' subsidiaries can also be attributed to strategic group affiliation. Third, we add to the literature the impact of the financial crisis on the insurance industry by showing that the insurers' business models appear to be mostly unaffected by the consequences of the crisis.

The results have valuable implications for insurance executives, shareholders and regulators. For managers, our analyses provide valuable knowledge on the

[40] As an example, Mascarenhas (1989) shows that only up to 10% of the firms in the offshore oil-drilling industry change their strategic group affiliation during crisis-times.

competitive situation in the German insurance market that can be used to analyse the firms’ competitors. For shareholders, our analyses show profitable strategic groups and insurance groups in the insurance sector that might outperform their competitors in the long run and thus provide superior investment opportunities. Insurance regulators can use the findings to gain further knowledge on the impact of the financial crisis on the German insurance sector.

3 Solvency Prediction for Property-Liability Insurance Companies: Evidence from the Financial Crisis

Abstract

The financial crisis of 2008 generated sizeable losses in the financial sector around the world. Because regulators are used to predict insurers' financial strength to detect financial distressed firms as early as possible, we question how reliably regulators can forecast the financial strength, especially during a financial crisis. We use company-level data of German property-liability insurers from 2004 through 2011 to examine factors that affect the insurer's regulatory solvency ratio. Furthermore, we develop a prediction model to classify the insurers regarding their financial strength. We show that in particular the lagged solvency ratio can be used to predict the future regulatory solvency ratio irrespective of the economic conditions. Thus, our results imply that German regulators are able to detect insurers in financial distress early enough to take appropriate actions to protect the policyholders' interests. Our results do not support the adoption of tighter regulations or higher capital requirements.

3.1 Introduction

The financial crisis of 2008 generated sizeable operating losses in the financial sector around the world. In the banking industry, the turmoil in the financial markets led to an erosion of the bank's equity and thus a substantial amount of failures within the sector (Acharya et al., 2011). Despite these failures, the insurance industry was not affected as strongly as other industries in the financial sector (Harrington 2009), due to their proper financial strength and conservative business models among others. However, we question how reliably insurance regulators can assess and predict the financial strength of insurers to detect distressed firms as early as possible, especially in times of economic downturns.

In this research, we examine the effect of the most recent financial crisis on the prediction quality of German property-liability insurers' financial strength from the regulator's perspective. We use publicly available accounting data to examine factors that affect insurers' regulatory solvency ratio. Additionally, following the common German regulatory practice we develop a prediction model to classify insurers regarding their financial strength two years in advance. This model allows us to investigate the prediction quality of financially distressed firms during financial crises.

The need for reliable solvency prediction models for insurance companies arises from asymmetric information problems in insurance markets. Due to costly information and agency problems (Munch and Smallwood, 1982), consumers are not able to properly assess the insurers' financial strength before purchasing insurance coverage. Thus, failures in the insurance industry can have severe consequences. In order to overcome the asymmetric information problem, insurance companies around the world are subject to particularly strong supervision and regulation. An important subcategory of insurance regulation is solvency regulation. The aim of solvency regulation is to protect the policyholders by ensuring that the insurer will be able to meet its financial obligations in the future (Klein, 1995). To be able to intervene as early as possible and to minimize the potential costs associated with insurer financial distress, regulators use early warning systems to detect financially distressed companies.

Our research builds on a large amount of prior studies that have been devoted to the prediction of the insurers' (in-)solvency.[41] However, to protect policyholders it is important to examine how reliable these predictions are in times of economic downturn. As macroeconomic factors can severely influence the solvency of insurance companies (Browne and Hoyt, 1995; Cheng and Weiss, 2012), it is of particular interest how the recent financial crisis affected the credibility of solvency prediction for insurance companies. The deterioration of the overall economic situation can lead to severe losses in the insurance sector and thus erode the company's equity base. Solvency prediction has to remain consistent even in times of crisis and prediction models have to provide reliable estimates of the insurers' future financial situation.

We use company-level data of German property-liability insurers from 2004 through 2011 to examine factors that predict insurers' regulatory solvency two years in advance, in particular focusing on the financial crisis and the subsequent recession in 2008 and 2009. We use the solvency ratio as defined by German regulatory law as an indicator for the insurers' future financial strength. Using OLS regressions for each year separately, we find that today's solvency ratio is a reliable indicator for the insurers' future solvency ratio even in times of financial crisis, while a prediction model that excludes today's solvency ratio has much lower explanatory power. Hence, we show that a two-year ahead prediction model allows German regulators to detect companies in distress early enough even in times of economic downturns. Moreover, we show that aggressively increasing premiums to raise market share can lead to a deterioration of the

[41] See for example Grace, Harrington and Klein (1998); Cummins, Grace and Phillips (1999); Carson and Hoyt, (1995); Browne and Hoyt (1995); Cheng and Weiss (2012); Chen and Wong (2004); Sharpe and Stadnik (2007); Kleffner and Lee (2009); Berry-Stölzle, Koissi and Shapiro (2010).

insurers' solvency ratio in an economic downturn, but also in the years surrounding the crisis. In addition, we examine the impact of investment risk on German insurers' solvency ratio. Given the turmoil in the financial markets during the financial crisis, insurers with risky assets might have suffered more from the downturn and thus their solvency ratio might have been negatively affected. However, our empirical results indicate that investment risk is not a good predictor of insurance companies' solvency.

Our results contribute to the literature on solvency prediction in several ways. First, we provide evidence that the solvency ratio of German property-liability insurers can be assessed with a high degree of accuracy even in times of financial crisis. Second, we show that in particular today's solvency ratio can be used to predict the future solvency ratio regardless of the economic conditions. Thus, our results imply that German regulators are able to detect insurers in financial distress early enough to take appropriate action to protect policyholder's interests. Third, we contribute to the literature on insurance regulation, as the analysis shows a high level of stability within the German insurance industry, indicating the industry was able to bear the consequences of the financial crisis.

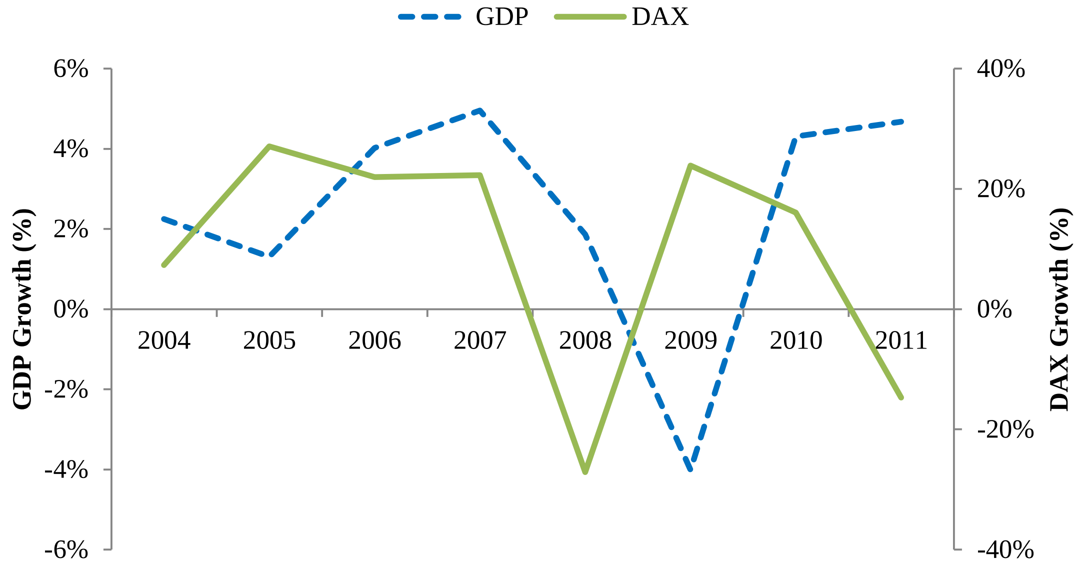
The paper proceeds as follows. The next section provides a summary of trends in solvency ratios and profitability for the German property-liability insurance industry as a whole. The following section provides a conceptual background and some regulatory details on solvency regulation in Germany. The subsequent section describes our data and methodology, and the ensuing section presents our results. The final section concludes.

3.2 Time Trends in the German Property-Liability Insurance Industry

We begin by illustrating the impact of the financial crisis and subsequent recession on the income and capital positions of German property-liability insurers.

Figure 1 shows the impact of the financial crisis on two macroeconomic indicators, the growth of the German Gross Domestic Product and the development of the German Stock Index (DAX). Both lines show that Germany was substantially affected by the financial crisis, as is shown in the substantial drop of the indicators in 2008 and 2009. This raises the question of how the financial crises affected the German property-liability insurers and their financial strength in particular.

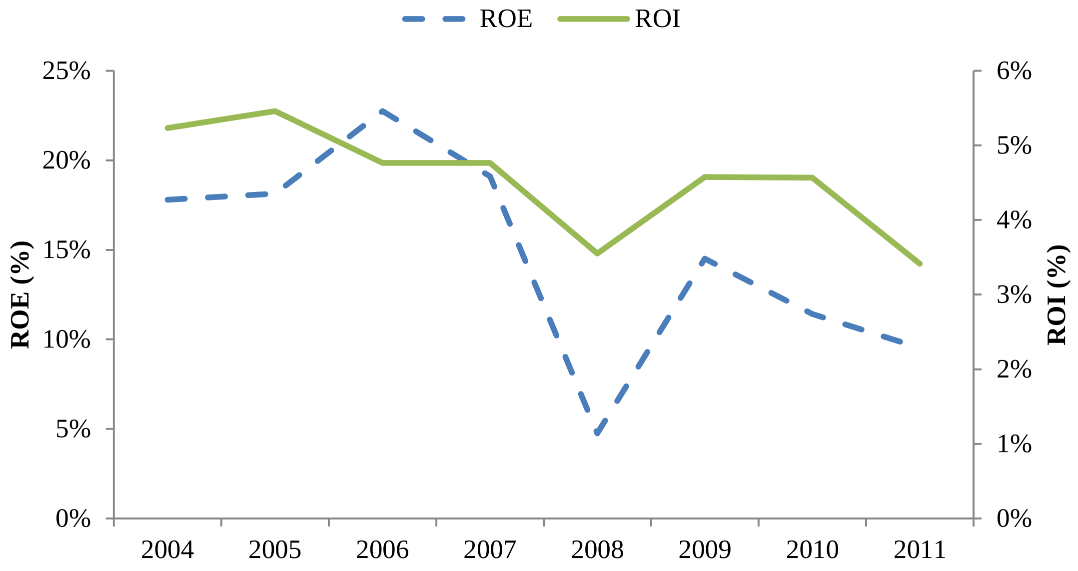
Figure 1 German Macroeconomic Indicators: 2004-2011



Note: This figure plots the growth of the German gross domestic product (GDP) and the DAX (German stock exchange index) for the years 2004 – 2011. The solid line presents the DAX Growth; and the dashed line shows GDP Growth.

Figure 2 provides an overview of the German property-liability insurers' average return on equity (ROE) and return on investment (ROI), measured by the realized investment return for the year. Both lines show that the German property-liability insurers were substantially affected by the financial crisis. Property-liability insurers experienced a dramatic drop in ROE during 2008 while ROI fell slightly.

Figure 2 German Property-Liability Insurers' ROE and ROI: 2004-2011



Note: This figure plots the return on equity (ROE) and the return on investment (ROI) for the sample of property-liability insurers described in the text. The solid line presents the ROI; and the dashed line shows the ROE.

Figure 3 plots the average regulatory solvency ratio for German property-liability insurers from 2004-2011. On average, the insurers' regulatory solvency ratio over the whole time period seems not to be strongly negatively affected by the crisis. In fact, the average solvency ratio remains at a relatively constant level of about 400%, showing that the average insurer is far from financial distress. However, there is an observable drop in 2008 indicating that the reliable prediction of the single insurers' regulatory solvency remains an important question even in times of economic downturns. Given that the failure of one or more large insurers can have severe consequences for the economy and the insurance sector, regulators are concerned about individual insurers' solvency in addition to the industry's average situation.

Figure 3 German Property-Liability Insurers' Solvency Ratio: 2004-2011

Note: This figure plots the solvency ratio for the sample of property-liability insurers. We measure the solvency ratio using the specific level of equity as a function of underwriting risk of an insurance company required by the German law.

3.3 Solvency Prediction and Solvency Regulation in Germany

3.3.1 Solvency Prediction Literature

Solvency prediction models that help regulators, investors and other stakeholders to determine the kind of information that is useful for predicting financial distress or insolvency as early as possible have been discussed in the literature extensively. Since Altman (1968) introduced business failure models, similar approaches have been developed for industrial companies and banks, as well as for insurance companies. Failure prediction models for insurance companies were first developed by Trieschmann and Pinches (1973) and were primarily used to predict failures in the U.S.-insurance industry (see for example Grace, Harrington and Klein (1993, 1998); Cummins, Grace and Phillips (1999) Browne and Hoyt (1995); Cheng and Weiss (2012)).

In the absence of insurer insolvencies in Germany during recent decades, these models are not appropriate for our analysis. Therefore, we refer to the literature on solvency prediction (the prediction of insurers' regulatory solvency ratios instead of insurer failures) as follows. To our knowledge, only a few studies have been published using data from outside the U.S. Kramer (1996) assesses the financial strength of property-liability insurers in the Netherlands. For the reason that bankruptcies are rare, the dependant variable is a ternary variable, subdividing the firms in financially strong, moderate and weak companies. Chen and Wong (2004) examine the financial health of property-liability and life insurers from Japan, Singapore, Malaysia and Taiwan. The insurers' solvency is used as dependant variable because no insurer failures occurred in these countries, with the exception of Japan. Sharpe and Stadnik (2007) predict financial distress among Australian general insurers. Berry-Stölzle, Koissi and Shapiro (2010) develop a prediction model for German insurers using the two year lagged solvency ratio to predict insurers' future regulatory solvency. The focus of the study is to develop a test that detects fuzzy regression coefficients. The model that is used to predict the solvency of German insurers thereby serves as a test to detect those regressors. Because their prediction model is developed for the year 2004 only, it has not been tested in times of economic downturn. Furthermore, it does not test its ability to correctly classify insurers regarding their financial strength.

Given the fact that wrong classifications, for example assuming a distressed insurance company to be financially healthy, can be associated with substantial costs and unfavorable consequences, regulators need prediction models that have a sufficiently high predictive power in order to fulfill their regulatory function to protect policyholders. However, the prediction models constructed in previous studies can classify insurers regarding their financial strength with a relatively high degree of accuracy. But so far, no research has been devoted to the question how precisely the solvency prediction of German property-liability insurance companies can be assessed especially during a financial crisis.

3.3.2 Solvency Regulation in Germany

The rationale for solvency regulation stems from inefficiencies in insurance markets due to costly information and agency costs (Munch and Smallwood, 1982). In the absence of solvency regulation, the lack of consumer information and the existence of agency costs could promote insurer insolvencies. Hence, solvency regulation aims to decrease insurers' insolvency risks in dependence of the society's preference for safety (Klein, 1995).

Germany has a long history of supervision and regulation in the financial sector. Since 1901 German insurance companies have been broadly and tightly supervised and regulated.[42] Due to close supervision and large capital holdings there have been no relevant failures since the Second World War. Solvency regulation is an important part of the German insurance supervision. Its main purpose is to protect the policyholders. It aims to guarantee an adequate level of capitalization for each insurance company in order to absorb potential losses and maintain the ability to settle its claims. The regulations described below are based on European-wide standards (Solvency I) in the German insurance regulatory system. Because Solvency II has not been fully implemented within the European insurance sector, yet, the analysis in this paper is based on the current Solvency I accounting standards.

The current solvency regulation is mainly covered in the insurance regulatory law (*Versicherungsaufsichtsgesetz*) and the Solvency Ordinance (*Kapitalausstattungsverordnung*).[43] The regulation is undertaken by the German Federal

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[42] The insurance supervision is mainly codified in the *Versicherungsaufsichtsgesetz* and the *Gesetz über die Bundesanstalt für Finanzdienstleistungsaufsicht*. See Berry-Stölzle and Born (2012) for a more detailed discussion of the German insurance market and its regulatory environment.

