Charles University in Prague

Faculty of Social Sciences
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MASTER THESIS

Stability of the Financial System: Systemic Dependencies between Bank and Insurance Sectors

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Declaration of Authorship

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Abstract

The central issue of this thesis is investigating the eventuality of systemic breakdowns in the international financial system through examining systemic dependence between bank and insurance sectors. Standard models of systemic risk often use correlation of stock returns to evaluate the magnitude of interconnectedness between financial institutions. One of the main drawbacks of this approach is that it is oriented towards observations occurring along the central part of the distribution and it does not capture the dependence structure of outlying observations. To account for that, we use methodology which builds on the Extreme Value Theory and is solely focused on capturing dependence in extremes. The analysis is performed using the data on stock prices of the EU largest banks and insurance companies. We study dependencies in the pre-crisis and post-crisis period. The objective is to discover which sector poses a higher systemic threat to the international financial stability. Also, we try to find empirical evidence about an increase in interconnections in recent post-crisis years. We find that in both examined periods systemic dependence in the banking sector is higher than in the insurance sector. Our results also indicate that extremal interconnections in the respective sectors increased, while an increase in bank-to-insurer relationships is the most noticeable.

JEL Classification	F12, F21, F23, H25, H71, H87
Keywords	financial stability, systemic risk, dependence in extremes, Extreme Value Theory

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Abstrakt

Ústředním tématem této práce je zkoumání existence možnosti systémových poruch v mezinárodním finančním systému prostřednictvím zkoumání systemických závislostí mezi bankami a pojišťovnami. Standardní modely zabývající se systemickým rizikem většinou k posouzení míry závislosti mezi finančními institucemi využívají vzájemnou korelaci akciových výnosů. Jedním z hlavních nedostatků této metody ovšem je, že se orientuje pouze na pozorování, která se vyskytují v centrální části rozdělení výnosů, a nezachycuje strukturu závislosti mezi odlehlými pozorováními. Z tohoto důvodu aplikujeme metodu, která vychází z Teorie extremálních hodnot a soustředí se výhradně na zachycení závislostí v extrémních hodnotách. Analýzu provádíme s využitím dat o cenách akcií největších bank a pojišťoven v Evropské Unii. Strukturu závislostí sledujeme v obdobích před krizí a během krize. Cílem je odhalit, který ze zkoumaných sektorů skýtá pro mezinárodní finanční stabilitu větší hrozbu v podobě systémových selhání. Snažíme se také získat empirické svědectví o nárustu extremálních závislostí v posledních letech. Zjišťujeme, že v obou sledovaných obdobích je úroveň systemických závislostí v bankovním sektoru větší než v sektoru pojišťovnictví. Naše výsledky také naznačují, že vzájemné závislosti mezi institucemi v jednotlivých sektorech vzrostly, z nichž nejvíce je zaznamenán nárůst závislostí v extrémních negativních výnosech mezi bankami a pojišťovnami.

Klasifikace JEL F12, F21, F23, H25, H71, H87

Klíčová slova finanční stabilita, systemické riziko, závislost v extrémech, Teorie extremálních hodnot

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Acronyms

EVT Extreme Value Theory

CLT Central Limit Theory

GEV Generalized Extreme Value Distribution

GPD Generalized Pareto Distribution

BM Block Maxima Method

POT Peak-over-threshold Method

Master Thesis Proposal

Author	Bc. Jana Procházková
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Proposed topic	Stability of the Financial System: Systemic Dependencies between Bank and Insurance Sectors

Topic characteristics The events of recent years starting in the U.S. by the Lehman bankruptcy have considerably impaired the stability of financial systems globally. The breakdowns of individual institutions no longer remain an issue of those institutions but they distribute widely across other entities and even the borders. This fact stands behind an extraordinary interest in investigating dependencies among financial entities. Given the very close interaction in the interbank market and similarity of balance sheets, which makes banks extremely vulnerable to systemic risks, most empirical studies have focused their attention on developing methods for measuring dependencies in banking systems. However, to ensure the stability of the entire financial system it is necessary to uncover potential linkages beyond banks. The objective of my thesis will be to examine systemic dependencies between banks and insurance companies in the European Union. Interconnections between these two financial subsystems in such large geographical area are not discussed that much in the literature and they thus might pose a threat to financial stability. The dependencies will be examined in three sample periods (before, during and after the financial crises 2008/2009) with the aim of uncovering a changing pattern in systemic risk over time and under different market conditions. For this purpose I am going to apply financial time series of the EU publicly listed banks and insurance companies.

Hypotheses

1. Systemic dependencies in the banking sector are stronger than in the insurance sector.
2. Dependencies evolve in time based on the prevailing macroeconomic conditions.
3. The post-crises period exhibits stronger systemic dependencies between both sectors than the pre-crises period.
4. In comparison with the multivariate dependence of stock returns the bivariate dependence is much higher.l

Methodology Systemic dependencies will be investigated using the daily stock market returns of the European banks and insurance companies that are publicly listed. Data will be obtained from a sample of the 15 EU member states and it will cover the period from 2000 up to the present. For each member state the 5 largest banks and insurance companies will be chosen. The selection of financial entities will be made based on the balance sheet criteria meaning that entities with the highest asset value will be included in the model. Such procedure allows creating a unique dataset consisting of 75 banks and insurers. Dependencies will be subsequently modeled within and across both industries. With respect to the method employed, characteristic feature of the stock market time series is that it is distributed in a way which does not correspond to normal distribution and the data thus shows the presence of heavy tails. Consequently, when modeling dependencies it is necessary to make use of techniques that go beyond the simple correlation. Following approach employed by Hartmann et al. (2005) and other related works, I am going to apply the measure which draws on the Extreme Value Theory and examines dependencies in extremes. In addition to bivariate dependence modeling defined as the probability with which an entity goes bankrupt assuming that another entity does so, I would also like to focus on modeling multivariate dependence of stock returns.

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Author Supervisor

Chapter 1

Introduction

The aftermath of recent crisis demonstrates the necessity of financial stability in the financial system and the whole economy. With rising number of financial insitutions operating currently in more countries or even continents, the international financial stability is becoming increasingly important issue. Due to the vast expansion of markets we have been witnessing over the last several years, financial regulatory authorities have broadened their attention beyond borders of individual countries. The cenral point of their supervision has become the development of international financial systems. Improvements in financial intermediation accompanied by a growing magnitude of financial transactions and complex financial products have resulted in deepening interconnections among international financial systems. Such development entails new risks. Most importantly, it creates a huge potential for an easy spread of financial turbulences across countries. This phenomenon is known as systemic risk and it has become the major contributor to the severity of the global financial crisis 2008/2009.

The objective of this thesis is to investigate the eventuality of simultaneous systemic breakdowns in the EU financial system through examining systemic dependencies between bank and insurance sectors. We test the level of mutual dependencies between financial institutions in the respective sectors as well as across them with the aim of uncovering which sector poses higher systemic threat to the international financial stability. The answer is important especially from the regulatory point of view. Given the very close interactions of banks due to their operations on the interbank market, it is reasonable to assume that stronger systemic dependencies will be present in the banking sector, resulting in a higher potential to systemic risk. If this happens to be true, it is a clear sign for regulatory authorities to concentrate on the mitigation of systemic threat in the banking industry by, for instance, reflecting this risk in higher capital requirements for banks. In the opposite case, closer supervision should be pointed towards insurance companies. In addition, we examine systemic dependencies in the pre-crisis and post-crisis period in order to find evidence about an increase in mutual interconnections in recent years. That would again be a signal for regulators to ultimately introduce some regulatory measures thanks to which the international financial system would be more stable and better prepared to resist systemic failures.

Standard models of systemic risk often employ correlation of returns to assess the degree of interconnectedness between institutions. The concept of correlation has gained much of its popularity in finance since it has become a part of the Modern Portfolio Theory (Perrin and Shaw 2009). Despite its popularity, it is necessary to stress that it effectively works as a reliable measure of dependence only when limiting assumption about normality of financial returns is fulfilled. Nevertheless, extensive research in finance produces plenty of evidence which is in contradiction with normality of returns. In the real world, financial data in most cases contain many outlying observations, which document the existence of extreme market situations. Relying on the assumption of normality leads to underestimating the effect of these observations, as they are empirically observed more frequently than the normality-based models would suggest. To account for the effect of outliers in financial data, we apply method which does not impose any assumption on statistical distribution and hence allows capturing dependence in extreme stock returns. This method is derived from the Extreme Value Theory. For application of such method in our thesis we got inspiration from papers Slijkerman et al. (2005) and De Vries (2009).

There are only few empirical applications in which the extreme value methodolgy has been utilized for analysis of systemic dependence between financial institutions. Compared to Slijkerman et al. (2005) and De Vries (2009), we substantially extend the dataset, as we work with the sample of the top 20 largest banks and insurance companies in the European Union. It allows us to have a notion about the level of interdependence between most systemically important institutions and as a result, to draw meaningful conclusions about the stability of the international financial system and threat of systemic risk in the European Union. In addition, we are not aware of any other work that would investigate systemic dependencies between bank and insurance groups in the pre-crisis and post-crisis period.