[43] See Directive 2002/13/EC of the European Parliament and the council Directive 73/239/EEC. According to German law insurers' equity contains the sum of paid-in capital stock, additional paid-in capital, retained earnings, profit-sharing rights outstanding and subordinate debt minus expenditure for the start-up or the expansion of business operation, goodwill of the company, and deferred taxes, and minus the net loss for the year if applicable.

Financial Supervisory Authority (*Bundesanstalt für Finanzdienstleistungsaufsicht, BaFin*). Each individual insurance company is subject to regulation at the company-level. The regulation distinguishes between life insurers, health insurers and property-liability insurers. Given the fact that the analysis in this study is restricted to property-liability insurers, regulation regarding life and health insurance companies will not be examined in more detail.

Because individual German insurers are not traded no market data exist.[44] Therefore, regulators use the insurers' regulatory solvency ratio to measure and to monitor insurers' financial strength. The calculation of the solvency ratio according to German solvency regulation is undertaken in two steps. First, the *required solvency* is derived as the amount of capital the insurer has to hold in dependence of the amount of its underwriting risk. Second, this value is compared to the company's *current solvency*, the assets that can be used to back its obligations. The ratio of the insurers *required solvency* and its *current solvency* has to be equal or greater than one. If this ratio falls below one, insurance regulatory law provides several actions the regulatory authority can undertake to re-establish a sufficient degree of solvency.[45] In general, German property-liability insurers hold much more capital than required by this law. In 2011, the current solvency for all property-liability insurers amounted to 314% on average of the required solvency (BaFin: Annual Report 2011). Regulatory supervision is mainly based on observing the development of the regulatory solvency ratio.[46]

As Table 7 indicates, the solvency ratio is subject to some fluctuation, as single insurers' solvency ratios might increase or decrease much stronger than their mean,

[44] Only large holding companies like Allianz Group are traded, but not the single affiliates.

[45] See para. 81b section 1 VAG (insurance regulatory law). For example, the BaFin can require a solvency plan that includes measures to either increase the current solvency (e.g. by increasing the company's equity) or to decrease the required solvency (e.g. by increasing reinsurance).

[46] However, the BaFin possesses internal information in addition to the solvency ratio in order to assess the insurers' financial condition.

justifying the monitoring of individual companies in order to prevent unexpected decreases in the solvency ratio. Panel A shows the mean change, the standard deviation and the number of observations of the solvency ratio in our observation period, showing some degree of fluctuation in the ratio. Panel B confirms this finding. For each year, we subdivide the insurers into quantiles, depending on their solvency ratio. Panel B shows the number of companies that moved between these quantiles from year *t* to *t+1*. It can also be seen that in each year about 17%-23% change their quantile, indicating a certain degree of fluctuation. In addition, we examine the shift of regulatory solvency ratio in each year, since large, unexpected changes in the ratio might severely endanger the firms. Panel C shows the number of insurers whose solvency ratio changed by at least 5%, 10% and 20%, respectively, compared to the preceding year. We find evidence for a certain degree of fluctuation of the solvency ratio at the company-level.[47]

3.4 Data and Methodology

3.4.1 Sample Selection

We use company-level data from the annual reports of German property-liability insurance companies for the years 2004 to 2011. We include all property-liability insurance companies with premiums greater than 50 million Euros, covering about 96% of the premiums written. We drop insurer-year observations with negative or zero surplus, total assets, and net premiums written. Since we use two-year lagged variables, we exclude firm-year observations for which two-year lagged variables are not available. Our final sample consists of 863 observations from 2004 through 2011.

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[47] We analyzed companies whose solvency ratios fell below 100% in a given year individually. The unreported results show that in all cases except one, the solvency ratio exceeded 100% in the following year again and did not fall below 100% again during our examination period, providing evidence for the effectiveness of the German approach to capital requirements in initiating regulatory action before insurers become insolvent. In one case (Mondial Assistance), the ratio kept fluctuating for several years. However, the company was part of the Allianz group and is still in business.

Table 7 Changes in Solvency Ratio

	2006	2007	2008	2009	2010	2011	Total
Panel A: Percentage of Change in Regulatory Solvency Ratio							
Mean Change	6.11%	0.72%	-0.64%	12.26%	0.11%	-2.96%	2.73%
Std. Dev.	27.10%	18.26%	18.04%	17.81%	14.47%	15.53%	19.65%
Obs.	105	107	106	107	102	94	621
Panel B: Number of Changes between 25%- Quantiles							
Changed 25%-Quantile	22	18	19	25	20	16	120
% Change	20.95%	16.82%	17.92%	23.36%	19.61%	17.02%	19.32%
Remained in same 25%-Quantile	83	89	87	82	82	78	501
Panel C: Number of Significant Changes in Regulatory Solvency Ratio							
Change >5%	77	79	80	89	61	64	450
% of all	73.33%	73.83%	75.47%	83.18%	59.80%	68.09%	72.46%
Change >10%	42	53	57	61	33	37	283
% of all	40.00%	49.53%	53.77%	57.01%	32.35%	39.36%	45.57%
Change >20%	10	17	27	31	8	10	103
% of all	9.52%	15.89%	25.47%	28.97%	7.84%	10.64%	16.59%

Note: Panel A shows the mean change, the standard deviation and the number of observations of the solvency ratio in our observation period. In Panel B, we subdivide the insurers into quantiles, depending on their solvency ratio. The first quantile consists of 25% of the insurers with the lowest solvency ratio; the fourth quantile consists of 25% of the insurers with the highest solvency ratios. The second and third quantile consists of insurers whose solvency ratios are among 25%-50% and 50%-75%. The columns indicate the number (percentage) of companies that changed their quantile from year *t* to *t+1* or remained in their quantile from year *t* to *t+1*, respectively. Panel C shows the number (percentage) of insurers whose solvency ratio changed by at least 5%, 10% and 20%, respectively, compared to the preceding year.

3.4.2 Summary Statistic

Table 8 shows summary statistics for the variables used in our regression analysis. All monetary values are inflation adjusted and converted to 2011 Euros. The average solvency ratio for all insurers in our sample is 418%.[48] Furthermore, the average return on assets is 3.1%. The average combined ratio is 95.34% indicating that the average insurer in our sample makes underwriting profit. The average premium growth amounts to 2.4% per year. Our sample consists of 10% mutual insurers and 8% public insurers. The remaining insurers are stock companies.

[48] With respect to multicollinearity of the variables used in our analysis, the unreported results indicate low variance inflation factors (1.8 on average), with a maximum of 3.25 between two variables in the year 2011. Hence, we assume that multicollinearity aspects can be ignored in our analysis.

Table 8 Summary Statistics from 2004-2011

Variable	Obs	Mean	Std. Dev.	Min	Max
Solvency Ratio (%)	863	418.11%	491.94%	69.49%	4025.25%
Ln (solvency ratio)	863	5.74	0.67	4.24	8.30
Investment Risk	863	0.26	0.17	0.00	0.81
Premium Growth (%)	863	2.41%	13.89%	-110.47%	143.72%
Ln (Assets)	863	6.17	1.32	3.46	10.33
Operational Leverage	863	2.78	8.99	-0.54	261.13
ROA (%)	863	3.07%	3.99%	-18.20%	19.13%
Combined Ratio	863	95.34	10.64	40.80	145.29
Herfindahl Index	863	0.50	0.31	0.13	1
Indicator: Mutual	863	0.10	0.30		
Indicator: Public	863	0.08	0.27		

Note: This table reports summary statistics for variables used in the subsequent analysis. All monetary values are inflation adjusted and converted to constant 2011 Euros and are reported in million Euros. *Solvency Ratio* is the solvency ratio as defined by the German regulatory law: The equity capital held by an insurance company divided by the amount of equity capital required for the company. *Ln(solvency ratio)* is the natural logarithm of solvency ratio. *Investment Risk* is the percentage of stocks and real estate in the investment portfolio. *Premium Growth* is the year-on-year percentage change in net written premiums. *Ln(Assets)* is the natural logarithm of total general account assets. *Operational Leverage* is the ratio of net premiums written and equity capital. *ROA* is the return on assets measured as the ratio of net income and total assets. *Combined Ratio* is the ratio of the sum of losses and expenses and earned premium. *Herfindahl Index* is $\Sigma a_i^2/(\Sigma a_i)^2$, where a_i represents the gross premiums earned in business line *i*. *Indicator: Mutual* is a dummy variable indicating for whether the insurer is organized as a mutual insurer and *Indicator: Public* is a dummy variable indicating for whether the insurer is organized as a public insurer.

3.4.3 Solvency Prediction Model

We perform an ordinary least squares (OLS) regression with robust standard errors to examine the factors affecting the solvency ratio.[49] We run separate analyses for each year to test whether there are differences in the relationship between the solvency ratio and the other factors in times of crises and in times of non-crisis. In the absence of failures in the German insurance market, we follow the German regulator’s perspective and predict the insurers’ regulatory solvency ratio as defined by the BaFin. The BaFin uses a two-year forward-looking prediction model to decide whether insurance companies are in financial distress and have to be inspected or need to develop a

[49] Following Berry-Stölzle, Koissi and Shapiro (2010), we suspect the standard errors to be heteroskedastic. The results of a Breusch-Pagan-Test indicate a substantial amount of heteroscedasticity in our model. Therefore, we use robust standard errors for our estimation.

business plan to restore its solvency to the appropriate level. Therefore, we use a prediction model of insurers' solvency ratio as defined in the regulatory law and we include all independent variables in the model with a two-year lag. This approach is similar to Berry-Stölzle, Koissi and Shapiro (2010), Chen and Wong (2004) and Kramer (1996) who predict the solvency ratio instead of the insurers' insolvency.

We use standardized coefficients in order to compare the magnitude of the effects of the indicators on the insurers' solvency ratio. The specification of the model is as follows:

$$\begin{aligned} Ln(solvency\ ratio)_{i,t} = {} & \beta_1\, Ln(solvency\ ratio)_{i,t-2} + \beta_2\, Investment\ Risk_{i,t-2} \\ & + \beta_3\, Premium\ Growth_{i,t-2} + \gamma' X_{i,t-2} + \varepsilon_{i,t-2} \end{aligned} \tag{3}$$

where the dependent variable is *ln(solvency ratio)* measured as the natural logarithm of insurer *i*'s solvency ratio in year *t*. We use the natural logarithm of the solvency ratio and not the solvency ratio itself because the solvency ratio is skewed to the right (Hair et al., 2006, Berry-Stölzle, Koissi and Shapiro, 2010). All independent variables are lagged two years.

We include the *two year lagged solvency ratio* in our model.[50] Berry-Stölzle, Koissi and Shapiro (2010) find a significant positive relationship between the solvency ratio and its two year lag for German property-liability insurers. We examine if this finding holds in times of economic downturn. Kramer (1996) includes the prior solvency as well and results indicating a strong relation to insurers' current financial strength. Moreover, Cummins and Nini (2002) state that safer insurance companies can demand higher prices as insurance prices proxy for insolvency risk (Sommer, 1996), and thus keep their solvency ratios on high levels.

[50] The use of lagged variables to detect factors that influence insurers' solvency proved to be successful in several related studies, as for example Barrese (1990) who finds the two-year reserve development as strong predictor of insurer distress.

Furthermore, we examine the impact of *Investment Risk* on insurers' solvency ratio. Given the turmoil in the financial markets during the financial crisis, insurers with a high proportion of volatile financial assets and real estate and thus a high exposure to market risks might have financially suffered more from the downturn. Hence, their equity base and their solvency might have been negatively affected. Harrington and Nelson (1986) provide evidence that the proportion of stocks negatively affects the insurers' financial strength. Cummins and Nini (2002) state that insurers with a higher proportion of stocks and real estate hold more capital in order to compensate for higher asset risks and should thus show higher degrees of solvency. However, German insurers are required by law to engage in safe and diversified investments and are not permitted to engage in speculative or risky business, making their investments relatively safe. To measure *Investment Risk* we use the percentage of stocks and real estate in the investment portfolio.

Moreover, we examine the impact of *Premium Growth* on insurer solvency. High premium growth is associated with an increase in the company's risk, as an aggressive growth strategy could increase the risk of insolvency (For example, U.S. General Accounting Office, (1989), Kim et al. (1995), Lee and Urrutia (1996)). In particular, excessive growth is a problem in times of economic downturn (For example during the Asian Financial Crisis, see Chen and Wong 2004). If the firm takes on substantial risks by increasing premium income, for example by underpricing, and thereby its market share it might not be able to bear the financial consequences in case of unfavorable development in the short run due to under reserving, even though such a strategy might pay off in the long run. This could lead to a higher risk of insolvency. Thus, the solvency of insurers with aggressive growth strategies might have deteriorated during the financial crisis. *Premium Growth* as included in our analysis is the year-on-year percentage change in net written premiums.

Additionally, we include a set of control variables in our regression model, denoted by X_i. Chen and Wong (2004), Cummins, Grace and Phillips (1999) and Cummins, Harrington and Klein (1995) find that larger property-liability insurers have stronger solvency. Hence, the vector of control variables includes a measure of insurer size. We measure size as the natural logarithm of the insurers' total assets.

BarNiv and McDonalds (1992), Trieschmann and Pinches (1973) and Lee and Urrutia (1996) use operational leverage as a proxy for the firm's sales aggressiveness and show that higher operational leverage leads to lower solvency of property-liability insurers. The *Operational Leverage* is measured as the ratio of net premiums written and equity capital.

Insurers with higher profitability should have a lower risk of decreasing solvency, because premium and investment income excess the claims and other expenses and therefore positively influence the company's equity and solvency. Moreover, a high degree of profitability might indicate efficient management and therefore lower risks, leading to lower risk of insolvency (BarNiv and McDonald, 1992). Therefore, we include the *Return on Asset* measured as the ratio of net income and total assets in our analysis.

Eck (1982), Chen and Wong (2004) and Sharpe and Stadnik (2007) show that the combined ratio as an overall measure of the cost of providing insurance coverage negatively affects insurer solvency. We include the *Combined Ratio* measured as the ratio of the sum of losses and expenses and earned premium in our analysis.

Moreover, we control for insurers' business mix because more diversified insurers might be less likely to suffer from financial distress (Sommer, 1996; Berry-Stölzle, Koissi and Shapiro, 2010). However, if it writes business in lines in which it is not competitive and/or in high-risk lines without having the knowledge to properly price and underwrite the exposures it assumes, then this could negatively affect its solvency.

We measure line of business diversification by including the *Herfindahl Index* based on gross premiums earned in the respective line of business in our analysis.[51]

Following agency and adverse selection theory, Lamm-Tennant and Starks (1993) provide evidence that mutual insurers take less risk than stock insurers and that stock insurers write relatively more business in lines with higher risk. Therefore, stock insurers should have a higher probability of insolvency than mutual insurers. Given their organizational structure, the incentive to increase risks after issuing their policies should be much lower for mutual insurers than for stock insurers. Cummins, Harrington and Klein (1995) and Cummins, Grace and Phillips (1999) include a dummy variable for mutual insurers in their prediction models and find that being a mutual insurer negatively affects the probability of insolvency. Another organizational form that might influence the insurers' solvency in Germany are public insurers, insurers which are under public law.[52] Berry-Stölzle, Koissi and Shapiro (2010) include a dummy variable for public insurers as they might have an incentive to write relatively more business given the fact that the government could bail them out in case of financial distress as they are owned by local and state authorities. Therefore, their solvency ratios might be lower. However, public insurers cannot raise money from the capital markets and since their mandate is to provide reliable insurance coverage and they are owned by public institutions they might have higher solvency ratios than stock insurers. We include two indicator variables in our analysis: *Mutual* is a dummy variable (1 indicating the insurer

[51] We follow Berry-Stölzle, Koissi and Shapiro (2010) and define the Herfindahl index as $\Sigma a_i^2/(\Sigma a_i)^2$, where a_i represents the gross premiums earned in business line i. The calculation uses premium data reported in the insurance companies' annual reports for the following lines of business: Personal Accident, Liability, Auto Liability, Other Auto, Fire, Homeowners Personal Property, Residential and Commercial Building Damage, Transportation and Aircraft, Legal Expenses, Credit and Collateral and Others.