The rest of the thesis is structured as follows. Chapter 2 discusses different sources of dependencies among bank and insurance companies that could promote the propagation of systemic breakdowns. Chapter 3 provides a comprehensive review of contemporary literature on systemic risk. In Chapter 4 we introduce various statistical concepts used for the analysis of dependence between random variables. In Chapter 5 we present methodology, data and results of empirical application. At last, Chapter 6 concludes.

Chapter 2

Sources of Dependence among Banks and Insurers

A smooth functioning of financial systems is conditioned by proper identification of potential risks and sources of instabilities. Within the context of systemic risk and its system-wide perspective, however, the identification of mutual dependencies among those risks is of crucial importance.

In the following chapter we elaborate on linkages among banks and insurance companies that may belong to driving forces in propagation of systemic breakdowns. We develop a theoretical background by discussing sources of interdependencies and explaining relationships underlying the thesis. In the first section we focus on interconnections that occur among individual institutions within each sector. Next, we proceed to identify channels through which systemic risk can spread across both sectors.

2.1 Intra-sector Dependencies

In this section we provide an economic rationale for interconnections in the two sectors separately. Firstly, we concentrate on a bank-to-bank relationship. The same procedure is applied to entities in the insurance sector.

2.1.1 Bank-to-Bank

In general, banks are exposed to similar risks due to a homogeneous structure of assets on their balance sheets (De Vries 2005). This is probably what put them most in danger of simultaneous co-crashes. A typical feature of developed banking systems is the existence of interbank markets. Banks interact very closely on the interbank deposit markets where they either provide liquidity for financing operations of other banks or, alternatively, they get funding from them to cover temporary liquidity shortages. Apparently, these interactions are beneficial for both parties; on the other hand, they create direct risk exposures among banks (De Vries 2005). In addition, a widespread use of financial engineering techniques encountered in recent years has contributed to a creation of new complex financial products such as derivatives. Derivative transactions have become a popular investing tool among banks as they enable an effective dispersion of risks into the system. Nevertheless, such shift from risk concentration towards risk diversification has built up new potential channels through which shocks may be transmitted (David and Lehar 2011). In terms of banking operations, business activities of individual banks are to a large degree similar and there is no wonder that significant sources of dependence emerge from them. Banks' core activities have traditionally focused on providing long-term loans, mortgages and other forms of credit. In addition to direct credit risk exposures arising from loan provisions, these activities also interconnect banks indirectly through changes in macroeconomic environment. For instance, the level of interest rates set by the central bank is a key driver of banks' credit risk, as it considerably influences the extent of counterparties' defaults (De Vries 2005).

Focusing now on dependencies stemming from banks' liabilities, one can also find a number of risk exposures that banks have in common. Liability side of banks' balance sheets is for the most part composed of customers' short-term deposits. Contrary to credit risk, which is closely connected to banks' assets, banks' liabilities are associated with risks coming from the market, namely interest rate risk and liquidity risk (Memmel and Schertler 2009). The development of interest rates is one of the key drivers of banks' deposit holdings, as it determines the degree to which clients are willing to keep their investments in banks. Instability and rapid changes in interest rates may trigger early deposit withdrawals and induce clients to transform their investments into different asset classes such as cash. Consequently, the volume of deposits on banks' balance sheets may vary significantly and so banks can get into difficulties due to insufficient liquidity (De Vries 2005).

To sum up, the magnitude of common direct and indirect interdependencies together with their quantitative nature determine whether a shock to a bank results in its expansion to other banks (De Nicolo and Kwast 2002).

2.1.2 Insurer-to-Insurer

Insurance industry and its operations have been dynamically evolving over the last decades. Such development entails two consequences. Firstly, growing importance of insurance companies within financial system resulting in reinforcing their role among other financial intermediaries. Secondly, new financial vehicles offered by insurance companies and thus modification of risks the insurance sector may encounter (Lorent 2008).

Similarly to bank-to-bank relationships, interconnections among insurance companies primarily emerge from similarity of their balance sheets (Cummins and Weiss 2011). Uniform structure of assets and liabilities implies that insurers are exposed to common shocks and they have to withstand the same types of risks.

Starting with the interlinkages on the asset side, the main activities of insurance companies have traditionally included covering risks faced by their clients and transferring them to third parties. The core business of insurance companies thus has been far from savings-based activities so typical for banks. However, the ongoing development in the insurance industry extends the long-established scope of activities to new non-core forms of business. As a result, new risks through which insurers are interconnected arise. For instance, nowadays insurance companies start offering vehicles with rather investment features, such as guaranteed investment constracts, unit-linked contracts or universal insurance contracts (Lorent 2008). These instruments make insurance companies vulnerable to market fluctuations and expose them to market risk. Moreover, advanced techniques of financial engineering produce derivative contracts, which have become a popular investment tool within the insurance industry. Given that derivatives are characterized by a large degree of complexity and low transparency, they represent a new potential source of risk for insurance companies (Lorent 2008). Interconnections among insurers are further established through reinsurance (Cummins and Weiss 2011). Reinsurance contracts represent a standard risk management tool under which insurance companies protect themselves by purchasing re-insurance at other insurance companies to make them participate in claims incurred. Intuitively, reinsurance agreements create an intricate network of relationships among insurers where *"the failure of major reinsurers triggers the failure of their reinsurance counterparties who in turn default on their obligations to primary insurers"* (Cummins and Weiss 2011, p. 26). Therefore, in terms of systemic interdependencies, reinsurance business poses a significant threat to the insurance industry.

2.2 Inter-sector Dependencies

In this section we elaborate on mutual dependencies that can be found between bank and insurance groups.

Banks and insurance companies have had historically different functions in the economy. Whereas the main task for banks is collecting deposits and putting them again into circulation through providing credits, insurance companies' main activities involve risk mitigation and risk transferring. Due to differences in business models both groups have also enjoyed differences in risk exposures faced. However, the dynamic development in the finance industry results in the convergence of activities of both groups and the strict distinction between them is no longer possible. At present, interconnections across both sectors occur as some of their operations crosses during the course of their business. From the macro-prudential point of view, it is crucial that interconnections between bank and insurance groups are monitored and properly examined.

2.2.1 Bank-to-Insurer

One possible channel of systemic risk between bank and insurance groups can be found in declining diversity of products in their portfolios. Nowadays, insurance companies extend the scope of their activities beyond offering solely typical insurance products and they assimilate more into banking-type activities (Lorent 2008). This diversion carries a potential for insurers to create interconnections with banks. Focusing on investment activities, innovative derivative products are increasingly popular among banks and insurers. Their popularity lies in unique features of these instruments such as transferring risks between both groups. Since banks act as counterparties in derivative transactions with insurance companies and vice versa, these transactions create a direct connection between both groups. Moreover, widespread use of these instruments, however, *"may lead to a convergence of the investment portfolios of banks and insurers"* (Slijkerman et al. 2005, p. 9). In addition to derivatives, both groups hold in their portfolios syndicated loans and they engage in equity investments. Similar structure of investment portfolios thus may approximate their risk profiles and make them prone to systemic crashes (Slijkerman et al. 2005). Another source of interdependencies emerges in connection with reinsurance transactions in the insurance sector (Koijen and Yogo 2014). Banks play an important role in these transactions. They issue letters of credit through which they collateralize reinsurance agreements among insurers and reinsurers. When the insurance sector happens to be hit by a systemic shock, it may *"trigger a sudden demand for credit that constrains the banking sector"* (Koijen and Yogo 2014, p. 4).

Chapter 3

Review of Literature

The recent financial crisis has pointed out the threat of systemic risk to the financial system. As a consequence, extensive literature investigating systemic dependencies among financial institutions has been produced in the last couple of years. Given the fact that banks have been traditionally regarded as the most systemically important, the major research of the field concentrates predominantly on the banking system. In this chapter we present a broad overview of contemporary literature on systemic risk and systemic interconnections.

3.1 Systemic Risk and Financial Structure

The first presented is a group of papers examining a relationship between the manner in which systemic risk propagates through the system and a network structure financial entities form with each other.

Gai and Kapadia (2010) examine the propagation of financial contagion in networks of institutions having arbitrary financial structure. The authors argue that in addition to traditional risk exposures which arise from banking operations on the interbank market, there also exist some indirect linkages and these are connected to banking assets. Both types of interconnections then determine the severity with which systemic risk propagates. The authors detect *'robust-yet-fragile tendency'*, meaning that financial systems characterized by a high level of interconnectedness are less likely to suffer contagion; however, once it occurs it tends to bring widespread consequences. Ladley (2011) claims that a recipe for an optimal financial network which would best cope with the effects of contagion does not exist, as it largely depends on nature and size of a shock. He comes to the conclusion that highly interconnected financial structures are better able to resist contagion occurring as a result of small shocks, whereas more intensive shocks worsen their impacts. Another contribution into the existing literature is the paper proposed by Allen and Gale (2000). Similarly to other authors, they focus on the way financial contagion moves through the interbank market and what consequences it brings to the stability of financial system. The authors argue that complete interbank structure characterized by symmetric bank-to-bank exposures is more resilient to contagion, as thanks to such favorable network liquidity shocks may evenly distribute into the system and their adverse effect is minimized. Babus (2007) produces a paper which is basically an extension of the analysis performed by Allen and Gale (2000). Her novelty is in allowing the financial network to be modeled endogenously. The key findings in her analysis reveal that banks have capacity to form networks that completely eliminate the potential for contagion. Contrary to the outcome of Ladley (2011) who claims that no optimal financial network can be achieved, Babus comes to the conclusion that there exist an equilibrium network among banks for which the probability of contagion is approaching zero. Castiglionesi and Navarro (2010) also study the financial network modeled endogenously. The authors highlight fragility of financial network stemming from risky operations that banks undertake as a consequence of insufficient capital stock. Nevertheless, even the fragile financial network can be stable provided that banks hold enough capital to abandon moral hazard. At last, Anand et al. (2011) investigate the potential for spread of systemic risk in a financial structure comprising three mutually interconnected market participants. These include domestic banks, international financial intermediaries and business companies. Their model uncovers that modern financial systems characterized by a diverse heterogeneity and large degree of interconnectedness are vulnerable to system-wide breakdowns.