[52] Public insurers are founded as non-profit organizations under public law to serve a certain region or administrative district; they can be owned by public institutions like cities, counties, states, other public insurers or municipal savings banks which are non-profit organizations under public law as well.

is organized as a mutual insurer and 0 otherwise). *Public* is a dummy variable (1 indicating the insurer is organized as a public insurer and 0 otherwise).[53]

3.4.4 Prediction Quality

In addition, we examine to what extend these factors are able to predict the future solvency ratio of the respective firm correctly. We thereby verify whether our prediction model correctly classifies insurers according to their financial strength, even in times of crisis. For this purpose we use a logistic regression model. As our dataset does not contain insolvencies, we follow Berry-Stölzle, Koissi and Shapiro (2010), Sharpe and Stadnik (2007) and Kramer (1996) and predict the insurers' solvency ratio. Hence, our prediction model aims to identify insurance companies that can be seen as financially distressed from the regulator's perspective two years in advance.

Regarding the fact that German insurers are well capitalized, the early identification of financially distressed insurers in the absence of insolvencies is arbitrary. We know that the BaFin takes regulatory action in case the company's regulatory solvency ratio falls below 100% and 33%, respectively (para. 81b sec. 1 VAG). To examine whether our model is able to detect these companies early enough before falling under the 100% criteria we follow Berry-Stölzle, Koissi and Shapiro (2010) and classify insurers into financially weak and strong based on whether their solvency ratio is below or above a specific reference point. Thus, even relatively financially weak companies in our sample are on average well capitalized and meet the 100% criteria of the BaFin easily. Hence, it remains subjective at which magnitude of

[53] Previous literature on solvency prediction includes a vast amount of additional factors that have been tested regarding their impact on insurer solvency. For example, Grace, Harrington and Klein (1998) and Cummins, Grace and Phillips (1999) include larger set of variables, including regulatory RBC and FAST ratios. However, given the data availability provided by the German insurance regulation, we cannot include these kind of factors in our analysis. Furthermore, we used different ratios for our control variables in additional regression analyses. The unreported results show no significant differences to the results presented in this paper. In addition, several factors that might affect insurer solvency like falsified financial statements or mismanagement could not been included in our model due to a lack of data.

the solvency ratio the insurer can be regarded as endangered. Therefore, we run three different prediction models using different intervals of financial distress in order to provide results for different levels of regulatory intervention.[54] We start with a rather broad definition of financial distress in order to identify endangered companies and subsequently seek to understand how precise our predictions are for companies with lower solvency ratio levels. We estimate the following logit model:

$$\begin{aligned} \textit{Financially Endangered}_{i,t} &= \beta_1 \textit{ Ln(solvency ratio)}_{i,t-2} + \beta_2 \textit{ Investment Risk}_{i,t-2} \\ &+ \beta_3 \textit{ Premium Growth}_{i,t-2} + \gamma' X_{i,t-2} + \varepsilon_{i,t-2} \end{aligned} \tag{4}$$

Financially Endangered is a dummy variable equal to one if we classify the insurer as endangered regarding our definition of financial distress and zero otherwise. The right hand side variables are identical to the variables described in equation (3).

We first define *Financially Endangered* companies as those having a solvency ratio of less than 200%. Second, we use a solvency ratio of 175% in order to distinguish between endangered and not endangered companies. Third, we use 150% as a cut-off point. We do not use a solvency ratio of 100% or lower as an indicator for endangered companies as this would be too narrow a definition of financial distress, regarding the fact that companies with less than 150% of the required solvency ratio can quickly fall below 100% in case of unexpected events.

Hence, we estimate three logit models using the above definitions of *Financially Endangered* companies. We drop mutuals and public insurers in the prediction model because both explain the financially not endangered category perfectly. Thus, the number of observations in the Prediction Quality Model is smaller than in the Solvency Prediction Model. An observation is classified correctly using a cutoff point of 50% for the predicted probability. Wrong classifications can be interpreted as type I and type II

[54] Thus, our methodology is similar to the U.S. RBC Authorized Control Levels that represent different levels of insurer capital holdings (200%, 150%, 100%, 70%).

errors, indicating potential costs of misclassifying insurers (BarNiv and McDonald, 1992).

3.5 Results

3.5.1 Solvency Prediction Model

Table 9 presents the OLS regression results for each year from 2006 through 2011 separately. The R-squared for all models is above 0.887 indicating a good model fit. This holds even in times of financial crisis. The factors included in our prediction model are thus able to assess the insurers' regulatory solvency regardless of the economic circumstances. This holds in particular for the lagged solvency ratio. Consistent with Berry-Stölzle, Koissi and Shapiro (2010), we find the lagged solvency ratio to be a strong predictor for the future solvency ratio in each period, regardless of the macroeconomic conditions. The lagged solvency ratio is significant at the one percent level in all years. The effect of the lagged solvency ratio on the current solvency ratio is much stronger in all years in comparison to *Premium Growth* and *Investment Risk*. We thus conclude that the lagged solvency ratio is an appropriate indicator of the insurers' future solvency ratio.

Table 10 supports this assumption, showing the results of our solvency prediction model when the lagged solvency ratio is excluded. It can be seen that this leads to a significant loss of explanatory power. The adjusted R-squared strongly decreases while in addition the *Akaike (AIC)* and *Schwarz information criteria (BIC)*[55] indicate that the exclusion of the lagged solvency ratio leads to significantly worse estimation results. The insurers' solvency ratio is now mostly explained by *Operational Leverage* and the organizational form. Hence, our results provide evidence that the

[55] Lower AIC and BIC values indicate a better fit of the model. See Akaike (1974) and Schwarz (1978).

current regulatory approach can successfully identify financially weak insurers based on their current solvency ratio.

Table 9 Regressions of ln(solvency ratio) on Insurers Characteristics

	2006	2007	2008	2009	2010	2011
Ln(solvency ratio)$_{t-2}$	0.928***	0.974***	0.903***	0.866***	0.882***	0.812***
	(0.043)	(0.058)	(0.051)	(0.040)	(0.038)	(0.071)
Investment Risk$_{t-2}$	0.742**	-0.016	-0.119***	-0.066**	0.001	-0.006
	(0.138)	(0.120)	(0.136)	(0.114)	(0.135)	(0.157)
Premium Growth$_{t-2}$	-0.105**	-0.139***	-0.102***	-0.083***	-0.025	-0.011
	(0.174)	(0.339)	(0.169)	(0.173)	(0.137)	(0.122)
Ln(Assets)$_{t-2}$	-0.024	-0.095**	-0.056	0.048	0.092**	0.055
	(0.019)	(0.023)	(0.021)	(0.019)	(0.022)	(0.024)
Operational Leverage$_{t-2}$	0.155***	0.092**	-0.047	-0.050	0.051**	-0.094
	(0.001)	(0.023)	(0.022)	(0.022)	(0.003)	(0.041)
ROA$_{t-2}$	0.039	-0.004	-0.079	-0.087**	-0.025	-0.027
	(1.054)	(1.034)	(1.006)	(0.878)	(0.841)	(0.920)
Combined Ratio$_{t-2}$	-0.062	-0.100	-0.052	-0.060	-0.066	-0.101
	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)	(0.004)
Herfindahl Index$_{t-2}$	0.017	0.018	0.030	0.069**	0.038	0.025
	(0.094)	(0.112)	(0.069)	(0.073)	(0.093)	(0.111)
Indicator: Mutual$_{t-2}$	-0.008	0.050	0.135***	0.132***	0.094***	0.070**
	(0.054)	(0.083)	(0.078)	(0.070)	(0.061)	(0.065)
Indicator: Public$_{t-2}$	0.006	0.085	0.060	0.050*	0.040	-0.023
	(0.066)	(0.137)	(0.103)	(0.060)	(0.063)	(0.151)
AIC	-4.939	14.308	-23.927	-46.995	-33.225	4.573
BIC	23.935	43.290	5.266	-18.120	-4.568	32.313
R-squared	0.897	0.886	0.919	0.932	0.925	0.891
Adjusted R-squared	0.886	0.874	0.911	0.924	0.916	0.877
Observations	102	103	105	102	100	92

Note: This table reports estimated coefficients from an ordinary least squares regression with *ln(solvency ratio)* as the dependent variable using standardized regression coefficients. All independent variables are measured at of the end of the period two years ago and are described in Table 8. The table reports five different models. The second column reports the model using *ln(solvency ratio)* as dependent variable based on 2006 data and all independent variables based on 2004 data. The third column reports the model using *ln(solvency ratio)* as dependent variable based on 2007 data and all independent variables based on 2005 data. The following columns are estimated for the dependent and independent variables vice versa. AIC and BIC refer to the test statistics for the Akaike and Schwarz information criteria, respectively. Standard errors are robust to arbitrary heteroscedasticity. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

Table 10 Regressions of ln(solvency ratio) on Insurers Characteristics excluding the Lagged Solvency Ratio

	2006	2007	2008	2009	2010	2011
Investment Risk$_{t-2}$	0.201*	0.086	0.034	0.118*	0.150*	0.050
	(0.421)	(0.278)	(0.290)	(0.255)	(0.362)	(0.274)
Premium Growth$_{t-2}$	-0.081	-0.121	-0.077	-0.073	-0.086	-0.003
	(0.278)	(0.588)	(0.259)	(0.358)	(0.328)	(0.168)
Ln(Assets)$_{t-2}$	0.202*	0.165*	0.185**	0.182**	0.154	0.258***
	(0.054)	(0.045)	(0.045)	(0.044)	(0.049)	(0.037)
Operational Leverage$_{t-2}$	-0.074	-0.493***	-0.534***	-0.492***	-0.128	-0.600***
	(0.002)	(0.051)	(0.061)	(0.071)	(0.022)	(0.051)
ROA$_{t-2}$	0.031	0.150	0.045	-0.054	-0.122	0.008
	(3.354)	(2.336)	(2.667)	(1.964)	(1.819)	(1.364)
Combined Ratio$_{t-2}$	-0.281	-0.073	-0.081	-0.177	-0.350***	-0.172
	(0.012)	(0.009)	(0.011)	(0.009)	(0.007)	(0.007)
Herfindahl Index$_{t-2}$	0.036	0.040	0.037	0.033	0.040	0.059
	(0.223)	(0.203)	(0.192)	(0.186)	(0.197)	(0.161)
Indicator: Mutual$_{t-2}$	0.275**	0.229**	0.283***	0.292***	0.391***	0.219**
	(0.302)	(0.218)	(0.222)	(0.223)	(0.256)	(0.185)
Indicator: Public$_{t-2}$	0.187**	0.124**	0.120*	0.133**	0.184**	0.022
	(0.178)	(0.148)	(0.158)	(0.129)	(0.186)	(0.182)
AIC	174.077	147.659	141.589	127.333	165.432	106.691
BIC	200.326	174.007	168.129	153.583	191.484	131.909
R-squared	0.394	0.577	0.603	0.617	0.439	0.662
Adjusted R-squared	0.334	0.536	0.565	0.579	0.383	0.625
Observations	102	103	105	102	100	92

Note: This table reports estimated coefficients from an ordinary least squares regression with *ln(solvency ratio)* as the dependent variable using standardized regression coefficients. All independent variables are measured at of the end of the period two years ago and are described in Table 8, except *ln(solvency ratio)* that is excluded in this regression. The table reports five different models. The second column reports the model using *ln(solvency ratio)* as dependent variable based on 2006 data and all independent variables based on 2004 data. The third column reports the model using *ln(solvency ratio)* as dependent variable based on 2007 data and all independent variables based on 2005 data. The following columns are estimated for the dependent and independent variables vice versa. AIC and BIC refer to the test statistics for the Akaike and Schwarz information criteria, respectively. Standard errors are robust to arbitrary heteroscedasticity. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

Moreover, Table 9 shows a significant negative relationship between *Investment Risk* and financial strength only for the years 2008 and 2009. Thus, the solvency ratio of insurers that hold a larger proportion of their assets in stocks and real estate was negatively influenced during the financial crisis.

The results are furthermore consistent with Chen and Wong (2004) as higher *Premium Growth* leads to weaker financial strength in 2008 and 2009, indicating that an aggressive growth strategy negatively influences the insurers' solvency in times of economic downturn. Moreover, *Premium Growth* is significant and negative in the years 2006 and 2007 as well. Hence, the negative impact of aggressive growth strategies in the German insurance market cannot be restricted to times of financial crisis, but also holds during the years preceding the crisis.

3.5.2 Prediction Quality

Table 11 shows the classification results for the logit model using different degrees of solvency ratios as a proxy for the insurers' financial situation. In Panel A, companies are defined as endangered if their solvency ratio is below 200% of the required solvency. Panel B and C use 175% and 150%, respectively, in order to define financially endangered insurers. The table shows the amount of insurers that were classified correctly (or incorrectly) as well as the overall percentage of correctly classified insurers for each year separately.

The results indicate that the model is able to correctly classify the vast majority of insurers according to their financial strength. Table 11 shows that in each year, at least 84% of the insurers are classified correctly by our model. The classification results remain on a high level over time and are not influenced by the financial crisis. Thus, the financial strength of German insurers can be classified with a high degree of accuracy even in times of crisis.

Table 11 Classification results

Panel A (200%)	2006	2007	2008	2009	2010	2011
Correctly classified as healthy	56	46	45	61	59	43
Incorrectly classified as healthy	4	7	7	6	5	6
Correctly classified as endangered	19	23	28	12	13	18
Incorrectly classified as endangered	6	8	6	4	4	6
Total	85	84	86	83	81	73
Correctly predicted	88.24%	82.14%	84.88%	87.95%	88.89%	83.56%

Panel B (175%)	2006	2007	2008	2009	2010	2011
Correctly classified as healthy	65	61	59	72	70	59
Incorrectly classified as healthy	3	7	9	2	0	2
Correctly classified as endangered	14	13	13	8	11	9
Incorrectly classified as endangered	3	3	5	1	0	3
Total	85	85	86	83	81	73
Correctly predicted	92.94%	88.10%	84.71%	96.39%	100.00%	93.15%

Panel C (150%)	2006	2007	2008	2009	2010	2011
Correctly classified as healthy	78	70	74	77	76	68
Incorrectly classified as healthy	0	5	5	0	0	3
Correctly classified as endangered	7	8	6	6	5	1
Incorrectly classified as endangered	0	1	1	0	0	1
Total	85	85	86	83	81	73
Correctly predicted	100.00%	92.86%	93.02%	100.00%	100.00 %	94.52%

Note: Panel A shows the classification table of the two years lagged insurer characteristics as described in Table 8 using a logistic regression with a dummy variable equal to one if the firm's solvency ratio is above 200% and zero otherwise as dependent variable. An observation was classified as correctly respectively incorrectly classified using a cutoff point of 50% for the predicted probability. Panel B is equivalent to Panel A except the fact that we use a dummy variable equal to one if the firm's solvency ratio is above 175% and zero otherwise as dependent variable. Panel C is equivalent to Panel A except the fact that we use a dummy variable equal to one if the firm's solvency ratio is above 150% and zero otherwise as dependent variable.

Furthermore, the results show that the model is particularly precise in detecting endangered insurers with solvency ratios close to the required minimum solvency ratio. Panel C shows that the model can classify companies with solvency ratios of less than 150% with at least 92.86% accuracy in each year. The amount of correctly predicted companies in Panel A and Panel B is lower in each period. Hence, seriously financially endangered insurers can be detected two years in advance with a high degree of accuracy, leaving time to take regulatory actions in order to protect the policyholder's interests.

3.6 Conclusion

The need for reliable solvency prediction models for insurance companies arises from asymmetric information problems in the insurance market. Due to costly information and agency problems, consumers are hardly able to properly assess the insurers' financial strength before purchasing insurance coverage. Particularly during times of economic downtown, reliable solvency prediction models are needed to protect policyholders' interests. We question how reliably insurance regulators can assess the financial strength of German property-liability insurers, especially in times of financial crisis.

This research examines the factors that affect the insurers' regulatory solvency ratio, focusing on times of economic downturns over the period from 2004 through 2011 using company-level data of German property-liability insurers. Furthermore, we develop a prediction model for German property-liability insurers, following the regulators approach that allows us to classify the insurers regarding their financial strength.