3.2 Systemic Dependencies among Banks

Subsequently, we present a group of papers investigating systemic dependencies in banking systems. It is widely accepted that banks are extremely vulnerable to systemic risk, as they get into close interactions due to their interbank cooperation and similarity of activities. Hence, most empirical studies focus their attention on developing methods for measuring dependencies in banking systems.

Hartmann et al. (2005) examine interdependencies of banks' stock returns in the United States and the Euro area and in both banking sectors they use it as an indicator of systemic risk. The authors utilize an econometric measure drawing on the Extreme value theory. Their findings suggest that the Euro banking system presents higher stability as opposed to the US banking sector, which is more vulnerable to systemic failures. Also, the importance of systemic risk has increased substantially since 1990's in both banking systems. Árvai et al. (2009) study potential spillover effects through financial interconnections between countries of Central, Eastern and Southeastern Europe (CESE) and Western European countries. In addition, they also analyze the magnitude of financial exposures across borders. They come to the conclusion that *"financial interlinkages within Europe are economically significant"* (Árvai et al. 2009, p. 5). Moreover, they uncover that the majority of CESE countries is highly connected to banks located in Western Europe, whereas the same does not hold for the dependence of European banks on CESE countries. There are only two exceptions , Austria and Sweden. Elsinger et al. (2006) use data on Austrian banks to evaluate how resilient the banking system is to systemic breakdowns. The authors combine standard risk management instruments drawing on correlation with a model encompassing interbank loans. Their key findings suggest that banks' portfolios of assets are highly correlated and the correlation is the main driver of systemic risk. Moreover, contagion in the banking system occurs rarely, but its widespread effects can damage a great deal of the banking sector. Festic et al. (2011) examine a relationship between the development of non-performing loans and a set of macroeconomic variables at a sample of Baltic countries enlarged about Bulgaria and Romania. They succeeded to confirm a hypothesis that the growth of credit volume might threaten the performance of the banking system. With respect to a performance of the Czech banking sector, Cihak et al. (2007) present the outcome of their paper stating that the Czech banking sector is resilient enough to withstand potential adverse effects of macroeconomic and prudential shocks. Despite the stability of the banking sector as a whole, the authors recognize that some banks are more or less sensitive to certain shocks. They particularly mention a shock to interest rate and interbank contagion. At last, De Vries (2005) argues that there are several channels through which banks are interconnected, and the risk of systemic breakdowns exists as a consequence of similar exposures. In his concept asset as well as liability side of banks' balance sheets can be regarded as a linear combination of risks. The potential for systemic breakdowns varies depending on the distribution of banking exposures. He concludes that exposures having normal distribution lead to weak tendencies to systemic risk, whereas fat tailed exposures occurring more frequently in financial systems cause a strong potential for systemic risk.

3.3 Systemic Dependencies beyond Banks

At last, we present a group of empirical studies examining systemic dependence between banks and other financial subsystems including insurance companies, pension funds, mutual funds, etc.

To begin with, we summarize papers where analysis of systemic risk is mostly carried out using the methodology based on the Extreme value theory. Systemic risk is here characterized by mutual dependencies in lower tails of distributions of stock returns. De Vries (2009) examines systemic risk in Europe by studying interconnections between the two most important financial subsystems; banks and insurance companies. The author models dependencies within and across both sectors. With respect to within-sector dependencies, he concludes that higher downside risk is hidden in insurance sector. Regarding cross-sector interdependencies, these are of rather negligible importance. Similarly to De Vries (2009), Slijkerman et al. (2005) also concentrate on differences in downside risk between European bank and insurance groups. Using first a normal distribution measure, they reveal that such method appears to be inappropriate for measuring systemic risk, as it strongly underestimates the magnitude of downside risk. To account for that, the authors present an alternative measure which is better able to address downside dependence present in the data. The authors' findings suggest that *"risk dependence between a bank and an insurer is significantly different from the dependence structure between two banks or between two insurers"* (Slijkerman et al. 2005, p. 22). Bühler and Prokopczuk (2010) compare the magnitude of systemic dependencies between the banking industry and other financial and non-financial sectors. Employing data for the US economy, they find evidence for high systemic risk in the banking sector, whereas negligible systemic risk is detected in the insurance sector. Moreover, they reveal a negative relationship between the magnitude of systemic risk end the actual state of the economy. Billio et al. (2010) investigate interdependencies between four financial industries including banks, brokers, hedge funds and insurance companies. As opposed to the other papers mentioned in this group, they apply distinct econometric measures. Outcomes of Principal components analysis and Granger-causality test suggest that interdependencies significantly increased during the last decade and systemic risk appears as a result of complex network of relationships among the selected sectors. Also, the authors emphasize that selected methodology serves as a good indicator of crisis periods.

Secondly, there is a broad literature applying standard correlation to capture systemic dependence between financial institutions. Patro et al. (2013) find correlation of stock returns as a reliable indicator of systemic risk among financial institutions. They analyze daily changes in correlation on a sample of the largest bank holding companies and investment banks. Their findings support the view that correlation of stock returns in the banking industry follows an increasing trend, whereas no obvious trend can be observed in stock returns correlation among non-banking entities. Huang et al. (2012) examine systemic risk tendencies in banking systems of eight countries belonging geographically to the regions of Asia and the Pacific. To illustrate how global crisis spread to Asian area, the authors develop a unique systemic risk measure, which allows detecting the likelihood with which individual banks might default as well as correlation among defaults. De Nicolo and Kwast (2002) use a sample of US large banks to analyze the development of stock returns correlation over time. Concluding that dependence among bank institutions follows a positive trend, their findings confirm the outcomes of many authors saying that systemic risk in the financial sector has increased markedly in recent years. Following De Nicolo and Kwast (2002), Schüller (2002) employs identical methodology and looks for the evidence whether systemic dependencies among banks exist also at the European level. He manages to confirm his hypothesis and concludes that a potential for systemic risk in Europe increased substantially over the 15 years horizon.

Chapter 4

Measures of Dependence

In statistical terms, dependence is used to describe a statistical relationship between random variables. It may arise when stochastic behavior of variables which are scrutinized is somehow interlinked (Coles et al. 1999). Estimating the level of dependence between risky financial assets has become a central issue in a variety of financial applications including portfolio theory, risk management, option pricing and hedging (Mashal and Zeevi 2002). In particular, it plays a significant role when assessing the total magnitude of risk exposures.

We present various measures of dependence in this chapter. The first section is devoted to conventional dependence measures. An approach based on simple correlation has been historically employed as a standard measure of dependence. Nevertheless, given the limitations of its use, risk management welcomes alternative measures examining dependencies beyond classical correlation. Those are provided in the second section. At last, extreme value methodology is introduced in the third section. Its uniqueness lies in the fact that unlike classical correlation, which examines dependence structure of ordinary values gathering around the centre of the distribution, the extreme value measure studies dependence in extremes. With respect to an empirical application focused on the estimation of extreme dependence afterwards, this section will be of a particular importance.

4.1 Conventional Dependence Measures

In modern finance, dependence is often interchanged with correlation. However, one needs to distinguish both terms, as they are not identical. Correlation is a limited concept and very often leads to a misleading inference on actual dependencies (Mashal and Zeevi 2002). In the following subsection we focus in more details on the ordinary Pearson linear correlation. It produces a single number summarizing the information about the dependence structure between two random variables.

4.1.1 Pearson Linear Correlation

This subsection draws on Embrechts et al. (1999), Bradley and Taqqu (2001) and McNeil et al. (2005).

Pearson correlation is a measure of linear dependence between two variables. Due to its computational simplicity and some other useful properties, it represents one of the most popular instruments for measuring dependence and is widely used in the finance industry. Nevertheless, in order to provide a valid conclusion, some restrictions on the statistical distribution of returns are imposed. It is necessary to keep in mind that correlation only provides reasonable inference about the dependence between assets, when multivariate normal distribution is taken into account. If it is not the case, correlation ceases to be a reliable measure of dependence.

Let us consider X and Y to be a pair of random variables. The linear correlation coefficient between both variables can be then expressed as:

$$\rho[X,Y] = \frac{\text{Cov[X,Y]}}{\sqrt{\text{Var[X]}Var[Y]}} = \frac{E[XY]-E[X]E[Y]}{\sigma[X]\sigma[Y]},$$

where the numerator of the equation denotes covariance between X and Y and the denominator contains squared roots of variances of X and Y.

The above formula suggets that correlation can only be defined when variances of random variables are assumed finite. When this assumption holds, Y is almost surely an affine transformation of X, that is $Y = aX + b$ for any arbitrary constant $a \in \mathbf{R}\backslash\{0\}$, $b \in \mathbf{R}$, and the correlation coefficient takes on values within the interval $\langle$-1,1$\rangle$.

Let us now take a look at some specific cases of dependence between random variables. If random variables X and Y are independent, then $cov[X,Y] = 0$ and so $\rho[X,Y] = 0$. It is important to stress that the converse implication does not hold, since $\rho[X,Y] = 0$ does not automatically imply the independence of the random variables. If the relationship between X and Y is characterized by a perfect linear dependence, it holds that $Y = aX + b$ almost surely for $a \in \mathbf{R}\backslash\{0\}$, $b \in \mathbf{R}$, and $\rho[X,Y] = 1$ in case of the positive perfect linear dependence and $\rho[X,Y] = -1$ in case of the negative perfect linear dependence. If X and Y are imperfectly linearly dependent, the correlation coefficient $\rho[X,Y]$ is to be found within interval (-1,1).

Limitations of Correlation

Having introduced the concept of correlation, we briefly summarize its main drawbacks.

- Firstly, correlation cannot be defined when variances of two random variables are not finite. Complications occur particularly when working with heavy-tail distributed data. It is an empirical fact that distribution of returns in the finance industry is far from being normal and shows the presence of fat tails. In such a world, correlation is not apparently an ideal measure (Embrechts et al. 1999).

- Another contra-argument is the absence of direct implication of independence from zero correlation. More precisely, independence in the data implies zero correlation, yet the zero correlation does not necessarily implies independence (Embrechts et al. 1999). A simple example supporting this claim can be found in Embrechts et al. (1999). Let us consider X and Y to be two random variables with the following properties. X is normally distributed with zero mean value and constant variance, i. e. $X \sim N(0, \sigma^2)$, and $Y = X^2$. Then the covariance of X and Y yields:

  $$Cov[XY] = E[XY] - E[X]E[Y] = E[X^3] - 0E[Y] = E[X^3] = 0.$$

  Eventually, we can see that both variables prove strong dependence structure even despite their uncorrelatedness. This is so because X and Y are marginally normally distributed, yet not jointly normally distributed. Hence, the multivariate normal distribution is an ultimate assumption for zero correlation to imply independence (Embrechts et al. 1999).

- Third, risk management is particularly concerned with the left-hand part of the distribution of returns. Therefore, while at the forefront is modelling left-tailed loss dependence, correlation is a rather global measure, which is mainly driven by observations coming from the centre of the distribution (De Vries 2009). If the dependence of tail observations differs significantly, a financial institution relying entirely on the conclusion of correlation could be exposed to a threat of bankruptcy. Hence, linear correlation is not a meaningful concept for modeling dependence in extremes (Poon et al. 2003).

- Finally, correlation analysis is a rational measure of dependence only for linear relationships. For increasing transformations which are strictly linear it thus satisfies (Embrechts et al. 1999):

$$\rho(\alpha X + \beta, \gamma Y + \delta) = \rho(X, Y),$$

where $\alpha, \gamma \in \mathbf{R}\backslash\{0\}$ and $\beta, \delta \in \mathbf{R}$. However, for non-linear transformations $T : \mathbf{R} \to \mathbf{R}$ it generally holds:

$$\rho(T(X), T(Y)) \neq \rho(X, Y).$$

4.2 Alternative Dependence Measures

Limitations of linear correlation summarized in the previous subsection provide the main justification why it is often not an appropriate measure for analysis of dependence of financial risks. As a result, there is a need for alternative measures of dependence. In the following subsections the concept of copulas as well as other dependence measures derived from copulas are introduced.

4.2.1 Copulas

To estimate the overall riskiness of a portfolio of assets, one needs to get well familiar with the complete joint distribution of risk factors. Every joint distribution function is basically delineated by two partial elements. The first is a marginal distribution of individual risk factors; the latter involves their mutual dependence. A copula is a tool for extracting the dependence structure (McNeil et al. 2005).

This concept is useful to be defined from a number of reasons. Copulas can be surely regarded as a superior measure to simple linear correlation, as they allow better understanding of the dependence. Thanks to a quantile scale representation of dependence, they are especially useful for describing dependence in extremes. They find wide applications in risk management where marginal behaviour of individual risk factors is usually easier to detect than the dependence structure of these factors. In terms of credit risk, for instance, in spite of the fact that estimating an individual's default probability is a challenge itself, it is still more passable to handle than estimating dependence among default probabilities of several obligors. Lastly, the copula approach also forms the basis for defining other alternatives for dependence modelling (McNeil et al. 2005).

The Copula Function and Properties

Following Coles et al. (1999) and Embrechts et al. (1999), we introduce the copula function for a random vector $(X_1, X_2, \dots, X_n)^T$.

The distribution function which describes the dependence structure among given random variables has the form:

$$F(x_1, x_2, \dots, x_n) = P(X_1 \leq x_1, X_2 \leq x_2, \dots, X_n \leq x_n).$$

We further suppose that the marginal distribution functions for the vector $(X_1, \dots, X_n)$ are continuous, i. e. $F_i(X) = P(X_i \leq x)$. A copula is such multivariate distribution function for which marginal distributions are uniform. Hence, we need to somehow transform marginal distributions into the required uniformity. This can be achieved by applying the probability integral transformation T:

$$T : \mathbf{R}^n \mapsto \mathbf{R}^n, (x_1, x_2, \dots, x_n)^T \mapsto (F_1(x_1), F_2(x_2), \dots, F_n(x_n))^T.$$

Having gained uniform marginal distributions, the copula of the random vector $(X_1, X_2, \dots, X_n)^T$ is then defined as the joint distribution function C of $(F_1(X_1), F_2(X_2), \dots, F_n(X_n))^T$:

$$\begin{aligned} F(x_1, x_2, \dots, x_n) &= P[F_1(X_1) \leq F_1(x_1), \dots, F_n(X_n) \leq F_n(x_n)] \\ &= C[F_1(x_1), F_2(x_2), \dots, F_n(x_n)]. \end{aligned}$$

Ultimately, the function C contains complete information about the joint behaviour of random variables $(X_1, X_2, \dots, X_n)$, whereas neglecting the information about their marginal distributions. As stated in McNeil et al. (2005), an n-dimensional copula $C(u) = C(u_1, u_2, \dots, u_n)$ needs to satisfy the following properties:

- $C(u_1, u_2, \dots, u_n)$ is increasing in each component $u_i, i = 1, \dots, n$.
- $C(1, \dots, 1, u_i, 1, \dots, 1) = u_i$ for all $i \in \{1, \dots, n\}$; $u_i \in [0, 1]$.

- For all $(a_1, \ldots, a_n), (b_1, \ldots, b_n) \in [0,1]^n$ with $a_i \leq b_i$ we have

$$\sum_{i_1=1}^{2} \cdots \sum_{i_n=1}^{2} (-1)^{i_1+\ldots+i_n} C(u_{1i_1}, \ldots, u_{ni_n}) \geq 0,$$

where $u_{j1} = a_j$ and $u_{j2} = b_j$ for all $j \in \{1, \ldots, n\}$.

4.2.2 Rank Correlation

Rank correlation is a dependence measure of a copula-based type. This characteristic gives the measure better properties than the standard Pearson linear correlation. Unlike linear correlation, which depends on the copula of a bivariate distribution as well as on the marginal distribution probabilities, rank correlation does not rely on the marginal distributions. The name of the statistics indicates what its main idea is. Rank correlation examines the relationship between the ranks of particular variables. To be more precise, the rank statistics is only interested in the ordering of observations of a particular variable instead of focusing on actual values (McNeil et al. 2005).

The two well-known rank correlations are Kendall's tau and Spearman's rho. As stated in Embrechts et al. (2001), they stand for the best alternative measures of dependence for the class of non-elliptical distributions, for which the linear correlation coefficient provides a misleading conclusion.

Following McNeil et al. (2005), the Kendall's correlation can be viewed as a measure of concordance for a category of bivariate random vectors. Let us assume (x_1, y_1) and (x_2, y_2) to be points defined in $\mathbf{R}^2$. These are denoted as

- *concordant* if $(x_1 - x_2)(y_1 - y_2) > 0$
- *discordant* if $(x_1 - x_2)(y_1 - y_2) < 0$.

Considering further a pair of random vectors (X_1, Y_1) and (X_2, Y_2), both having the same distribution but the vector (X_2, Y_2) being independent of (X_1, Y_1), Kendall's rank correlation can be expressed simply as a difference of probability of concordance and probability of discordance:

$$\rho_\tau(X_1, Y_1) = P[(X_1 - X_2)(Y_1 - Y_2) > 0] - P[(X_1 - X_2)(Y_1 - Y_2) < 0].$$

Regarding the second rank correlation measure, Spearman's rho, it can be expressed similarly to Kendall's tau in terms of concordance and discordance.