We use the solvency ratio as defined by German law as a proxy for the insurers' solvency ratio. Our results suggest that the prior solvency ratio is a reliable indicator of the insurers' future solvency ratio even in times of financial crisis. Moreover, we find that high premium growth can lead to a deterioration of the insurers' solvency in an economic downturn, but also in the years surrounding the crisis. In addition, we show that investment risk is negligible for the solvency of German insurers compared to prior solvency ratios. Furthermore, we have developed a prediction model that classifies the vast majority of the insurers correctly according to their financial strength. The classification results remain constant and show a strong ability to predict correctly even in times of financial crisis.

This research has important public policy implications. We show that in particular the lagged solvency ratio can be used to predict the future solvency ratio regardless of the economic conditions. Thus, our results imply that regulators are able to detect insurers that are financially distressed early enough to take appropriate action to protect policyholder's interests, even in times of economic downturn. We contribute to the literature on insurance regulation, as our results indicate a high degree of stability in the German property-liability insurance sector, even during economic downturns. The industry was able to bear the consequences of the financial crisis given the current regulatory system. However, given that our analysis focused mainly on capital requirements, the regulatory system could still be improved by a modernization that takes into account additional perspectives other than regulatory capital. Hence, because our analysis is based on Solvency I requirements, further research is needed after the adoption of Solvency II.

4 Policy Interventions and Banking Shocks: Evidence from the Insurance Sector

Abstract

We analyze the impact of monetary policy interventions during the financial crisis of 2007-2009 and banking-sector shocks on the stock prices of U.S. insurance firms. We use an event study methodology and a database of 89 policy announcements to analyze if such measures could restore stability in the insurance sector. In addition, we analyze the stock market response of insurers towards 10 banking sector events (bailouts and frauds). Our results indicate that different types of policy interventions led to diverse market reactions. Moreover, our results also show that insurers are highly exposed to shocks from the banking sector. In addition, we conduct a second stage analysis to examine firm level determinants of the insurers' stock price responses, finding that various factors affect the insurers reaction to banking shocks and policy interventions. Our results are valuable from a policymaker's perspective regarding the effectiveness of policy interventions in times of crisis and for investors of insurance firms regarding the diversification benefits of their investment portfolio.

4.1 Introduction

The financial crises of 2007-2009 exposed systemic linkages throughout the financial sectors of the economy. Given the effects of the Lehman failure on the overall financial sector, we know that major shocks from the banking sector affected companies from other sectors, and in particular insurance firms (Cummins and Weiss, 2014; Baluch, Mutenga and Parsons, 2011). To mitigate the consequences of the crises, policymakers around the world responded with a wide-ranging set of interventions. Apart from "conventional" measures such as interest rate decreases, their interventions comprised a set of "non-conventional" measures such as *monetary easing* and *liquidity provision*. The primary target of these interventions was to restore the stability of the financial and the banking sector (Ricci, 2015; Fiordelisi, Galloppo and Ricci, 2014). Previous papers examine the effectiveness of such measures regarding their ability to address the fragility of the banking sector and to restore confidence in financial markets (Aït-Sahalia, et al., 2012). However, how these measures affected firms from the insurance sector is an open question. In addition, despite the role of the Lehman failure for the outbreak of the financial crisis, knowledge on the impact of shocks from the banking sector on insurance firms is likewise limited.

In this research, we examine the impact of banking shocks and monetary policy interventions during the financial crisis of 2007-2009 on the stock prices of firms from the U.S. insurance sector. In particular, central banks around the world became major actors in restoring stability in the aftermath of the financial crisis, hence knowledge on the effectiveness of their measures regarding their ability to stabilize sectors provides valuable knowledge from a policymaker's perspective. However, while previous papers analyze the impact of policymakers' interventions on banks (Ricci, 2015), interbank risk permia (Aït-Sahalia et al., 2012) and aggregate markets (Fiordelisi, Galloppo and Ricci, 2014), research on the effectiveness of non-conventional measures regarding their ability to stabilize the insurance sector does not exist. Given that previous papers showed that the insurance sector has been strongly affected by the financial crisis that originated in the banking sector (Cummins and Weiss, 2014; Baluch, Mutenga and Parsons, 2011),[56] knowledge on the type of interventions that can restore the stability in the insurance sector is valuable for regulators, managers and policyholders of insurance firms. In addition, previous papers showed that the impact of different types of interventions differed between banks, aggregate markets and risk premia (Ricci, 2015; Aït-Sahalia et al., 2012; Fiordelisi, Galloppo and Ricci, 2014). Hence, the findings of previous papers might not be directly applicable to the insurance sector.

Moreover, apart from non-conventional measures, central banks intervene regularly in the markets through conventional measures, such as changes in interest rates. Specifically, during the crisis, central banks around the world reduced interest rates to unprecedented low levels to promote economic activity and mitigate the consequences of the crisis. Such monetary announcements affect aggregate stock markets (e.g. Bernanke and Kuttner, 2005), interest rates (e.g. León and Sebestyén, 2012) and in particular banks, given their interest-sensitive business models (e.g. Madura and Schnusenberg, 2000; Yin, Yang and Handorf, 2010; Yin and Yang, 2010; Kim, Wu and Lee, 2013). However, and somewhat surprisingly, the impact of central banks' interest rate decision on insurers has not been analyzed yet. Given the interest-rate sensitivity of insurance firms (Brewer III et al., 2007) and the fact that previous papers found a significant effect of such decisions on firms from the banking sector, such policy interventions are also quite likely to affect insurance firms, especially those with assets and liabilities exposed to interest rate risk. Knowledge on the impact of the

[56] For example, the life insurance stock price index lost 85% of value during the crisis, and the property-casualty index lost 58%. Moreover, the life insurer failure rate five folded during the crisis (Cummins and Weiss, 2014). In addition, Baluch, Mutenga and Parsons (2011) state that the impact of the banking crisis on insurers has been uneven, given that some parts of the insurance markets have been affected fairly severe, while other sectors remained unaffected.

Federal Reserve's (FED) interest rate decisions provides valuable knowledge regarding the effectiveness of the central bank's policy decisions and insurers' exposure towards such announcements.

Analyzing conventional and non-conventional policy measures regarding their ability to affect insurance firms during the crisis will shed light on their effectiveness to counteract a shock that originated from the banking sector. However, knowledge on the general impact of shocks from the banking sector on the stock price of insurance firms is limited. Given that the financial crisis was largely caused by an idiosyncratic shock from the banking sector, we will provide valuable evidence on the general exposure of insurance firms from shocks arising from the banking sector. Billio et al. (2012) and Chen et al. (2014) develop measures of interconnectedness in the overall financial sector based on financial market data. They find a high degree of interconnectedness and that the relative impact of banks on insurers' results is much stronger than the reverse.[57] However, these measures of interconnectedness do not evaluate interconnectedness with respect to single, sector-specific events. Instead, they focus on measuring interconnectedness in a given time period[58] but they do not analyze the effect of shocks such as extremely severe single events like banking bailouts and financial frauds. However, such events have been shown to spill over to other banks (e.g. Hryckiewicz, 2014; Cummins, Lewis and Wei, 2006). Given the interconnectedness between different types of institutions in the financial sector, such events are likely to affect insurance firms. In addition, Chesney, Reshetar and Karaman (2011) show that insurance-related events such as natural catastrophes and terror attacks affect the stock

[57] These papers analyze the interconnectedness of the financial industry from a systemic risk perspective. See Acharya et al. (2010) regarding additional background on systemic risk in the banking sector and Baluch, Mutenga and Parsons (2011) and Cummins and Weiss (2014) for additional information on systemic risk in the insurance sector.

[58] E.g. the price of insurance against distressed losses over the next three months, Chen et al. (2013), and a systemic risk measure based on monthly stock returns, Billio et al. (2012).

prices of insurers, but banks remain mostly unaffected. This shows that investors can diversify idiosyncratic, insurance-related shocks away, for example by holding bank stocks. However, knowledge about the impact of shocks from the banking sector on insurance firms is limited. Hence, in addition to the policy interventions aiming to *counteract* the recent banking crisis, we also analyze the impact of banking-sector events (banking bailouts and trading frauds) that can *cause* turmoil in financial markets on the stock price of insurance firms.

We follow related papers (Ricci, 2015; Aït-Sahalia et al., 2012; Fiordelisi, Galloppo and Ricci, 2014; Cummins, Lewis and Wei, 2006) and measure the effect of monetary policy announcements and banking-related events on the stock market performance of insurance firms using an event study methodology. In addition, we conduct a second stage analyses to identify the individual firms' determinants of their stock market response. This analysis provides evidence on the types of firms and business models that are more sensitive to both banking shocks and policy announcements from an investor's perspective

To examine the insurers' stock price response towards policy announcements and banking events, we use a detailed, hand-collected database of central bank policy initiatives during and in the aftermath of the recent crisis (based on Aït-Sahalia et al., 2012) and banking bailouts and frauds between 2002 and 2012. For our empirical analyses, we use stock market and accounting data for listed U.S. insurance firms during that period. This creates a dataset of 89 policy announcements and 10 banking-sector events. Our results can be summarized as follows: Shocks from the banking sector do affect firms from the insurance sector. The impact and direction depends on the content of the shock and is state dependent, that is, depending on the economic conditions. However, the consequences of such shocks can be mitigated by adequate policy interventions, given that most measures positively affected the stock prices of insurers. In particular, we find *financial sector policies* (e.g. liability guarantees) and *liquidity support* had a positive effect on insurance firms.

Our results contribute to the literature in several ways. First, to the best of our knowledge, our paper is the first to examine the impact of non-conventional policy announcements on firms from the insurance sector during the recent financial crisis. This provides valuable policy insights, as it is possible to examine how such measures affect an important part of the financial system, i.e. the insurance sector. As a primary responsibility of insurance regulation is to protect policyholders against the default of insurance firms (Klein, 1995), this research provides valuable insights on how policy interventions affect this goal. Moreover, we add to the literature an analysis on how conventional central bank announcements affect insurance firms. Given their interest-rate sensitivity (Brewer III et al., 2007), this provides valuable knowledge for managers and regulators in the insurance sector. In addition, our findings are highly relevant for investors regarding their portfolio diversification of financial sector stocks. Chesney, Reshetar and Karaman (2011) show that investors can diversify away idiosyncratic shocks from the insurance sector by holding bank stocks, as they are not affected by insurance sector-specific events. However, given that insurance stock price reactions are strongly affected by shocks from the banking sector, these assets are not suitable to diversify bank-specific risk.[59] Given the increasing magnitude and number of such exogenous, sector-specific events in recent years, understanding their effects on insurance firms provides valuable knowledge for investors, managers and regulators of these firms. Moreover, we contribute to the literature on interconnectedness in the financial industry. While previous studies (Billio et al., 2012 and Chen et al., 2014) do

[59] This is in particular valuable for investors that fail to diversify their stock investments in a way which is recommended by portfolio theory. For example, employees of financial firms hold most of their wealth in one financial firm due to stock options or pension plans. Thus, by being exposed to the idiosyncratic risk of their firm, they bear more risk than rewarded by the returns of their stocks (Campbell et al., 2001).

not analyze the interconnectedness of insurers with the banking sector regarding major banking-specific events, we contribute to the literature by showing that insurance firms are strongly affected by such shocks, thereby indicating a high degree of interconnectedness.

The paper proceeds as follows. The next section provides a summary of the background and previous literature on policy interventions, banking shocks and interconnectedness in the financial sector. The following section describes the data and methodology used in our analysis, and the ensuing section presents the results. The final section concludes.

4.2 Background and Previous Literature

In this section we discuss three related strands of literature as they relate to our empirical tests and discussion. First, we provide background on the effect of policy announcements on the financial sector. Second, we examine evidence of how sector specific events particularly affected banks. Third, we review the literature on interconnectedness in the financial sector.

4.2.1 The Impact of Central Bank and other Policy Announcements on Financial Firms

The stock price reaction to announcements of central banks has been widely discussed in the literature, in particular for aggregate stock markets and banks. Monetary policy advocates believe that changes in interest rates affect asset prices and returns and therefore have a direct effect on stock prices.[60] For banks, interest income and expenses are highly correlated with interest rates, and loan demand changes in

[60] From an asset pricing perspective, the value of an asset is determined by the present value of its future cash flows. Thus, a firm’s market value reflects the present value of the dividends generated by its business activities. For financial firms, the revenue, expenses and gains (losses) on securities are all affected by interest rates and therefore are affected by monetary policy.

accordance with the level of interest rates (Yin, Yang and Handorf, 2010). Similarly, insurance firms' (in particular, life insurers') assets and liabilities are highly interest rate sensitive (Brewer III et al., 2007). The degree of exposure of banks' and insurers' stock prices to interest rate risk depends on the duration gap between its assets and liabilities (Papadamou and Siriopoulos, 2014). However, previous literature indicates an inverse relation between interest rates and the stock prices of banks (e.g. Madura and Schnusenberg, 2000; Yin, Yang and Handorf, 2010) and life insurers (Brewer III et al., 2007).[61] While the relation between central bank announcements and bank stock prices has been extensively studied in the literature, research on the impact of interest rates on insurance firms' stock prices is limited (Papadamou and Siriopoulos, 2014; Brewer III et al., 2007). Studies that analyze the impact of central bank interest rate announcements on insurance firms do not exist. Moreover, previous papers find that stock price reactions to central bank announcements can be state dependent, that is, depending on changes in the economic conditions (Yin, Yang and Handorf, 2010). Hence, we examine how such announcements affect insurance firms during different stages of the recent financial crisis.[62]

In addition to "conventional" central bank announcements containing interest rate decisions, central banks and other policymakers intervened the market during the crisis of 2007-2009 using a large set of "non-conventional" policy announcements (for example, monetary easing). Their primary goal was to restore monetary stability and

[61] Apart from interest rate sensitivity of the firms' business models, asset pricing theory postulates that interest rate changes affect firms' stock prices via bond markets by affecting investors' required rate of return: changes in interest rates affect market rates and bond returns (e.g. Cook and Hahn, 1989; Kuttner, 2001; Roley and Sellon, 1995). This in turn affects stockholders' required rates of returns in relation to these alternative investment opportunities and therefore stock valuations.

[62] The content of such announcements needs to be unexpected in order to affect stock prices (Bernanke and Kuttner, 2005; León and Sebestyén, 2012). In case investors anticipate the outcome correctly, the impact on interest rates should already be considered in asset prices. Moreover, the impact of such announcements does not only depend on the decision to change interest rate and the extent of this change, but also on the rationale of this decision and the central bank's communication. See León and Sebestyén (2012) for a comprehensive literature review.

thus increase the stability of the banking system and the overall financial sector (Ricci, 2015). The announcements contained measures that aimed to support funding conditions for banks in order to ensure lending to the overall economy and to reduce the threat of contagion in financial markets (Fiordelisi, Galloppo and Ricci, 2014; ECB, 2011). The use of such measures was a primary response to the crisis and strongly affected the structure of the financial market. For example, central banks mostly replaced the interbank market in times of extremely high uncertainty and turmoil. The policy announcements were highly heterogeneous in type, and therefore their impact on stock prices is likely to vary across type of measure. In general, given their aim was to restore stability and the experience from previous crises, such announcements are expected to have a calming (*positive*) effect on financial markets (Aït-Sahalia et al., 2012; Reinhart and Rogoff, 2008). For example, monetary easing programs are expected to reduce credit and liquidity risk premia, given that such measures relieve funding pressures and reduce counterparty risk. However, though policy announcements aim to calm financial markets, they can have adverse effects as they increase concerns about the soundness of the financial markets. In this case, they are considered as bad news for investors. This might trigger *negative* stock market reactions. In addition, analogous to conventional announcements, the effect of non-conventional policy announcements can be state contingent, as investors might advocate certain measures in times of crises as they can stabilize the endangered financial system and therefore outweigh fears of higher uncertainty in the markets. For example, Ricci (2015) finds that liquidity provisions negatively affected bank stock prices during the financial crisis, but positively in the aftermath. Previous papers focused on the question of what type of policy response is effective in times of crises. Given the substantial resources devoted to such measures, research on the impact of their interventions provides valuable insights from a policymaker's perspective. In addition, given the heterogeneity of their interventions, their impact can vary across type of policy for different sectors and indices. Hence, previous papers analyze the impact of policy announcements during the crisis on a variety of industries, aggregate markets and measures of risk in the financial markets. Aït-Sahalia et al. (2012) use an event study methodology to analyze the impact of financial sector announcements from different countries during the recent crisis on interbank credit and liquidity risk premia. They find that such measures overall reduced interbank risk premia, and that such interventions had international spillovers. Fiordelisi, Galloppo and Ricci (2014) and Ricci (2015) extend this research by analyzing the effect of policy announcements on aggregate stock markets, global systemically important financial institutions (G-SIFIs) and European banks. Their results indicate that such measures can affect both aggregate markets and banks, and that the effect strongly depends on the type of intervention and the stage of the crisis.