Considering random vectors $(X_1, Y_1), (X_2, Y_2)$ and (X_3, Y_3) being independent, Spearman's rank correlation for the random vector (X_1, Y_1) is defined as (Embrechts et al. 2001):

$$\rho_S(X_1, Y_1) = 3\big(P[(X_1 - X_2)(Y_1 - Y_2) > 0] - P[(X_1 - X_2)(Y_1 - Y_2) < 0]\big).$$

The truth is that literature often offers more intuitive definition based on copulas. Following the definition provided in McNeil et al. (2005), Spearman's rho for two random variables X and Y with distribution functions F_1 and F_2, respectively, can be expressed as:

$$\rho_S(X, Y) = \rho\big(F_1(X), F_2(Y)\big).$$

4.3 Extreme Value Measures

The risk of extreme events is ubiquitous in all areas of finance and being able to effectively handle it is one of the major tasks for risk management. This section deals with the issue of extreme values and more importantly, extreme value dependence. Given the fact that the Extreme value theory (EVT) is a central theory in the area of extreme values and forms the basis for modelling extremal dependence in the empirical part, we first introduce the EVT in more details and subsequently we proceed with methods which are commonly applied for analyzing dependence in extremes.

4.3.1 Extreme Value Theory

Extreme market events have occurred several times in the past. As a typical example one can recall the Stock market crash in October 1987, the Asian currency crisis in 1997 or, most recently, the Global financial crisis 2008/ 2009. The definition of an extreme market event is straightforward, as it is pretty clear from features common to the mentioned examples. Common denominators are mainly very low probability of occurrence, unexpectedness, and damaging consequences which, in the worst-case scenario, expand far beyond national borders.

Market conditions under stress are of considerable interest to regulatory authorities, as they are aware of stress events as a significant source of systemic risk. To protect the financial system as a whole, they impose requirements on the minimum amount of capital that financial institutions have to put aside to absorb large losses (Longin 2000). For ensuring that financial institutions are able to withstand exceptional market movements, it is vital to be able to determine the impact of those events on institutions, their returns, and subsequently, to model extreme returns as accurately as possible.

From the statistical point of view, extremes of random processes are common to both sides of the distribution of returns. A financial entity may encounter extreme positive returns lying on the right-hand tail of the distribution, yet of much greater importance are extreme negative returns, which appear on the left-hand tail. The EVT is a branch of statistics which is concerned with modelling these tails of the distribution (Longin 2000).

The uniqueness of this approach lies in its ability to deal with challenges such as lack of data. For instance, if our aim is to estimate the likelihood of a one-in-thousand years event, it is hardly possible to collect sufficient historical observations. However, the EVT can handle it as *"it approaches the modelling of these rare and damaging events in a statistical sound way"*(Bradley and Taqqu 2001, p. 39).

The limit theory of extremes has been developed in parallel with another theory of asymptotic behavior, namely the Central limit theory (CLT) (De Haan and Ferreira 2006). Following De Haan and Ferreira (2006), for random variables $X_1, X_2, \ldots, X_n \sim iid$ (independent and identically distributed), the limit behaviour described by CLT is $X_1+X_2 \ldots+X_n$ as $n \to \infty$. To find extreme value distributions, that is the limit distributions for $max(X_1, X_2, \ldots, X_n)$, let us assume $\hat{x}$ to be the right-end observation of the underlying distribution function F, that is $\hat{x} := sup\{x : F(x) < 1\}$. Then

$$max(X_1, X_2, \ldots, X_n) \xrightarrow{\text{Pr}} \hat{x}, n \to \infty,$$

where $\xrightarrow{\text{Pr}}$ refers to the convergence in probability, since it holds that

$$P\big(max(X_1, X_2, \ldots, X_n) \leq x\big) = P(X_1 \leq x, X_2 \leq x, \ldots, X_n \leq x) = F^n(x).$$

For $x < \hat{x}$ the probability approaches zero, for $x \geq \hat{x}$ it goes to one. Because we wish $max(X_1, X_2, \ldots, X_n)$ to have a non-degenerate limit as $n \to \infty$, we need to normalize it. Therefore, we suppose the existence of norming constants $\alpha_n > 0$ and $\beta_n \in \mathbf{R}$, for which the normalized maximum

$$\frac{max(X_1, X_2, \ldots, X_n) - \beta_n}{\alpha_n}$$

follows a non-degenerate limit distribution, such that

$$\lim_{n\to\infty} F^n(\alpha_n x + \beta_n) = G(x), \tag{4.1}$$

for $\forall x$ from a non-degenerate distribution G (De Haan and Ferreira 2006).

Generalized Extreme Value Distribution

The existence of non-degenerate function as in (5.1) guarantees that the limit of the extreme is characterized by one of a group of extreme value distributions. The group contains the Gumbel (γ_z), the Frechet (τ_z) or the Weibul (ω_z) type of distibution (Poon et al. 2003). These distributions have the following form (Bradley and Taqqu 2001):

$$\gamma_z(x) = exp\{-e^{-x}\}, x \in \mathbf{R}$$

$$\tau_z(x) = \begin{cases} 0 & \text{for } x \leq 0,\ z > 0 \\ exp\{-x^{-z}\} & \text{for } x > 0,\ z > 0 \end{cases}$$

$$\omega_z(x) = \begin{cases} exp\{-(-x)^z\} & \text{for } x \leq 0,\ z > 0 \\ 1 & \text{for } x > 0,\ z > 0 \end{cases}$$

The Generalized Extreme Value Distribution (GEV) has been developed within the EVT as a model integrating the three extreme value distributions into a single one. Therefore, the GEV can be expressed as (Poon et al. 2003):

$$G_{\xi,\mu,\sigma}(x) = \begin{cases} exp\{-\big(1+\xi(x-\mu)/\sigma\big)^{-1/\xi}\} & \text{for } \xi \neq 0 \\ exp\{-e^{-(x-\mu)/\sigma}\} & \text{for } \xi = 0, \end{cases}$$

where $\xi \in \mathbf{R}$ denotes the shape parameter of G, $\mu \in \mathbf{R}$ is the location parameter, and $\sigma > 0$ stands for the scale parameter. The distribution of the extreme is hidden in the the shape paremeter ξ, which is also reffered to as the tail index. The value of ξ specifies by which particular extreme value type the GEV distribution is driven. When $\xi > 0$, the GEV corresponds to the Frechet distribution. In case that $\xi < 0$, it follows the negative Weibul distribution. Eventually, when $\xi = 0$, the GEV is driven by the Gumbel distribution.

To keep it in perspective, for normally distributed data the maximum value corresponds to the Gumbell distribution. However, research in recent years has brought enough evidence for the presence of heavy tails in financial data.[1]

[1]See for instance Müller et al. (1998) or Cont (2001).

Therefore, in reality extreme values are likely to follow the Frechet distribution (Poon et al. 2003).

4.3.2 Extreme Value Identification

Two approaches can be basically used for identification of extremes in the data (McNeil 1999). The historicaly older approach is represented by the *Block maxima method* (BM), which simply models the largest observations in a set of identically distributed random variables. The extremes are modelled using the GEV distribution described in more details in the previous subsection. Due to high data demands, however, the applicability of this method is somewhat limited in practice. The more recent approach is the *Peak-over-threshold* (POT). This method is widely used in most empirical applications as it manages to better cope with the limited amount of data on extremes (McNeil 1999). The idea of this approach is to model values exceeding a certain high threshold rather than largest observations only. When the collection of observations occurring above the specific threshold is available, the POT method is more appropriate for extremes identification, since relying solely on maximum values from a fixed interval could impoverish the analysis (Poon et al. 2003). Selecting an optimal value of the threshold is the most challenging part in the POT analysis and it requires that the trade-off between bias and inefficiency has to be carefully optimised (Longin and Solnik 2001). On one hand, a low threshold value produces too many threshold exceedances, which leads to biases in estimation due to the fact that excessive number of observations is involved in the tail analysis. On the other hand, if the threshold value is determined too high, the opposite problem arises as only few observations happen to exceed it. As a consequence, inefficient estimates with large standard errors are produced (Longin and Solnik 2001). To deal with the issue of threshold selection, a variety of diagnostic tools can be applied. One possible technique is a bootstrap method *"which produces an optimal value that minimizes the empirical mean square errors of the tails index"*(Poon et al. 2003, p. 934).

In terms of the distribution of threshold exceedances, these follow the Generalized Pareto Distribution (GPD) (McNeil 1999). The functional form of the GPD is:

$$GPD_{\xi,\beta}(x) = \begin{cases} 1-(1+\xi x/\beta)^{-1/\xi} & \text{for } \xi \neq 0 \\ 1-exp(-x/\beta) & \text{for } \xi = 0, \end{cases}$$

where $\beta > 0$ is a scaling parameter and $\xi \in \mathbf{R}$ stands for the tail index. The tail index ξ provides information about the nature of tail. For the purpose of risk management, the case when $\xi > 0$ is of the highest relevance, as it refers to the distribution with heavy tails (McNeil 1999). Heavy tails are typical for instance for the Student-t distribution. When $\xi < 0$, the GPD corresponds to a finite distribution with completely eliminated tails. This type is common for normal or log-normal distributions. At last, exponential distribution refers to the case when the tail index ξ is equal to zero (Longin and Solnik 2001).