4.2.2 Analyses of Sector Specific Events in the Banking Industry

The effect of bailouts on banks: A vast amount of studies analyze the effects of bank bailouts on firms from the banking sector. From a theoretical perspective, the literature discusses two opposite effects of bailouts: First, bailouts increase the banks' level of safety due to increases in charter values (Cordella and Yehati, 2003). Keeley (1990) shows that higher charter values decrease the banks' incentive to engage in extremely risky activities, given the lower risk of losing future rents. In addition, proponents of government interventions state that regulatory interventions restore confidence in the banking sector, hence positively affecting firms from the banking sector (Hryckiewicz, 2014). Moreover, bailouts strengthen the bank's monitoring incentives (Mehran and Thakor, 2011). On the other hand, they might increase the bank's riskiness as they induce moral hazard in the banking sector due to the anticipation of bailouts (Hryckiewicz, 2014). This decreases market discipline in the sector and thus lowers incentives to monitor banks (Gropp, Hakenes and Schnabel, 2011). Duchin and Sosyura (2014) state that government interventions in the banking sector provide banks with a put option on their assets on the guarantor. They find that bailouts make the banking sector more risky, as bailed-out banks shift their investments towards riskier assets. Overall, the consequences of bailouts in the banking sector depend on the specific policy instrument chosen by the government and whether the positive effects outweigh the negative effects. Hence, the *overall* banking sector might be affected by government interventions in the form of bailouts, even with respect to the bailout of individual institutions. Gropp, Hakenes and Schnabel (2011) analyze the competitive effects of government bailouts, finding that government bailouts increase the risk-taking of *competitor* banks. Given the importance of the banking industry for the overall economy, such government interventions might also affect non-banking companies. For example, Miyajima and Yafeh (2007) find that Japanese non-financial firms are significantly affected by government bailouts in the banking sector. Given the interlinkages and similarities in business models between banks and insurers, such events also have the potential to affect insurance firms.

The effect of banking frauds on banks: Literature on operational risk and fraud events is vast and growing in the banking sector, in particular given the extraordinary losses of rogue traders in recent years such as the losses caused by traders at Société Générale in 2008 (5 billion Euro) or at UBS in 2011 (1.5 billion Euro).[63] These extreme events show that large losses due to fraud events can endanger the health of financial institutions. A vast number of papers use event study methodology to

[63] Given that new regulatory frameworks in the financial industry, such as Solvency II and Basel III, account for operational risk, knowledge on their impact on financial firms is particularly valuable from a regulatory perspective. In addition, recent trends in the financial sector, for example the growth of e-commerce or automation, increase the firms' focus on these types of risk.

analyze the effect of operational losses and fraud events on financial firms.[64] Even though such fraud events are one-time losses that should not affect future revenue streams, they still affect financial firms significantly, as they also damage the firms' reputation (Perry and de Fontnouvelle, 2005).[65] Most studies find that the stock market drops of firms in the aftermath of banking fraud events exceed the monetary loss (Gillet, Hübner and Plunus, 2010; Cummins, Lewis and Wei, 2006) due to reputational losses. Given that such events convey negative news about affected financial firms, they might also spill over to non-affected firms from the financial sector, as these firms are active in the same business and therefore might be prone to such events in the future. Cummins, Wei and Xie (2011) analyze information externalities attributable to operational risk events from financial firms that announce operational losses.[66] They find that the announcements of operational losses affect not only the announcing firms, but also unaffected institutions, i.e. severe fraud events can affect the overall industry negatively.

4.2.3 Interconnectedness in the Financial Industry

Previous literature provides evidence of strong systemic linkages between banks and insurers. As systemic risk arises from interconnectedness among financial institutions (Cummins and Weiss, 2014), findings regarding inter-sector

[64] See e.g. Perry and de Fontnouvelle (2005); Cummins, Lewis and Wei (2006) Sturm (2013), Gillet, Hübner and Plunus (2010), Cummins, Lewis and Wei (2011) and Fiordelisi, Soana and Schwizer (2014).

[65] In addition, fraud events might have *indirect* effects on affected firms, such as the loss of current or future customers, employees or managers, increased costs of funding or costs due to fines and other penalties (Perry and de Fontnouvelle, 2005; Sturm, 2013).

[66] Operational risk events cause investors to decrease estimates of expected future cash flows at similar firms in the financial sector, which leads to lower market values across the industry. This may be due to several reasons. Operational losses may indicate the potential for the occurrence of similar events affecting non-announcing firms in the future. In addition, they could indicate higher anticipated regulatory costs. Alternatively, the competition hypothesis (Lang and Stulz 1992) states that adverse events such as frauds weaken the affected financial firms and therefore lead to market value increases at its competitors, because customers shift their business away from the fraudulent banks (Cummins, Wei and Xie, 2011).

interconnectedness may provide valuable insights for regulators. Being interconnected is a necessary condition for the spreading of systemic risk events in the financial sector, as in the absence of interconnectedness, the failure, or severe problems of a single firm would leave the other institutions and the rest of the economy unaffected. Given the fact that severe banking events like the failure of Lehman Brothers and the subsequent financial crisis can severely impact firms from other sectors, it is an open question how banking-specific events in general affect the insurance sector.

From a theoretical perspective, the transmission of shocks between formerly separated sectors in the financial industry has increased given closer business ties and increased competition between firms from these sectors (Billio et al., 2012). With the repeal of the Glass-Steagall Act in 1999[67] and through financial innovations, interrelationships between banks, insurers and funds increased, leading to a highly interconnected financial industry. Thus, their exposure to common shocks (e.g. changing market prices and economic conditions) converged (Billio et al., 2012). Hence, companies that provide similar products that serve similar economic needs can be expected to react similarly to informational events, regardless of their nominal industrial category (Cummins, Wei and Xie, 2011). Banks and insurers partly compete in certain services offered (Baluch, Mutenga and Parsons, 2011); hence, consumers might shift their business from firms that were negatively affected by those events to unaffected firms (*competition hypothesis*, Lang and Stulz, 1992).[68]

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[67] The Gramm-Leach-Bliley Act removed barriers between banks and insurance companies in November 1999. This essentially legalized the Citicorp–Travelers Group merger which occurred the previous year. Since then, commercial banks, investment banks, securities firms, and insurers were allowed to consolidate. See Carow (2001) for further information.

[68] In addition, Kaufmann (1999, 2000) states that an externality or a shock might create uncertainty about other firms and thus indirectly cause institutional instabilities, even though these shocks do not directly affect the firms. Similarly, Halstead, Hedge and Klein (2005) examine two types of financial contagion with respect to the bailout of LTCM (Long Term Capital Management) in 1998: direct or indirect exposure and non-fundamental based contagion, i.e. by firms unexposed to LTCM: Severe events can cause an irrational market response and affect other firms despite only a little real connection or interdependence between the firms. In particular, major banking-related events might affect firms from other sectors even if they are not directly exposed to them.

Several papers address the issue of spillover effects and connectedness between insurers and banks. Billio et al. (2012) use monthly returns of banks, hedge funds, brokers/dealers and insurers and granger-causality networks to measure the degree of connectedness in the overall financial industry. They find a high degree of interconnectedness in the financial sector that has been growing in the last years. Moreover, they state that shocks transmitted by banks have stronger effects on the other sectors than shocks from other industries. Chen et al. (2014) develop a systemic risk measure and analyze the interconnectedness in the financial sector. They find that banks and insurers are strongly interconnected, while the impact of banks on insurers is much stronger than vice versa.

Thus, the literature suggests that banks and insurers are interconnected and that they can influence each other's performance. Furthermore, banks can affect insurers much stronger than vice versa. Moreover, Chesney, Reshetar and Karaman (2011) show that insurance-related events such as natural catastrophes and terror attacks affect the stock prices of insurance firms, but the banking sector remains mostly unaffected. However, the previous literature has not examined the effect of individual, banking-specific events on the insurance industry. Hence, we analyze the degree of interconnectedness in the financial sector with respect to banking-specific events.

4.3 Data and Methodology

4.3.1 Data

We use daily stock price returns and financial statement data for all publicly traded insurance companies in the U.S. provided by SNL Financial. For our event study we drop firms if the stock prices are not available for the observed events or during the estimation period. Furthermore, for the regression analysis we drop firms with missing, negative or zero surplus or total assets and insurance companies with zero net premiums written. In addition, the data is winsorized at the 1 and 99 percentiles to control for extreme outliers. Insurers are divided into property-casualty insurers and life insurers, given their different business models and thus potentially different reactions towards the events based on the classification provided by SNL Financial.[69]

4.3.2 Central Bank Announcements and Banking Events

Building on Aït-Sahalia et al. (2012), Fiordelisi, Galloppo and Ricci (2014) and Ricci (2015) we compile a dataset of major policy initiatives announced during the financial crisis (between June 2007 and March 2009). In contrast to these papers, we purely focus on U.S. policy announcements, given their importance for the global economy, our sole focus on U.S. firms and the limited impact of foreign policy initiatives found in previous research (e.g. Kim, Lee and Wu, 2013). The announcements are identified based on official press releases, newspapers and search engines and are double checked with the database of Aït-Sahalia et al. (2012).[70] Consistent with their research, we include announcements from the following categories in our analysis:

Conventional central bank announcements include the FED's decisions to change interest rates or leave them unchanged. Following Aït-Sahalia et al. (2012), Fiordelisi, Galloppo and Ricci (2014) and Ricci (2015), *increases* and *no changes* are treated as a single category.

Liquidity support includes measures to provide liquidity through extended access to central bank refinancing, collateral framework or more frequent auctions or longer

[69] According to the definition in SNL, a company can be classified as both property-casualty insurer and a life insurer. Given that we aim to analyze the overall sectors' reaction we do not drop companies that are active in both sectors. In addition, all analyses are conducted separately for property-casualty insurers and life insurers, so a firm is never included twice in any of our regression. Furthermore, we include a dummy variable indicating if the firm is active in both property-casualty and life insurance in all our regression analyses.

[70] We thank the authors for making their database available to us. Our database is available upon request.

maturities (*Domestic currency liquidity support*). In addition, the provision of foreign currency liquidity through swap agreements (*Foreign currency swaps*) between central banks is included in this category.

Financial sector policies include measures to resolve systemic banking crises. This category includes *Asset purchases*, that is, the use of public funds to buy risky assets to protect banks from the losses from such assets. In addition, ring-fencing of bad assets is included. In addition, *Liability guarantees* are included, which are system-wide guarantees for (existing or newly-issued) wholesale financing, the enhancement of deposit protection schemes and the lender-of-last resort funding. Moreover, *Recapitalization* includes the announcements of system-wide recapitalization funds and capital injections. Finally, *Monetary policy* includes *Quantitative and credit easing (QE)*, that is, the central bank's purchases of government securities and purchases of private sector debt in primary or secondary markets.

Consistent with related studies, we need to deal with the issue of overlapping events. Given that, in contrast to related studies, we focus on policy announcements and firms from a single country only, the problem is somewhat mitigated, but some announcements still take place at the same day. In such cases, we follow Fiordelisi, Galloppo and Ricci (2014) and Ricci (2015) and treat announcements as a single event if they belong to the same category.[71] Following Aït-Sahalia et al. (2012), we include equally important policy announcements from different categories in the few cases they provide equally important information as separate entries in our database. To examine whether the impact of policy interventions is state dependent, that is, if it depends on changes in the economic environment over time, we subdivide our period into two sub-periods: The period before the Lehman failure (*Subprime Crisis*; from June 2007 until

[71] For example, on July 30, 2008, the FED released three measures to provide liquidity. These are included as a single announcement in our analysis.

September 14, 2008), and the period after the failure of Lehman between September 14, 2008 and March 31, 2009, which denotes the *Global Financial Crisis*. Table 12 reports the list of policy announcements examined in this study.

Table 12 List of Policy Announcements

Type	Measures	Example	Number of announcements	
Conventional announcements				
Interest rate decisions			18	
Interest rate cuts	Decision to decrease interest rates.			10
Interest rate increases and no changes	Interest rate increases and decisions to maintain interest rates unchanged.			8
Non-conventional announcements				
Liquidity support			33[72]	
Domestic currency liquidity support	Relaxation of collateral framework; change in funding terms or auction schedule; support of money markets.	U.S. Term Auction Facility (12/12/2007; 12/21/2007).		28
Foreign currency swaps	FX swaps and FX funding.	FOMC increases swap lines with the ECB by \$10bn and the SNB by \$2bn (03/11/2008).		5
Financial sector policies			33	
Asset purchases	Asset purchases; Ring-fencing of bad assets and asset guarantees.	Troubled Asset Relief Program (10/03/08).		7
Liability guarantees	Guarantees for old or new liabilities.	U.S. Temporary Liquidty Guarantee Program /10/14/2008).		9
Recapitalization	Capital injection and nationalization.	TARP capitalization of nine U.S. banks.		17
Monetary policy			5	
Quantitative and credit easing		FED buys long-term Treasuries (03/18/2009).		5
Total (conventional and non-conventional)			89	89

Note: This table reports all policy announcements used in our analysis. *Type* denotes the type of policy announcement. *Measures* describe the type of intervention. *Example* provides an example for the measure. *Number of announcements* denotes the amount of observations for each type of announcement.

[72] Two of these 33 measures were announced on March 16, 2008, three on July 30, 2008 and two on September 14, 2008. Consistent with Aït-Sahalia et al. (2012), these were treated as three individual events. Therefore, the final amount of *Liquidity announcements* in our analyses amounts to 29.

For banking sector-specific events, we include major bailouts of individual financial institutions (Hryckiewicz, 2014; Grace, 2011) and major banking fraud events (Gillet, Hübner and Plunus, 2010) that have been found to affect banking companies in previous studies.[73] We do not restrict our analysis to events that occurred in the U.S. and include important events from all over the world to examine how these major events have global systemic relevance in the financial industry.[74] Table 13 reports the list of events examined in this study and provides further information on the events.

Table 13 List of Banking Shocks

Event	Date	Category	Country	Description
Allied Irish Banks (AIB) Trader Scandal	February 4, 2002	FRD	USA	AIB announces trading loss of $0.8 billion due to fraudulent trading.
Société Générale Trading Loss Incident	January 24, 2008	FRD	F	Announcement of a $7.2 billion loss due to fraudulent trades by Société Générale.
Northern Rock Bailout	February 22, 2008	BLT	UK	Bailout of Northern Rock.
Bear Stearns Bailout	March 17, 2008[75]	BLT	USA	Bailout of Bear Stearns and merger with JP Morgan Chase.
Fannie Mae Bailout	September 7, 2008	BLT	USA	Bailout of Fannie Mae.
RBS Bailout	October 13, 2008	BLT	UK	Bailout of Royal Bank of Scotland.
Citigroup Bailout	November 23, 2008	BLT	USA	Bailout of Citigroup.
UBS Trader Scandal	September 15, 2011	FRD	UK	Announcement of a $2 billion loss due to fraudulent trades by UBS.
JP Morgan Chase Trading Loss	July 13, 2012	FRD	USA	Announcement of a $5.8 billion loss due to fraudulent trades by JPMorgan Chase.
LIBOR Scandal	July 27, 2012[76]	FRD	EU/USA	Announcements of high fines against banks that manipulated the LIBOR.

Note: This table reports all banking shocks used in our analysis. *Event* indicates the event's name. Date indicates the date the event occurred. *Category* denotes the respective categories: BLT: Bailout events; FRD: Fraud events. *Country* denotes the country in which the event occurred. *Description* provides a brief description of the event.

[73] We include bailouts of banks and frauds in the banking sector only to focus on shocks originating from the banking sector. Thus, bailouts (such as the bailout of General Motors during the financial crisis) and frauds of non-financial firms are not included in our analysis.