Chapter 5

Modelling Systemic Dependence

The previous chapters were aimed at constituting theoretical background for empirical application. As already mentioned, contemporary literature is not abundant in papers exploring systemic risk in the insurance industry. Indispensable role of banks in the financial system leads to the fact that most research in this field concentrates on the banking sector. Nevertheless, the insurance sector undoubtedly occupies a position of the second most important financial subsystem. In addition, in Chapter 2 we presented numerous sources of linkages among banks and insurers. These provide additional reasoning why insurance companies should be more scrutinized in the context of systemic risk.

The objective of this chapter is to contribute to the scarce literature by exploring systemic dependence between bank and insurance groups. After a brief introduction of systemic risk, we present data, the applied methodology and subsequently we proceed with empirical estimation.

5.1 Systemic Risk

The central issue of this thesis is investigating a depth of systemic dependencies between bank and insurance groups. There is no doubt that similar interdependencies contribute largely to the creation of systemic risk in financial markets, as they have a potential to result in systemic failures. Hence, this section will introduce briefly systemic risk in the context of financial systems and it will uncover the relevance of its control for maintaining financial stability.

To get a very general idea, systemic risk can be encountered in various areas of human life. For the simplest possible illustration De Bandt and Hartmann (2000) point at epidemic diseases. At the beginning individuals get contaminated by a disease and due to mutual interactions with other people the contamination propagates through population. Initially local problem with only a minor impact is continually growing to larger dimensions and it eventually results in a disaster with widespread consequences. This elementary example is a good representation of this phenomenon as it fully captures the essence of systemic risk.

In the light of recent economic events, systemic risk is most notably connected with financial sphere and institutions operating there. For the definition of systemic risk in financial systems, let us first clarify basic elements. De Bandt and Hartmann (2000) define a systemic event from two different perspectives. Their "closer concept" refers to an event *"where the release of "bad news" about a financial institution , or even its failure, or the crash of financial market leads in a sequential fashion to considerable adverse effects on one or several other financial institutions or markets, e.g. their failure or crash"*(De Bandt and Hartmann 2000, p. 10). The typical characteristic is the domino effect, which causes that troubles in individual entities spread to the others. In addition, their "broader concept" encompasses also *"simultaneous adverse effects on a large number of institutions or markets as a consequence of severe and widespread shocks"* (De Bandt and Hartmann 2000, p. 10). It is hardly possible to find a unique definition of systemic risk, nonetheless, there is a factor that all definitions have in common. It is always associated with a triggering event, which may have different forms (economic shock, failure of an institution, etc), resulting in a chain of adverse economic consequences (Schwarcz 2008).

Direct consequences of the recent crisis, a classic systemic risk event, are attempts of regulators to build a better operating financial system robust to random shocks. To achieve this, it is vital that sources of systemic risk are properly identified and controlled. According to BIS (2009), financial institutions such as banks and insurance companies should receive a special attention.

5.2 Data Description

The objective of the empirical part of the thesis is to investigate the level of systemic dependence between bank and insurance groups. Our data consists of historical closing stock prices of the EU banks and insurance companies publicly listed on the stock exchange. We focus our analysis on the sample of 20 banks and 20 insurance companies. We impose several criteria on institutions in the sample. First, we choose banks and insurance companies that rank among the largest in the EU, as we assume that those are the most systemically important and so they could play a major role in the propagation of systemic risk. With respect to that, the total volume of assets is used as an indicator determining the size of companies. Next, selected institutions are listed on local stock exchanges and their history provides sufficient length of time series. The final ranking of the 20 largest banks and insurance companies has been set based on the Forbes Global 2000, which provides information about the world's top 2000 public companies.

For most banks and insurance companies in the sample the time series is continually available from early 1999. The most recent observations come from April 2014. Data has been collected in daily frequencies. Therefore, the overall time span covers the period from January 4th, 1999 to April 17th, 2014, generating on average 3800 daily observations for each time series. All data has been downloaded from Bloomberg.

Table 5.1 presents the selected banks and insurance companies.[1]

Table 5.1: Selected Companies

Rank	**Bank**	**Notation**	**Insurer**	**Notation**
1	HSBC Holdings	HSBA	ING Group	INGA
2	Deutsche Bank	DBK	AXA Group	CS
3	BNP Paribas	BNP	Allianz	ALV
4	Credit Agricole	ACA	Generali Group	G
5	Barclays	BARC	Legal & General Gr.	LGEN
6	Royal Bank of Scotland	RBS	Aviva	AV
7	Societe Generale	GLE	Prudential	PRU
8	Banco Santander	SAN	Aegon	AGN
9	Lloyds Banking Group	LLOY	CNP Assurances	CNP
10	Unicredit Group	UCG	Munich Re	MUV2
11	Nordea Bank	NDA	Ageas	AGS
12	Banco Bilbao Vizcaya	BBVA	Unipol Gruppo	UNI
13	Commerzbank	CBK	Mapfre	MAP
14	Intesa Sanpaolo	ISP	Vienna Insurance	VIG
15	Natixis	KN	Mediolanum	MED
16	Standard Chartered	STAN	SCOR	SCR
17	Danske Bank	DANSKE	Sampo	SAMAS
18	Dexia	DEXB	Uniqua	UQA
19	Enskilda Banken	SEBA	Nďż˝rnberger	NBG6
20	Svenska Handelsbank	SHBA	Catolica Assicurazi	CASS

Source: Author

All banks in the sample belong to the group of major banks operating internationally except for Nordea Bank, which operates only regionally. Credit

[1]For more details on the sample institutions see Table A.1 and Table A.2 in AppendixA.

Agricole is the only institution not providing a full range time series, however, given the fact that it belongs to the top 5 EU banks, we decide to keep it in the sample, as its potential systemic impact is likely to be truly relevant.

Focusing on insurance companies, our sample involves insurance companies providing two different types of insurance services, namely diversified insurance and life & health insurance. When it comes to the selection of insurers, slight changes in the final ranking had to be made, as some institutions did not fulfilled the given criteria. For instance Standard Life, Delta Lloyd and Talanx were ommited from the sample, since they entered stock exchange in 2006, 2009 and 2012 respectively, and their short time series are not suitable for our analysis.

5.2.1 Descriptive Statistics

We convert the daily close values into the daily logarithmic returns in order to reflect intra-day changes in prices. Table 5.2 and Table 5.3 provide descriptive statistics for the banks' and insurance companies' equity returns over the period January 4th, 1999 up to April 17, 2014. Further in the analysis we are interested in examining daily loss returns, because negative values, and extreme negative values in particular, should be gained major attention from the risk management point of view. Therefore, to make our analysis simplier, we consider losses as positive numbers, meaning that maxima in Table 5.2 and Table 5.3 correspond to maximum losses and minima apply to maximum gains.

The very first impression from the data check seems to be in favour of non-normality of returns. For the majority of banks in the sample the quity returns are negatively skewed, suggesting the existence of longer left tail. Kurtosis also indicates sharper peaks for all banks. High values of kurtosis suggest that the returns are driven by leptokurtic distribution. To draw precise conclusion about the nature of the data, we formally test normality of returns using the Jarque-Bera test. The results are available in AppendixA. Based on the test, normality is strongly rejected for all banks, which gives support to the stylized fact about the non-normal distribution of financial data. The largest loss observed applies to Royal Bank of Scotland and it amounts to 66.7 %. This extreme movement came up between January 16, 2009 and January 19, 2009, when during one day the RBS equity price dropped from 3.94332 EUR to 1.27924 EUR. We definitely attribute this price drop to the events accompanying the Lehman bankruptcy, as it only reflects the general trend of falling stock market prices shortly after the outbreak of the crisis. More interestingly, another extreme loss of more than 40 % occured between exactly the same days at Lloyds Bank, suggesting that this period brought truly hard times to British banks.

Table 5.2: Descriptive statistics for the banks' daily equity returns

	Mean	**Min.**	**Max.**	**St. Dev.**	**Skewness**	**Kurtosis**
HSBA	0.0000	-0.1516	0.2200	0.0189	0.2888	11.6723
DBK	0.0001	-0.2252	0.1712	0.0254	-0.1712	7.3358
BNP	-0.0001	-0.1898	0.1893	0.0250	-0.2826	7.5728
ACA	0.0001	-0.2336	0.1435	0.0273	-0.2616	6.0762
BARC	0.0001	-0.5484	0.2938	0.0313	-1.1403	33.6055
RBS	0.0007	-0.3091	0.6672	0.0353	4.0465	82.1190
GLE	-0.0001	-0.2143	0.1771	0.0279	-0.0544	5.9628
SAN	0.0000	-0.2088	0.1280	0.0225	-0.2275	5.8301
LLOY	0.0005	-0.4120	0.4190	0.0319	0.8356	32.6873
UCG	0.0004	-0.1901	0.1895	0.0264	0.0874	6.9426
NDA	-0.0002	-0.1776	0.1386	0.0236	-0.2960	5.2381
BBVA	0.0001	-0.1991	0.1454	0.0220	-0.2864	5.3934
CBK	0.0007	-0.1973	0.2825	0.0296	0.0485	7.7361
ISP	0.0002	-0.1796	0.1846	0.0259	0.0967	5.4555
KN	-0.0001	-0.3279	0.1922	0.0271	-0.6741	16.1021
STAN	-0.0002	-0.2811	0.1789	0.0259	-0.2529	10.3451
DANSKE	-0.0002	-0.1397	0.1718	0.0209	0.0617	5.4326
DEXB	0.0015	-0.6931	0.4055	0.0642	-0.2386	18.4644
SEBA	-0.0002	-0.2542	0.2420	0.0273	-0.1180	9.7735
SHBA	-0.0003	-0.1549	0.1264	0.0207	-0.1794	5.7180