[74] A large amount of papers indicate the importance of international shocks on local financial firms (e.g. Bekaert et al., 2014). Gropp and Moermann (2004) show that idiosyncratic shocks of banks are transmitted to banks from other countries.

[75] The bailout took place on March 16, 2008, a Sunday. Thus, Monday 17 represents the next trading day.

[76] We use July 27, 2012 as event date, as this day presents the press cutting date, i.e. the date on which the scandal was made public to the media. This approach follows Gillet, Hübner and Plunus (2010) who analyze operational risk events using the press cutting date. For robustness, we repeat our event study using the dates on which fines were announced (December 4, 2013) instead of other dates to examine the *LIBOR Scandal*, as the scandal was made public through information leakages by newspapers long before the banks admitted the manipulation. Thus, the announcements of fines might be more unanticipated and therefore better capture the consequences of the *LIBOR Scandal* for the financial sector The results are consistent and do not depend on the date chosen.

4.3.3 Methodology

We start our analysis using event study methodology. Event studies can be used to measure the effects of economic events on the value of the respective firm, usually measured by the firm's common equity price.[77] Thus, we estimate the firms' normal returns based on the following model:

$$R_{i,t} = \alpha + \beta_i^{MKT} R_{i,t}^{MKT} + e_{i,t} \tag{5}$$

$R_{i,t}$ are the daily (t) stock market returns from each insurer (i). $R_{i,t}^{MKT}$ are the daily stock market returns from the broad stock market index (proxied by the S&P 500). We use a period from 280 to 30 days (250 days) prior to the event (*estimation window*) to calculate the individual stock's beta based on equation (5). Then, the abnormal returns are calculated during the event window ([-τ, +τ], with -τ as the amount of days before the event and +τ as the amount of days after the event).[78] Compared to other event studies that focus on single events or events from the same category in their analysis, our analysis includes different types of events that comprise different characteristics regarding their effects on firms. Hence, we use different event windows to take into consideration the heterogeneity of our events. For each event category, we use six event windows for our analysis that capture the events' effects on the firms to ensure the robustness of our results to the use of alternative time windows.

[77] Measuring the stock price reaction to examine the effect of such events has several advantages, as equity prices summarize all publicly available information, including firm risk and expectations on future performance, in one single number (Castrén et al., 2006). In addition, previous studies show that banks' stock price reactions to monetary announcements are a barometer for their effectiveness (Yin, Yang and Handorf, 2010). Finally, stock price information are available at a higher frequency than accounting measures (Fiordelisi, Galloppo and Ricci, 2014).

[78] Common methods for event studies might provide biased results in case an event has different effects on firms and if the returns' variances increase (Boehmer, Musumeci, and Poulsen, 1991). Severe events can change the risk and returns of stocks, as indicated by increases in the returns' variances (Brown, Harlow and Tinic, 1988; 1989). Such increases in variance might be cause by temporary changes in the firms' betas. We therefore control for the potential event-induced variance increases around event days by using a variance-adjusted Z-statistic proposed by Boehmer, Musumeci, and Poulsen (1991) which is robust against these event-induced changes of variances and incorporates information from both the estimation period and the event period. Robust standard errors are used when we perform the regressions and tests.

For policy announcements, we follow previous studies[79] and use event windows of [0; +1], [-1; +1] and [0; 0] in our analysis. For robustness, we include event windows of [-2; +1], [-2; +2] and [-1; +2]. For bailouts, we use event windows of [-8; +8] and [-16; +16]. In addition, we include windows that capture effects in case of prior information leakages ([-8; +2]) due to long pre-event periods and short-term windows ([0; +2]; [-2; +2]; [-1; +1]) to analyze if the effects close to the bailout's official announcement date. For frauds, we focus on short-term windows, as these events should be unknown for the wide public and therefore be unanticipated by investors.[80] Hence, we include event windows of [-5; +5]; [-8; +2]; [-1; +1]; [0; +4]; [-4; +2] and [-2; +2] in our analysis (Cummins, Lewis, and Wei, 2006). For each event, the abnormal return for each stock i is calculated (i.e. the difference between the predicted and the actual return during the event window) in each window separately. Finally, we calculate the cumulative abnormal return (CAR) as the sum of the abnormal returns over the event window for each firm.

4.3.4 Regression Analyses to analyze Firm-Level Determinants

Moreover, we conduct regression analyses in order to identify the individual firms' determinants of their stock market response. This provides evidence on the types of firms and the business models that are more sensitive to policy announcements and idiosyncratic shocks from other sectors.[81] This approach is consistent with that used elsewhere (e.g. Ricci, 2015; Cummins, Lewis and Wei, 2006). Following this approach

[79] Aït-Sahalia et al. (2012), Fiordelisi, Galloppo and Ricci (2014) and Ricci (2015).

[80] In addition, their monetary impact should be relatively clear, thus event windows that consider long periods after the announcements should not add further information on the impact (Cummins, Wei and Xie, 2006). For robustness, we include an event window that considers a long period prior to the event in order to control for prior information leakage ([-16; +16]) and the fraud events' long-run effects. Our results remain qualitatively unchanged.

[81] Altunbas, Manganelli and Marques-Ibanez (2011) show that the business models of financial institutions' strongly affected their risk exposure during the recent financial crisis. Therefore, we expect that the firms' business models also affect their exposure towards shocks from other sectors.

we use the firm's market value response (CAR) for each event window separately as the dependent variable. We conduct those analyses separately for each type of event, i.e. we have separate regression analyses for conventional announcements, non-conventional announcements and banking shocks. Hence, we start by estimating the following model:[82]

$$CAR_{i,j} = \alpha + \delta' X_{i,l,j} + \theta' CONTR_{i,k,j} + \gamma Crisis + \varepsilon_{i,j} \quad (6)$$

where $CAR_{i,j}$ is the individual firm i's CAR and $X_{i,l,t}$ is a vector of l firm-specific variables that are expected to affect the firms' stock responses based on previous research. $CONTR_{i,k,j}$ is a vector of k control variables. *Crisis* is a dummy variable equal to one if the event takes place during the *Global Financial Crisis* (between September 14, 2008 and March 31, 2009). j denotes the respective event. δ, θ, and γ are the coefficients to be estimated. The firm-specific variables $X_{i,l,j}$ contain factors that affected the firms' reaction to sector-specific events in pervious papers or other characteristics of their business models that are likely to affect their capital market response. We include a measure of the insurers' default risk, given that firms that are perceived as more risky by investors are expected to be more sensitive to policy interventions (Yin and Yang, 2013). The same holds for banking sector shocks. We include the firms' *Z-Score* to measure the insurers' riskiness.[83] Similarly, we expect that insurers with a better capitalization are less exposed to monetary policy interventions and banking shocks. Madura and Schnusenberg (2000) show that banks with lower leverage are less sensitive to monetary policy changes as they are perceived less risky

[82] As we pool the data from different years, we use clustered standard and include firm fixed effects. Moreover, we test for multicollinearity among the independent variables using variance inflation factors (VIFs). In all models, the mean VIF is well below the benchmark of 10, indicating that multicollinearity appears to be no concern in our analysis (Belsley et al., 2005; Chatterjee et al., 2013).

[83] The Z-Score is defined as the financial firm's return on asset plus its capital ratio divided by the standard deviation of its return on assets for the previous 5 years.

by investors and their interest margins are less sensitive to interest rates. Regarding banking shocks, higher capitalized firms have been shown to better withstand market shocks (Ricci, 2015). We include the ratio of equity to total assets to measure the insurers' *Leverage*. We include the natural logarithm of the firm's total assets (*Size*) to control for company size. In general, larger firms can be expected to be less affected by shocks and policy interventions as such firms are usually to be better collateralized and more immune from binding credit constrains (Guo, 2004). However, Brewer III et al. (2007) find that larger life insurers are more sensitive to interest rates and can therefore be expected to be more affected by monetary policy announcements. In addition, we include $CONTR_{i,k,j}$, a vector of control variables. We include *Asset Risk* (Stocks and bonds divided by surplus) to control for the firms' asset exposure, *Market Share* (based on premium income) to control for its market power and *Cost Efficiency* (The insurer's expense ratio for life insurers and the insurer's combined ratio for PC insurers) to control for the firms' cost efficiency. In addition, we include *Premium growth*, defined as the change in net premiums compared to the previous year. High premium growth can result in higher default risk in times of crises (Chen and Wong, 2004) and therefore affect the firm's response to banking shocks and monetary interventions during the recent financial crisis. Finally, we include *Multi*, a dummy variable equal to one if the firm is active in both life and property-casualty business.

4.4 Results

4.4.1 Descriptive Statistics

Table 14 shows the summary statistics of firm level variables used in our regression analysis. Note that while we include events from different years, we only include summary statistics for the years that match the events in our analysis (2002, 2007, 2008, 2009, 2011 and 2012). It can be seen that the insurance firms can be considered as relatively safe, given their levels of *Z-Score*. Furthermore, PC insurers show higher levels of capitalization compared to life insurers.

Table 14 Summary Statistics

		PC			Life		
Variable	Definition	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Size	The natural logarithm of the firm's total assets	375	15.03	1.59	217	16.30	2.14
Leverage	The ratio of equity to total assets	375	0.32	0.10	217	0.12	0.10
Z-Score	The firm's return on asset plus its capital ratio divided by the standard deviation of its return on assets for the the previous 5 years.	375	22.72	22.96	217	17.32	16.03
Asset Risk	Stocks and bonds divided by surplus.	375	0.25	0.26	217	0.37	0.37
Cost Efficiency	The insurer's expense ratio for life insurers; The insurer's combined ratio for PC insurers.	375	1.06	0.33	217	0.14	0.09
Market Share	The insurer's market share.	375	0.02	0.03	217	0.03	0.04
Growth	The change in net premiums compared to the previous year	375	0.07	0.25	217	0.05	0.27
Multi	A dummy variable equal to one if the firm is active in both life and property-liability business.	375	0.21	0.41	217	0.37	0.48
Crisis	A dummy variable equal to one if the event takes place between September 14, 2009 and March 31, 2009.	375	0.62	0.49	217	0.61	0.49

Note: This table reports summary statistics and definitions for the firm level variables used in our regression analysis. It includes observations from the years 2002, 2007, 2008, 2009, 2011 and 2012 that match the events (banking shocks and policy announcements) in our analysis. *PC* denotes property-casualty insurers. *Life* denotes life insurers.

4.4.2 Event Study Results

Table 15 presents the results of our event study for non-conventional policy announcement during the crisis between 2007 and 2009.[84] For each different type of announcement, we present the results of pooled event studies for property-casualty insurers (*PC*), life insurers (*Life*) and all insurers (*All*) separately. Panel A presents the results for the *Subprime Crisis*, while Panel B presents the results for the *Global Financial Crisis*.

Our results indicate that *Financial sector policies* had a positive effect on the stock prices of insurance firms during the financial crisis. Indeed, our results are consistent with Aït-Sahalia et al. (2012), as they indicate mostly positive stock market responses in the aftermath of the announcements of *Asset purchases*, *Liability guarantees* and *Recapitalizations* during the *Global Financial Crisis*. This shows that

[84] Note that, while some firms focus on only one sector, a company can be classified as both property-casualty insurer and a life insurer in SNL. Therefore, the sum of insurance firms in our sample in Table 15 - Table 17 (*All*) differs from the sum of property-casualty insurers (*PC*) and a life insurers (*Life*), given that several firms are included in our subsample of property-casualty insurers and life insurers.

measures that primarily aim to stabilize the banking sector and financial markets also have a stabilizing effect on insurance firms. Hence, policymakers can efficiently use such measures as they directly transfer risks from banks' balance sheets to sovereigns. This also benefits firms from other sectors such as insurance firms.[85]

For *Liquidity support*,[86] our results indicate that such measures have a positive impact on the insurance sector in the *Global Financial Crisis*. This is consistent with Fiordelisi, Galloppo and Ricci (2014), Ricci (2015) and Aït-Sahalia et al. (2012), who find positive stock market responses of banks and aggregate stock markets and decreases in risk premia for these announcements. Consistent with these papers, the impact of *Liquidity support* is strongly state dependent, as the stock prize reactions are less significant in most event windows during the *Subprime Crisis*. Thus, providing liquidity in times of crisis indicates to be an efficient mechanism for policymakers to support not only banks and aggregate markets, but also insurance firms.

Regarding *Quantitative and credit easing*, our results indicate that such measures had ambiguous effects on the stock prices of insurance firms. This is consistent with the findings of Fiordelisi, Galloppo and Ricci (2014) and Aït-Sahalia et al. (2012) regarding aggregate stock markets and decreases in risk premia. Thus, such measures were hardly able to counteract the effects of the financial crisis and to restore stability in the insurance sector. Given that the introduction of *Quantitative and credit easing* has been widely debated and criticized in the public prior to its implementation due to its undetermined consequences, our results provide valuable implications from a policymaker's perspective.

[85] The impact of *Liability guarantees* during the *Subprime Crisis* is rather negative, indicating that such measures are state dependent as they depend on the economic conditions. However, our dataset includes only a single announcement of *Liability guarantees* during the *Subprime Crisis*.

[86] Following Fiordelisi, Galloppo and Ricci (2014) and Ricci (2015), we combine *Domestic currency liquidity* support and *Foreign currency swaps* in a single category (*Liquidity support*).

Table 15 Event Study Results – Non-Conventional Announcements

Panel A: Subprime Crisis				***Panel B: Global Financial Crisis***			
Financial sector policies - Asset purchases							
Event Wind.	PC	Life	All	Event Wind.	PC	Life	All
-2/+1	NA	NA	NA	-2/+1	0.713***	0.627**	0.542***
-2/+2	NA	NA	NA	-2/+2	0.241	-0.028	0.069
-1/+1	NA	NA	NA	-1/+1	0.430**	0.799***	0.428***
-0/+1	NA	NA	NA	-0/+1	0.130	0.412	0.165
-0/+0	NA	NA	NA	-0/+0	0.013	0.128	0.029
-1/+2	NA	NA	NA	-1/+2	-0.042	0.144	-0.045
N	0	0	0	N	453	259	610
Financial sector policies - Liability guarantees							
Event Wind.	PC	Life	All	Event Wind.	PC	Life	All
-2/+1	-2.755***	-2.333***	-2.322***	-2/+1	0.996***	0.458	0.845***
-2/+2	-1.013**	-1.302**	-0.884**	-2/+2	1.330***	0.734	1.267***
-1/+1	-1.883***	-1.596***	-1.559***	-1/+1	0.632**	0.071	0.384
-0/+1	-1.506***	-1.357***	-1.291***	-0/+1	-0.443*	-1.295***	-0.719***
-0/+0	-0.924***	-0.536***	-0.750***	-0/+0	0.148	0.098	0.113
-1/+2	-0.14	-0.565	-0.121	-1/+2	0.966***	0.346	0.806***
N	63	37	85	N	445	259	600
Financial sector policies - Recapitalization							
Event Wind.	PC	Life	All	Event Wind.	PC	Life	All
-2/+1	NA	NA	NA	-2/+1	0.371***	0.039	0.195*
-2/+2	NA	NA	NA	-2/+2	0.233**	-0.196	0.043
-1/+1	NA	NA	NA	-1/+1	0.458***	0.317*	0.310***
-0/+1	NA	NA	NA	-0/+1	0.275***	0.167	0.183***
-0/+0	NA	NA	NA	-0/+0	0.082	0.108	0.051
-1/+2	NA	NA	NA	-1/+2	0.321***	0.081	0.158*
N	0	0	0	N	1052	592	1415
Liquidity support - Domestic currency liquidity support and Foreign currency swaps							
Event Wind.	PC	Life	All	Event Wind.	PC	Life	All
-2/+1	0.092	0.199*	0.093	-2/+1	0.997***	0.670**	0.889***
-2/+2	0.111	0.268**	0.144*	-2/+2	0.148	-0.581	-0.011
-1/+1	-0.012	0.058	-0.026	-1/+1	1.018***	0.974***	0.974***
-0/+1	-0.148**	0.002	-0.122*	-0/+1	0.868***	0.843***	0.842***
-0/+0	-0.015	-0.023	-0.049	-0/+0	0.330**	0.489**	0.366***
-1/+2	0.007	0.127	0.025	-1/+2	0.169	-0.277	0.075
N	1305	777	1767	N	449	259	605
Monetary policy - Quantitative and credit easing							
Event Wind.	PC	Life	All	Event Wind.	PC	Life	All
-2/+1	NA	NA	NA	-2/+1	0.252	0.470	0.304
-2/+2	NA	NA	NA	-2/+2	-0.324	-0.923*	-0.528*
-1/+1	NA	NA	NA	-1/+1	0.159	0.207	0.250
-0/+1	NA	NA	NA	-0/+1	0.057	-0.137	0.153
-0/+0	NA	NA	NA	-0/+0	0.482***	0.865***	0.657***
-1/+2	NA	NA	NA	-1/+2	-0.417	-1.186**	-0.582**
N	0	0	0	N	320	184	431

Note: This table shows the pooled standardized CAR (cumulated abnormal return) and its level of significance (adjusted as in Boehmer, Musumeci, and Poulsen, 1991) for the respective sector of the insurance industry at the 10% (*), 5% (**) and 1% (***) significance level for each category of announcements. *Event Wind.* denotes the event windows on that we base our analyses. *N* denotes the amount of observations for each firm type for the respective event. *PC* denotes property-casualty insurers. *Life* denotes life insurers.

Overall, our findings for non-conventional measures indicate that such measures are in general able to affect firms from the insurance sector. This is consistent with the findings of related papers for other sectors and aggregate markets. Mostly, the impacts of these announcements are positive, which justifies the resources devoted to such measures and help to attain the primary goal of insurance regulation, which is to protect policyholders (Klein, 1995). However, there was no silver bullet to contain the consequences of the crisis, as some measures were ineffective or affected insurance firms negatively.[87]

Table 16 presents the results of our event study for conventional policy announcements during the crisis between June 1, 2007 and March 31, 2009.[88] Again, the results of pooled event studies are reported for property-casualty insurers (*PC*), life insurers (*Life*) and all insurers (*All*), separately, for the *Subprime Crisis* (Panel A) and for the *Global Financial Crisis* (Panel B). Regarding *Interest rate increases and no changes*, our findings indicate that property-casualty insurers remain unaffected during the *Subprime Crisis*, which is consistent with the findings in Ricci (2015) and Aït-Sahalia et al. (2012) who find negligible effects of these measures prior to the Lehman failure. This indicates that the content of these announcements have been mostly correctly anticipated (Bernanke and Kuttner, 2005; León and Sebestyén, 2012). For life

[87] For robustness, we conduct our analyses with respect to non-conventional announcements that particularly focused on insurance firms or the insurance sector. Our dataset includes 5 of such announcements: The announcement of Lincoln National, Hartford Financial Services Group, and Genworth Financial to purchase lenders/depositories and thus qualify as savings and loan companies to access TARP funding and 4 events regarding capital injections and credit extensions for AIG. Our event study results indicate that these events had negative effects on the stock prices of insurance firms. Hence, from an investor's perspective, such announcements increase concerns about the stability of the insurance sector, given the firms' need for funds during the crisis. The results are available upon request.

[88] While non-conventional announcements are only available between 2007 until 2009, we conduct a robustness check including conventional announcements prior to the crisis to provide a more comprehensive picture on their impact on insurance firms in non-crisis times. Hence, we examine the impact of conventional announcements between 2002 and July 2007 (*Pre-Crisis Period*) to analyze how these announcements affect insurers' stock prices in more tranquil times. The results are consistent with the findings during the *Subprime Crisis*, that is, conventional announcements do mostly not affect the stock prices of insurers. Only some event windows indicate significant effects during this period. The results are available upon request.

insurers, we find negative stock market responses, which is consistent with theory (Brewer III et al., 2007) and the findings for the banking sector in previous research, who find an inverse relation between central bank interest decisions and banks' stock prices (e.g. Madura and Schnusenberg, 2000). However, we do not find positive stock price responses for insurers for *Interest rate cuts* prior to the crisis.[89]

However, during the *Global Financial Crisis*, our results change as *Interest rate increases and no changes* lead to positive stock price responses, while *Interest rate cuts* affect insurers mostly negative. This is consistent with the findings for banks in Ricci (2015) during this period. Apparently, the stock market rather appreciates the efforts of central banks to improve the economic environment by lowering interest rates instead of emphasizing the impact on the interest rate business models of insurance firms. Moreover, our results confirm the results of previous papers that show that non-conventional policy measures are at least as important as conventional policy instruments, given that both types of measures can affect financial markets and the insurance sector in particular.

[89] Note that these results do not contradict the findings of Brewer III et al. (2007) who find that interest rate changes affect life insurers' stock prices. Our results only indicate that the *announcements* of central banks regarding interest rate changes do not affect insurance firms, while *changes* in interest rates still affect insurance firms. One explanation might be that the announcements have been mostly correctly anticipated by investors and should therefore not affect stock prices.

Table 16 Event Study Results – Conventional Announcements

Panel A: Subprime Crisis				*Panel B: Global Financial Crisis*			
Conventional Measures: Interest rate increases and no changes							
Event Wind.	PC	Life	All	Event Wind.	PC	Life	All
-2/+1	-0.033	-0.533*	-0.183	-2/+1	0.430	-0.110	0.318
-2/+2	-0.326	-0.797**	-0.406*	-2/+2	0.735**	0.153	0.599**
-1/+1	0.300	-0.042	0.202	-1/+1	0.734***	0.252	0.652***
-0/+1	0.056	-0.408*	-0.126	-0/+1	0.408**	-0.036	0.301**
-0/+0	0.006	0.007	0.000	-0/+0	0.807***	0.600***	0.758***
-1/+2	0.006	-0.306	-0.021	-1/+2	1.039***	0.514	0.932***
N	248	148	336	N	264	148	355
Conventional Measures: Interest rate cuts							
Event Wind.	PC	Life	All	Event Wind.	PC	Life	All
-2/+1	-0.203	-0.039	-0.157	-2/+1	-2.386***	-4.641***	-2.831***
-2/+2	-0.357*	-0.038	-0.250	-2/+2	-0.909*	-2.557***	-1.071**
-1/+1	-0.037	-0.059	-0.055	-1/+1	-2.176***	-3.691***	-2.402***
-0/+1	-0.026	0.009	0.004	-0/+1	-1.343***	-3.269***	-1.772***
-0/+0	0.017	-0.037	-0.012	-0/+0	-0.242	-0.969**	-0.384*
-1/+2	-0.192	-0.059	-0.147	-1/+2	-0.699	-1.607*	-0.642
N	435	259	589	N	189	111	255

Note: This table shows the pooled standardized CAR (cumulated abnormal return) and its level of significance (adjusted as in Boehmer, Musumeci, and Poulsen, 1991) for the respective sector of the insurance industry at the 10% (*), 5% (**) and 1% (***) significance level for each category of announcements. *Event Wind.* denotes the event windows on that we base our analyses. *N* denotes the amount of observations for each firm type for the respective event. *PC* denotes property-casualty insurers. *Life* denotes life insurers.

Table 17 presents the results of individual event studies for banking bailouts (Panel A) and banking frauds (Panel B). Regarding bailouts, our results indicate that all events significantly affect firms from the insurance sector. The stock price reactions are strongly significant in most event windows, indicating that the insurance sector is highly exposed to shocks originating from the banking sector. Hence, while insurance-related events such as natural catastrophes and terror attacks affect the stock prices of insurance firms, but banks remain mostly unaffected (Chesney, Reshetar and Karaman, 2011), shocks from the banking sector *do* have an effect on insurers. In addition, our results are consistent with Miyajima and Yafeh (2007), who find that Japanese non-financial firms are significantly affected by bailouts in the banking sector. The direction of the effect, however, is not homogeneous: While the *Northern Rock Bailout* and the *Bear Stearns Bailout* have a negative effect on insurance firms, the *Royal Bank of Scotland Bailout*, the *Fannie Mae Bailout* and the *Citigroup Bailout* positively affect their stock prices. Hence, consistent with the theory (Cordella and Yehati, 2003; Keeley; 1990;

Hryckiewicz, 2014), the consequences of bailouts in the banking sector depend on the specific policy instrument chosen by the government and weather the positive effects outweighs the negative effects. Moreover, the results appear to be highly state-dependent: While the results are negative prior to the Lehman failure (the *Northern Rock Bailout* and the *Bear Stearns Bailout*), they are positive for bailouts that occurred close to or after the Lehman failure (the *Royal Bank of Scotland Bailout,* the *Fannie Mae Bailout* and the *Citigroup Bailout*), which represents the peak of the turmoil in financial markets. Hence, from an investor's perspective, the negative consequences of bailouts such as increases in moral hazard are strongly present in tranquil market environments, but are overweighed by the calming effects and signaling of regulatory strength during peak crisis times.[90] Similarly, the results for fraud events (Panel B) are strongly state dependent in our analysis. While fraud events prior to the crisis (the *Allied Irish Banks (AIB) Trader Scandal* and the *Société Générale Trading Loss Incident*) do barely affect insurance firms, they have an economically and statistically strong, negative impact after the crisis (the *UBS Trader Scandal*, the *JP Morgan Chase Trading Loss* and the *LIBOR Scandal*). This indicates that the market did not recognize the threat of banking shocks as severe enough to significantly endanger firms from the insurance sector. However, the outbreak of the financial crisis showed the exposure of firms from other sectors towards shocks from the banking sector. Hence, investors are more sensitive to shocks from the banking sector in the aftermath of the crisis, given their potential to significantly threat firms from other sectors.

[90] This finding is supported by the results of event studies for related, non-banking bailouts that have been conducted for robustness. In particular, we follow Grace (2011) and Bhanot et al. (2014) and analyze the impacts of the bailout of the insurance firm AIG and the bailout of Greece in May 2010 on insurance firms. Both events took place after the Lehman failure and during peaks of a major crisis (the global financial crisis in the case of AIG and the Euro crisis in the case of the Greece bailout). Consistent with the bailouts of banks in this study, our results indicate positive effects of these non-banking bailouts on insurance firms and hence a stabilizing effect. The results are available upon request.

Table 17 Event Study Results – Banking Events

Panel A: Bailouts

Event Wind.	PC	Life	All
Northern Rock Bailout			
-8/+8	-3.239***	-2.727***	-3.047***
-16/+16	-3.196***	-6.296***	-4.234***
-0/+2	0.151	0.01	0.045
-2/+2	-0.026	0.438	0.082
-1/+1	-0.257	0.114	-0.147
-8/+2	-1.805***	-0.573	-1.357***
N	63	37	85
Bear Stearns Bailout			
-8/+8	-1.000**	-1.178	-1.363**
-16/+16	-1.658***	-1.574	-2.078***
-0/+2	-0.786**	-0.695	-0.928***
-2/+2	-1.585***	-0.598	-1.366***
-1/+1	-0.703**	-0.545	-0.607**
-8/+2	-1.295***	-2.501*	-2.069***
N	63	37	85
Fannie Mae Bailout			
-8/+8	5.462***	2.783	5.126***
-16/+16	6.916***	3.214*	5.826***
-0/+2	0.558*	0.571	0.700***
-2/+2	1.147***	1.067***	1.176***
-1/+1	0.724**	0.793***	0.745***
-8/+2	3.668***	3.773***	3.650***
N	63	37	85
Royal Bank of Scotland Bailout			
-8/+8	0.384	-3.437*	-0.689
-16/+16	1.454	-1.904	0.106
-0/+2	4.135***	6.788***	4.168***
-2/+2	4.009***	5.742***	4.051***
-1/+1	5.741***	10.271***	6.847***
-8/+2	0.608	0.772	0.523
N	63	37	85
Citigroup Bailout			
-8/+8	3.114***	1.910	2.409***
-16/+16	5.560***	7.932***	6.056***
-0/+2	2.507***	4.422***	3.011***
-2/+2	2.379***	3.521***	2.541***
-1/+1	2.179***	4.766***	2.846***
-8/+2	1.541***	-0.764	0.736
N	63	37	85

Panel B: Frauds

Event Wind.	PC	Life	All
Allied Irish Banks (AIB) Trader Scandal			
-5/+5	0.271	-0.184	0.159
-8/+2	0.476	-0.878*	0.392
-2/+2	0.158	0.111	0.208
-1/+1	-0.211	-0.13	-0.166
-4/+2	0.085	-0.064	0.123
-0/+4	0.229	0.382	0.217
N	48	28	64
Société Générale Trading Loss Incident			
-5/+5	1.042*	-0.193	0.782
-8/+2	0.702	0.957	0.67
-2/+2	-0.247	-0.943*	-0.445
-1/+1	-0.015	-0.638	-0.194
-4/+2	-0.355	-0.444	-0.32
-0/+4	0.052	0.154	0.151
N	63	37	85
UBS Trader Scandal			
-5/+5	-1.422***	-1.541***	-1.551***
-8/+2	-1.449***	-1.316***	-1.402***
-2/+2	-1.642***	-1.343***	-1.621***
-1/+1	-0.653***	-0.513	-0.725***
-4/+2	-1.421***	-0.637	-1.258***
-0/+4	-2.146***	-2.473***	-2.340***
N	68	38	93
JPMorgan Chase Trading loss			
-5/+5	-1.651***	-0.877*	-1.373***
-8/+2	-0.342	-0.138	-0.235
-2/+2	-0.860***	-0.560*	-0.774***
-1/+1	-0.506***	-0.359**	-0.457***
-4/+2	-0.686***	0.155	-0.373
-0/+4	-1.811***	-1.870***	-1.859***
N	69	40	95
LIBOR Scandal			
-5/+5	-1.863***	-0.964*	-1.780***
-8/+2	-2.764***	-2.979***	-3.077***
-2/+2	-1.097***	-1.370***	-1.369***
-1/+1	-1.204***	-0.909***	-1.171***
-4/+2	-1.200***	-1.160**	-1.380***
-0/+4	-0.609*	0.023	-0.443
N	69	40	95

Note: This table shows the standardized CAR (cumulated abnormal return) and its level of significance (adjusted as in Boehmer, Musumeci, and Poulsen, 1991) for the respective sector of the financial industry at the 10% (*), 5% (**) and 1% (***) significance level for each event separately. *Event Wind.* denotes the event windows on that we base our analyses. *N* denotes the amount of observations for each firm type for the respective event. *PC* denotes property-casualty insurers. *Life* denotes life insurers. Panel A denotes the results for *Bailouts* and Panel B the results for *Frauds*.

Concluding, our results indicate a strong degree of interconnectedness in the financial sector, as shocks from the banking sector can not only affect banks, but can also spillover to insurance firms. Hence, such assets are not suitable to diversify bank-specific risk. Our findings indicate that insurance firms are prone to banking-related events, while previous papers (e.g. Billio et al., 2012; Chesney, Reshetar and Karaman; 2011) indicate a low potential for insurance firms and insurance-related events to threat firms from the banking sector.

4.4.3 Regression Analysis Results

Finally, Table 18- 23 present the results of regression analyses to identify firm-specific determinants of the firms' stock price responses for property-casualty and life insurers separately.[91] Our results indicate that in particular property-casualty insurers with low levels of capitalization (indicated by *Leverage*) and risky asset portfolios (*Asset Risk*) were positively affected by non-conventional announcements (Table 18 and Table 19). Hence, such announcements were perceived as particularly helpful for insurers with risky business models from an investor's perspective. In addition, the coefficient of *Crisis* is positive and significant in most regressions, indicating a higher effect of policy announcements in times of crises. This provides additional evidence on the state dependency of such announcements.

For conventional announcements (Table 20 and Table 21), we find that property-casualty insurance firms with lower default risk (*Z-Score*)[92] are less affected by conventional announcements. This is consistent with the findings for banks (e.g. Ricci, 2015; Yin and Yang, 2013). Moreover, life insurers' asset portfolios (*Asset Risk*) affected their stock price response. Again, this shows that investors consider the riskiness of the firms' when evaluating the effect of policy interventions. In addition,

[91] For robustness, we conduct additional regression analyses using different sets of variables to proxy for the firm level characteristics in our regression. These include, among others, the risk-adjusted return on equity to measure the insurer's riskiness and different measures of efficiency. The results remain consistent and are available upon request.

[92] The Z-Score is an inverse measure of default risk, that is, a higher Z-Score indicates less default risk.

larger life insurers are more sensitive to interest rate announcements (consistent with Brewer III et al., 2007).