Source: Author's computations

Focusing on insurance companies, the stock market returns of insurers reveal similar characteristics as identified at banks. Again, the majority of insurance companies exhibits negatively skewed returns with high values of kurtosis. These properties support the assumption about non-normal distribution of returns. We test it formally using the Jarque-Bera test and for all levels of significance we strongly reject the eventuality that the returns are normally distributed. We record the largest loss for Belgian insurer Ageas. This time the intra-day price drop was even more extreme than in case of banks, as it reached enormous 77.57 %. We looked into the respective stock prices and found out that this extreme loss return was a result of a fall in price from 54.12 EUR to 12.16 EUR between October 3, 2008 and October 14, 2008. Given the fact that these prices are two consecutive observations, it is interesting to notice that there was an interruption in trading lasting for more than a week. It is likely that it has a connection with difficulties related to the forthcoming financial crisis. Other extreme losses above 40 % and 36 %, respectively, were suffered by insurers Aviva and SCOR.

Table 5.3: Descriptive statistics for the insurers' daily equity returns

	Mean	Min.	Max.	St. Dev.	Skewness	Kurtosis
INGA	0.0002	-0.2565	0.3214	0.0309	0.0155	12.4662
CS	0.0001	-0.1978	0.2035	0.0275	-0.2751	6.5766
ALV	0.0002	-0.1907	0.1493	0.0237	-0.2204	6.8724
G	0.0002	-0.1231	0.0923	0.0176	-0.0219	3.1056
LGEN	0.0000	-0.2490	0.3369	0.0267	0.2157	13.8191
AV	0.0002	-0.2427	0.4022	0.0275	0.7316	17.6071
PRU	-0.0001	-0.2181	0.2193	0.0281	-0.0280	9.6475
AGN	0.0005	-0.3022	0.2768	0.0302	-0.1238	10.9661
CNP	-0.0002	-0.1043	0.1444	0.0190	0.0159	3.0856
MUV2	0.0001	-0.1668	0.1682	0.0215	0.0048	6.8821
AGS	0.0004	-0.2589	0.7757	0.0316	3.8993	102.1700
UNI	0.0005	-0.3591	0.1966	0.0222	-1.2295	33.1384
MAP	-0.0002	-0.1619	0.1345	0.0220	-0.4717	5.0217
VIG	-0.0003	-0.1529	0.1974	0.0197	-0.1311	11.7574
MED	0.0000	-0.1646	0.1126	0.0249	-0.2701	2.8638
SCR	0.0005	-0.1906	0.3623	0.0266	1.2168	22.7936
SAMAS	-0.0005	-0.1367	0.1823	0.0204	0.1872	7.9146
UQA	0.0000	-0.0965	0.1730	0.0173	0.3817	8.7472
NBG6	0.0001	-0.1985	0.1330	0.0182	-0.3831	10.2530
CASS	0.0002	-0.1122	0.0979	0.0166	-0.0603	4.9865

Source: Author's computations

5.3 Methodology

"Systemic risk by its very nature is concerned wth the downside risk of the system" (De Vries 2009, p. 3). In the manner of this claim we address the downside risk in the EU banking and insurance sectors. We focus on bivariate dependence modelling which allows us to investigate dependencies in pairs of institutions. Similarly to De Vries (2009) and Slijkerman et al. (2005), we are interested in bank-to-bank, insurer-to-insurer and bank-to-insurer relationships. For the purpose of our analysis we apply methodology which builts on the Extreme value theory (EVT) and is concerned with the dependence in extreme values.

5.3.1 Dependence in Extremes

In a broad context, one can distinguish two categories of extreme value dependence, namely *asymptotic extreme dependence* and *asymptotic extreme independence* (Poon et al. 2003). Dependence between sufficiently large values of variables can be observed in either of these categories, the difference between both types occurs as far as real extremes are concerned. The extremal observations have tendency to occur jointly only for variables exhibiting asymptotically dependent behavior. For asymptotically dependent random variables X and Y it holds that

$$\lim_{t\to\infty} P(X > t \mid Y > t) > 0.$$

Considering variables characterized by asymptotical independence, however, the mutual dependence gradually disappears with observations becoming more extreme (Poon et al. 2003). In other words, for assymptotical independent X' and Y' it holds that

$$\lim_{t\to\infty} P(X' > t \mid Y' > t) = 0.$$

Following Poon et al. (2003), we illustrate both types of extremal behavior in Figure 5.1 and Figure 5.2. We present scatter plots of 3566 daily logarithmic returns of two pairs of equities covering the period January 4th, 1999 until April 17, 2014. Vienna Insurance equity is plotted against Uniqua equity, similarly HSBC equity is plotted against Deutsche bank equity. Focusing on Figure 5.1 one may notice that tail observations of one equity occur together with rather ordinary observations of another equity, suggesting the behavior of both equities corresponding to asymptotical independence. In contrast, Figure 5.2 indicates much stronger extremal dependence. The data uncovers an apparent tendency of extreme observations at both equities to coincide with each other. This persistence of dependence in tail areas reveals asymptotically dependent variables and requires an application of special tools dealing solely with extremes.

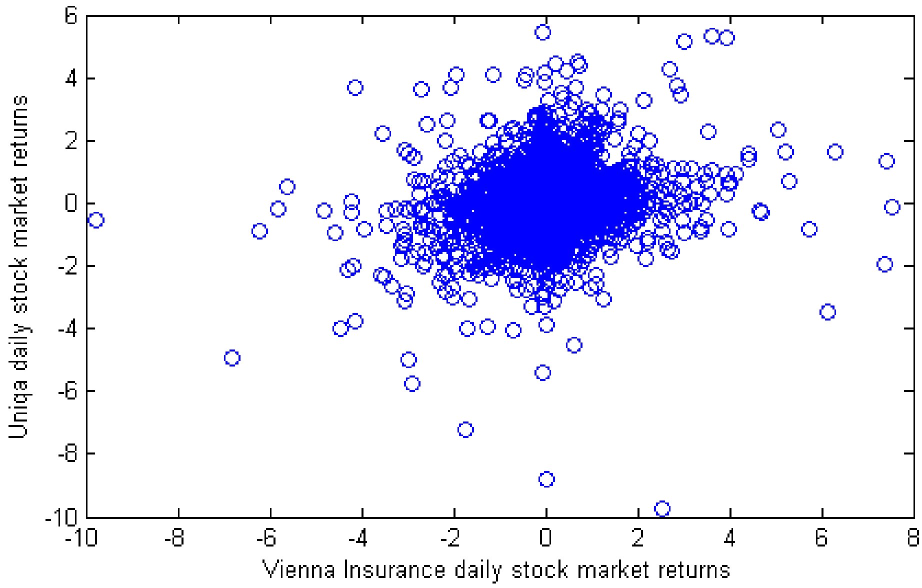
This illustration may serve as a motivation for an approach we intend to apply for empirical estimation. It is introduced in the following subsection.

5.3.2 Applied Dependence Measure

To meet the objectives of empirical part of the thesis, we follow an approach as in Slijkerman et al. (2005) and De Vries (2009) and utilize a measure developed within the EVT framework.

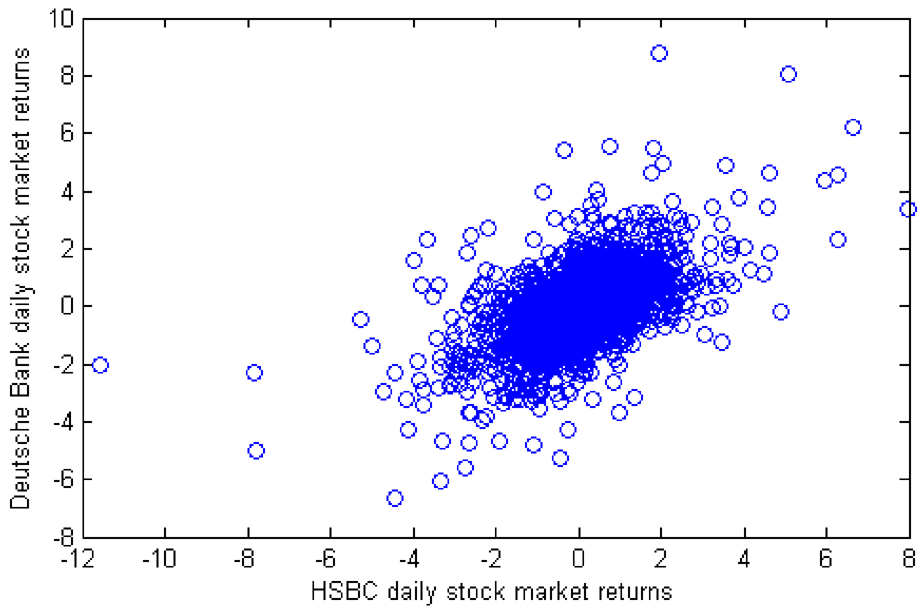
Figure 5.2 provides graphic evidence of the existence of tail areas in stock market returns. The fact that stock returns with similar characteristics are the subject of our analysis calls for applyig a measure, which is able to handle these critical parts of the distribution. Referring to limitations of correlation presented in Chapter 4, we possess meaningful arguments why correlation is not an appropriate solution to this case. Contrary to standard correlation which focuses on observations gathering towards the center, the EVT measure

Figure 5.1: Asymptotical independence of stock market returns



Source: Author's computations

Figure 5.2: Asymptotical dependence of stock market returns



Source: Author's computations

only deals with the observations located in tails (De Vries 2005). An argument against this approach is that it does not allow to detect an actual source of systemic failure. One thus can only assume whether it is driven by contagion or other macroeconomic risk factors (De Vries 2005). However, this drawback does not reduce the applicability of the measure in our thesis as it is rather irrelevant to the purpose of our analysis.