Table 18 Regression Results – Non-Conventional Announcements (PC Insurers)

	(1)	(2)	(3)	(4)	(5)	(6)
Event Window	(-2/+1)	(-2/+2)	(-1/+1)	(0/+1)	(0/0)	(-1/+2)
Size	-0.048	-0.039	-0.019	0.006	-0.002	-0.031
	(0.047)	(0.056)	(0.032)	(0.021)	(0.018)	(0.046)
Leverage	-0.186**	-0.191**	-0.135**	-0.072	-0.028	-0.142*
	(0.086)	(0.087)	(0.055)	(0.045)	(0.032)	(0.081)
Z-Score	0.000	0.000	0.000**	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Asset Risk	0.060**	0.049**	0.038**	0.035**	0.020*	0.048**
	(0.024)	(0.024)	(0.016)	(0.013)	(0.010)	(0.022)
Cost Efficiency	0.034***	0.038***	0.022***	0.017**	0.002	0.038***
	(0.011)	(0.012)	(0.006)	(0.007)	(0.002)	(0.011)
Market Share	-0.786***	-0.496**	-0.786***	-0.379**	-0.143	-0.609***
	(0.210)	(0.203)	(0.275)	(0.169)	(0.122)	(0.212)
Growth	-0.017	-0.019	-0.010	-0.010	-0.001	-0.015
	(0.019)	(0.022)	(0.012)	(0.011)	(0.006)	(0.018)
Multi	0.086***	0.034***	0.037***	0.026***	0.023***	0.052***
	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)	(0.003)
Crisis	0.007**	0.004	0.014***	0.010***	0.006***	0.006*
	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)
Constant	0.752	0.632	0.303	-0.128	0.005	0.478
	(0.777)	(0.924)	(0.531)	(0.354)	(0.296)	(0.762)
R^2	0.043	0.036	0.030	0.030	0.020	0.034
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,771	4,771	4,771	4,771	4,771	4,771

Note: The table shows the estimation results of fixed effects regression analyses using the CARs of different event windows as dependent variable. The variables are defined in Table 14. Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. Standard errors are clustered at firm level. Columns (1)-(6) denote different event windows.

Table 19 Regression Results – Non-Conventional Announcements (Life Insurers)

	(1)	(2)	(3)	(4)	(5)	(6)
Event Window	(-2/+1)	(-2/+2)	(-1/+1)	(0/+1)	(0/0)	(-1/+2)
Size	0.019	0.033	0.019	0.019	0.007	0.024
	(0.022)	(0.021)	(0.021)	(0.011)	(0.008)	(0.018)
Leverage	0.002	-0.033	-0.051	-0.046	-0.051	0.019
	(0.144)	(0.136)	(0.102)	(0.067)	(0.068)	(0.126)
Z-Score	-0.000	-0.000	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Asset Risk	0.047**	0.027	0.022	0.014	0.011	0.029*
	(0.022)	(0.017)	(0.020)	(0.011)	(0.009)	(0.017)
Cost Efficiency	-0.133	-0.267**	-0.166**	0.030	-0.086	-0.092
	(0.163)	(0.116)	(0.079)	(0.075)	(0.059)	(0.114)
Market Share	-1.281***	-1.046***	-1.109***	-0.613***	-0.366***	-1.094***
	(0.272)	(0.338)	(0.267)	(0.136)	(0.086)	(0.238)
Growth	0.001	-0.011	-0.005	-0.003	-0.005	-0.001
	(0.020)	(0.018)	(0.013)	(0.008)	(0.007)	(0.016)
Multi	0.064	0.116*	0.063	0.034	0.036	0.057
	(0.065)	(0.060)	(0.054)	(0.031)	(0.024)	(0.053)
Crisis	-0.003	0.002	0.016***	0.006**	0.009***	0.002
	(0.004)	(0.005)	(0.004)	(0.003)	(0.002)	(0.004)
Constant	-0.288	-0.494	-0.269	-0.325	-0.110	-0.375
	(0.385)	(0.352)	(0.360)	(0.201)	(0.138)	(0.306)
R^2	0.042	0.031	0.038	0.025	0.023	0.031
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,744	2,744	2,744	2,744	2,744	2,744

Note: The table shows the estimation results of fixed effects regression analyses using the CARs of different event windows as dependent variable. The variables are defined in Table 14. Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. Standard errors are clustered at firm level. Columns (1)-(6) denote different event windows.

Table 20 Regression Results – Conventional Announcements (PC Insurers)

Event Window	(1) (-2/+1)	(2) (-2/+2)	(3) (-1/+1)	(4) (0/+1)	(5) (0/0)	(6) (-1/+2)
Size	-0.003	-0.002	0.002	0.005^{*}	-0.004	-0.001
	(0.005)	(0.004)	(0.005)	(0.003)	(0.004)	(0.004)
Leverage	-0.019	-0.034	-0.005	0.022	-0.013	-0.020
	(0.031)	(0.025)	(0.030)	(0.015)	(0.016)	(0.030)
Z-Score	-0.000^{*}	-0.000^{*}	-0.000^{***}	-0.000^{***}	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Asset Risk	0.006	0.001	0.002	0.004	-0.005	0.005
	(0.007)	(0.007)	(0.004)	(0.004)	(0.003)	(0.005)
Cost Efficiency	0.004	0.000	0.002	0.005	0.006^{**}	0.004
	(0.006)	(0.007)	(0.005)	(0.005)	(0.002)	(0.005)
Market Share	-0.404	-0.162	-0.465^{*}	-0.359^{*}	-0.064	-0.300
	(0.292)	(0.143)	(0.266)	(0.211)	(0.075)	(0.221)
Growth	0.001	0.003	0.006	0.001	0.000	0.006
	(0.005)	(0.006)	(0.006)	(0.004)	(0.002)	(0.007)
Multi	-0.016^{***}	-0.056^{***}	-0.053^{***}	-0.039^{***}	-0.029^{***}	-0.024^{***}
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Crisis	0.004^{*}	0.007^{***}	0.000	-0.000	0.002^{**}	0.006^{**}
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Constant	0.075	0.106	0.031	-0.045	0.095	0.047
	(0.085)	(0.070)	(0.084)	(0.050)	(0.069)	(0.079)
R^2	0.011	0.013	0.011	0.013	0.020	0.013
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,778	5,778	5,778	5,778	5,778	5,778

Note: The table shows the estimation results of fixed effects regression analyses using the CARs of different event windows as dependent variable. The variables are defined in Table 14. Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. Standard errors are clustered at firm level. Columns (1)-(6) denote different event windows.

Table 21 Regression Results – Conventional Announcements (Life Insurers)

Event Window	(1) (-2/+1)	(2) (-2/+2)	(3) (-1/+1)	(4) (0/+1)	(5) (0/0)	(6) (-1/+2)
Size	0.041	0.028	0.106^{***}	0.085^{***}	0.054^{***}	0.031
	(0.043)	(0.022)	(0.033)	(0.026)	(0.016)	(0.027)
Leverage	0.163	0.080	0.115	0.122	0.026	0.081
	(0.226)	(0.080)	(0.305)	(0.229)	(0.083)	(0.121)
Z-Score	-0.000	0.000	0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Asset Risk	-0.023	-0.036^{**}	-0.110^{***}	-0.084^{***}	-0.063^{***}	-0.031
	(0.030)	(0.017)	(0.024)	(0.021)	(0.011)	(0.021)
Cost Efficiency	0.209	-0.123	0.292^{**}	0.369^{**}	0.215^{**}	0.084
	(0.231)	(0.162)	(0.108)	(0.140)	(0.086)	(0.231)
Market Share	-0.686	-0.164	-0.604	-0.647	-0.426	-0.207
	(1.053)	(0.505)	(0.641)	(0.507)	(0.426)	(0.620)
Growth	-0.002	-0.012	-0.011	-0.010	-0.021	-0.002
	(0.012)	(0.015)	(0.016)	(0.011)	(0.013)	(0.010)
Multi	0.054	0.063	0.202^{**}	0.125^{**}	0.093^{**}	0.060
	(0.089)	(0.053)	(0.077)	(0.059)	(0.038)	(0.064)
Crisis	-0.009	0.044^{***}	-0.022^{**}	-0.023^{***}	0.005	0.005
	(0.009)	(0.008)	(0.009)	(0.007)	(0.004)	(0.009)
Constant	-0.752	-0.446	-1.872^{***}	-1.534^{***}	-0.964^{***}	-0.550
	(0.732)	(0.376)	(0.560)	(0.442)	(0.278)	(0.463)
R^2	0.041	0.118	0.091	0.089	0.120	0.049
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	666	666	666	666	666	666

Note: The table shows the estimation results of fixed effects regression analyses using the CARs of different event windows as dependent variable. The variables are defined in Table 14. Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. Standard errors are clustered at firm level. Columns (1)-(6) denote different event windows.

Table 22 and Table 23 present the regression results for bailouts and frauds. The results indicate that, for property-casualty insurers, most firm level determinants remain insignificant, indicating a rather homogeneous stock price response of insurance firms towards shocks from the banking sector (Ricci, 2015). This provides unfavorable news for investors, as banking shocks affect the overall sector, and investments in for property-casualty insurance firms are unable to diversify banking risk away, given their homogeneous response. For life insurers, we find evidence that safer and larger life insurers are less affected by banking shocks, indicated by *Z-Score* and *Size*. Overall, these results provide valuable information from an asset pricing perspective for investors, given the severe consequences of banking events for insurance firms. Again, the coefficient of *Crisis* is mostly positive and significant, indicating that shocks from the banking sector have a more pronounced effect in the aftermath of the crisis.

Table 22 Regression Results – Finance Events (PC Insurers)

	(1)	(2)	(3)	(4)	(5)	(6)
Event Window	(-8/+8)	(-8/+2)	(0/+2)	(-2/+2)	(-1/+1)	(-8/+2)
Size	-0.019	-0.051	-0.030*	-0.027**	-0.028	-0.005
	(0.020)	(0.031)	(0.016)	(0.012)	(0.022)	(0.018)
Leverage	-0.149	-0.238	-0.159	-0.098	-0.087	-0.254**
	(0.129)	(0.175)	(0.133)	(0.123)	(0.142)	(0.127)
Z-Score	0.000	-0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Asset Risk	-0.060	-0.066	-0.061	-0.075**	-0.042	-0.086
	(0.048)	(0.053)	(0.042)	(0.031)	(0.037)	(0.066)
Cost Efficiency	0.044***	0.037*	0.028*	0.007	0.031	0.021
	(0.016)	(0.019)	(0.015)	(0.019)	(0.020)	(0.018)
Market Share	-0.266	2.197***	0.197	-0.023	0.666	-0.697
	(0.950)	(0.583)	(0.710)	(0.769)	(0.461)	(0.949)
Growth	0.002	-0.051	-0.028	-0.031	-0.023	-0.010
	(0.029)	(0.034)	(0.029)	(0.030)	(0.028)	(0.032)
Multi	-0.024*	0.031	0.008	0.022*	0.002	-0.072***
	(0.014)	(0.021)	(0.013)	(0.011)	(0.013)	(0.018)
Crisis	0.000	0.001	0.027***	0.029***	0.001	0.020**
	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.009)
Constant	0.335	0.821	0.516*	0.477**	0.441	0.190
	(0.352)	(0.542)	(0.298)	(0.231)	(0.400)	(0.308)
R^2	0.177	0.150	0.176	0.157	0.151	0.170
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	629	629	629	629	629	629

Note: The table shows the estimation results of fixed effects regression analyses using the CARs of different event windows as dependent variable. The variables are defined in Table 14. Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. Standard errors are clustered at firm level. Columns (1)-(6) denote different event windows.

Table 23 Regression Results – Finance Events (Life Insurers)

Event Window	(1) (-8/+8)	(2) (-8/+2)	(3) (0/+2)	(4) (-2/+2)	(5) (-1/+1)	(6) (-8/+2)
Size	-0.028	-0.022	-0.082***	-0.134***	-0.028*	-0.111***
	(0.017)	(0.022)	(0.024)	(0.029)	(0.016)	(0.022)
Leverage	-0.115	-0.280*	-0.235	-0.016	-0.122	-0.065
	(0.123)	(0.144)	(0.141)	(0.214)	(0.099)	(0.172)
Z-Score	-0.000	-0.001**	-0.000	-0.000	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Asset Risk	0.019	0.032	0.057*	0.087**	0.035	0.063**
	(0.023)	(0.026)	(0.031)	(0.042)	(0.021)	(0.030)
Cost Efficiency	-0.182	-0.230	-0.384***	-0.473***	-0.204*	-0.528**
	(0.169)	(0.161)	(0.131)	(0.149)	(0.109)	(0.220)
Market Share	0.013	0.174	0.619**	0.663*	-0.010	0.904***
	(0.217)	(0.250)	(0.297)	(0.362)	(0.225)	(0.292)
Growth	0.038	0.012	-0.021	-0.022	0.034	-0.029
	(0.032)	(0.034)	(0.032)	(0.044)	(0.028)	(0.037)
Multi	-0.007	0.030	-0.074	-0.269***	-0.018	-0.180***
	(0.045)	(0.054)	(0.070)	(0.091)	(0.045)	(0.064)
Crisis	-0.001	-0.002	0.055***	0.097***	0.017	0.058***
	(0.013)	(0.016)	(0.014)	(0.018)	(0.011)	(0.016)
Constant	0.529*	0.479	1.474***	2.412***	0.537*	2.008***
	(0.309)	(0.402)	(0.416)	(0.497)	(0.286)	(0.409)
R^2	0.102	0.155	0.205	0.277	0.141	0.265
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	367	367	367	367	367	367

Note: The table shows the estimation results of fixed effects regression analyses using the CARs of different event windows as dependent variable. The variables are defined in Table 14. Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. Standard errors are clustered at firm level. Columns (1)-(6) denote different event windows.

4.5 Conclusion

We analyze the stock market reaction of U.S. insurance firms to conventional and non-conventional monetary policy interventions undertaken during the financial crisis of 2007-2009 using an event study methodology. In addition, we examine how shocks from the banking sector (bailouts and frauds) affect the stock prices of firms from the insurance sector. In addition, we analyze the heterogeneity in insurer’s stock response by regression analyses. Our database consists of 89 policy announcements and 10 banking sector shocks.

Our results are consistent with the findings from aggregate markets, risk premia and banks (Aït-Sahalia et al., 2012, Fiordelisi, Galloppo and Ricci, 2014 and Ricci, 2015), as they indicate that policy interventions were indeed able to affect the stock prices of insurance firms during the crisis. Moreover, our results indicate that several types of announcements were state-dependent, as the same type of measure had different effects depending on the state of the crisis. In particular, the results for interest decisions indicate that investors reacted to such announcements partly consistent with theoretical predictions and previous literature (e.g. Madura and Schnusenberg, 2000; Brewer III et al., 2007) during the *Subprime Crisis*. During the *Global Financial Crisis*, however, the opposite is the case (consistent with the findings for banks in Ricci, 2015). Thus, the stock market rather appreciates the efforts of central banks to improve the economic environment by lowering interest rates instead of emphasizing the impact on the interest rate business models of insurance firms. Moreover, our results indicate that shocks from the banking sector significantly affect insurance firms. Again, the effects are strongly state dependent and increase in effect with the outbreak of the financial crisis.

Our results have important implications, in particular for investors and policymakers. From an asset pricing perspective, our results indicate that shocks from the banking sector affect insurance firms, while insurance-related events do not affect the banking sector as found in Chesney, Reshetar and Karaman (2011). Hence, insurance stocks are not suitable to diversify banking risk. In addition, this finding indicates a high degree of interconnectedness in the financial sector, as banks and insurers are affected similarly by such events. From a policymakers perspective, our results indicate that regulatory measures that primary aim to stabilize the banking and financial sector also affect the insurance sector, depending on their content and the economic environment. Hence, they help to achieve the primary target of insurance regulation, that is, the protection of policyholders (Klein, 1995). Hence, our research provides evidence that the insurance sector is highly exposed to shocks from the banking sector. Also, we show that this exposure increased since the outbreak of the financial crisis. Given that the recent crisis emerged in the banking sector from its subprime exposures, our results provide valuable knowledge for investors and regulators. However, our research also indicates that policymakers have adequate means to counteract such crises that emerged from the banking sector.

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