The approach adopted in our analysis integrates probabilities of extreme losses and institutional failures to address systemic risk. As an indicator of systemic risk we use so called *conditional probability measure* to *"directly study the probability of an extreme loss of a variable conditional on the loss of another variable"* (Slijkerman et al. 2005, p. 8). In other words, we are interested to know how many institutional breakdowns we might expect on average given that a minimum of one institution has already broken down (Slijkerman et al. 2005). It can be expressed as $E[\tau|\tau \geq 1]$, where τ stands for the expected number of failing institutions. This formulation represents our downside dependence measure, since we suppose an institution to fail when it encounters an extremely high loss defined upon exceeding a particular threshold t. Considering X_1 and X_2 random loss returns of a pair of institutions and t the respective threshold level causing their failures, following De Vries (2005) we can write the conditional measure as:

$$\begin{aligned} E[\tau|\tau \geq 1] &= \frac{P(X_1 > t, X_2 \leq t) + P(X_1 \leq t, X_2 > t)}{1 - P(X_1 \leq t, X_2 \leq t)} + 2\frac{P(X_1 > t, X_2 > t)}{1 - P(X_1 \leq t, X_2 \leq t)} \\ &= \frac{P(X_1 > t) + P(X_2 > t)}{1 - P(X_1 \leq t, X_2 \leq t).} \end{aligned} \quad (5.1)$$

Since we concentrate solely on pairs of institutions, the probability that both institutions go bankrupt, provided that at least one of them has already gone, can be expressed as (De Vries 2009):

$$\frac{P(X_1 > t) + P(X_2 > t)}{1 - P(X_1 \leq t, X_2 \leq t)} = E[\tau|\tau \geq 1] - 1.$$

As De Vries (2009) furher states, without posing additional assumptions on the threshold t, it is hardly possible to determine the precise level of t for which insititutions suffer a severe loss. Therefore, a possible way to account for that is to express systemir risk measure in terms of limit

$$SR(\tau) = \lim_{t \to \infty} E[\tau|\tau \geq 1].$$

"Extreme value theory then shows that even thought the measure is evaluated in the limit, it nevertheless provides a reliable benchmark for the dependency at hight but finite levels t" (De Vries 2009, p. 7).

5.4 Theoretical Dependence

In Chapter 2 we named major sources of dependence among banks and insurance companies and we identified that they ususally emerge from mutual risk exposures. We will now categorize these risks into general factors in order to derive dependence theoretically. The empirical application will follow straight afterward.

Following Slijkerman et al. (2005) and De Vries (2009), one can distinguish three broad classes of risks faced by companies in the finance industry. Macroeconomic risk (M) is a risk element that all institutions share together. Secondly, sector-specific risk (U and V) is a risk characteristic for given industry and it concerns all institutions operating within the field. Finally, insitution-specific risk (X_i and Y_j) is a risk unique to individual institutions and it may thus differ from one institution to another. Given our interest in application of the EVT, we assume these risks to be driven by distribution with heavy tails. To concretize the distribution, we adopt the convention that *"a random variable exhibits heavy tails if its distribution function $F(t)$ far into the tails has a first order term identical to the Pareto distribution"* (De Vries 2005, p. 819). That is for any arbitrary random variable $t \sim i.i.d.$

$$F(t) = 1 - t^{-\alpha} L(t) \; as \; t \; \to \infty,$$

where $L(t)$ is a function with the property

$$\lim_{d \to \infty} \frac{L(dt)}{L(d)} = 1, t > 0. \qquad (5.2)$$

Having knowledge of this property, we can easily derive the desired form of Pareto distribution:

$$\lim_{d \to \infty} \frac{1 - F(dt)}{1 - F(d)} = \lim_{d \to \infty} \frac{(dt)^{-\alpha} L(dt)}{d^{-\alpha} L(d)} = t^{-\alpha}, \alpha > 0, t > 0.$$

Getting now back to our risk factors, we will therefore assume them distributed in a way such that (Slijkerman et al. 2005):

$$P(M > t) = P(U > t) = P(V > t) = P(X_i > t) = P(Y_j > t) = t^{-\alpha}.$$

5.4.1 Bank-to-Bank

Being able to analyze downside risk dependence between two banks, we essentially need to start with introducing a concept describing convolutions of variables with tail properties (Slijkerman et al. 2005). Only then we are able to derive the probability of a joint collapse of two banks. This concept is in the literature regarding downside risk dependence known as Feller's convolution theorem, as it draws on key findings in Feller (1971,VIII.8).[2] However, we will introduce it very simply based on the result of the Feller convolution as summarized in De Vries (2009). According to De Vries (2009), the theorem says that if a pair of independent random variables A and B satisfies

$$P(A > t) = P(B > t) = t^{-\alpha},$$

then it implies for their convolution that

$$\lim_{t\to\infty} \frac{P(A + B > t)}{2t^{-\alpha}L(t)} = 1,$$

where $L(t)$ is a slowly varying function with the same characteristics as in (5.2).

Similarly to Slijkerman et al. (2005), we will express a bank's stock returns in terms of the risk factors defined in the previous subsection. Therefore, we can write $B_i = M + U + X_i$, where B_i stands for the i-th bank's stock returns, U is a risk related to the banking industry and X_i is the i-th bank's specific risk. Since we have decomposed the portfolio into mutually unrelated independent components, we can apply the convolution theorem.

Now we proceed to the point when Feller's convolution theorem finds its useful application. Since we are interested in the probability that the bank i breaks down, in fact, we want to know

$$P(B_i > t) = P(M + U + X_i > t).$$

Making use of the Feller's theorem, on condition that the threshold value t is

[2] See for example Slijkerman et al. (2005), Hyung and De Vries (2005) or De Vries (2005) for the application of Feller's convolution theorem.

large enough, we get (Slijkerman et al. 2005)

$$P(B_i > t) = P(M + U + X_i > t) = 3t^{-\alpha} + o(t^{-\alpha}).$$

Once we are already familiar with the probability of a single bank collapse, it is time to derive the probability of a simultaneous crash. Let us therefore consider $B_i, i = k, l$ for a pair of banks. Again, the convolution theorem implies that the probability of a double crash is equal to

$$P(B_k > t, B_l > t) = P(M+U+X_k > t, M+U+X_l > t) = 2t^{-\alpha}+o(t^{-\alpha}). \quad (5.3)$$

Why in this case the probability of the joint failure corresponds to the sum of two marginal probabilities, De Vries (2009) refers to the convolution theorem to provide argumentation as follows. The theorem stipulates that *"only the probability mass along the axes counts"*(De Vries 2009, p. 9). When considering the portfolio inequalities as in (5.3), for large threshold t they overlap only in those points above t, which are gathering along the $F + B$ axix. Only points in this area fulfil that both inequalities are parallelly satisfied. Consequently, it holds that

$$P(B_k > t, B_l > t) = P(M + U > t) + o(t^{-\alpha}) = 2t^{-\alpha} + o(t^{-\alpha}).$$

5.4.2 Insurer-to-Insurer

Next, we will move on to the estimation of tail dependence between two insurance companies. We will proceed in the same manner as in the case of bank-to-bank relationship. It will enable us to express an insurer's portfolio of stock returns in terms of risks it is exposed to. Since we now occupy the insurance sector, the only change appears in the industry-specific risk component. Let us define $I_j = M + V + Y_j$, where I_j refers to the j-th insurer's equity returns, V is a risk reflecting specifics of the insurance sector, Y_j is a risk unique to the j-th insurer. Once again, the insurance company defaults when its loss returns, or the sum of risk elements respectively, get out of tolerable levels and exceed a high threshold t. The probability that this event occurs is

$$P(I_j > t) = P(M + V + Y_j > t)$$

and Feller's convolution theorem ensures that it holds

$$P(I_j > t) = P(M + V + Y_j > t) = 3t^{-\alpha} + o(t^{-\alpha}).$$

Let us now consider two insurance companies and their returns portfolios $I_j, j = m, n$. The probability of their co-crash yields:

$$P(I_m > t, I_n > t) = P(M+U+X_m > t, M+U+X_n > t) = 2t^{-\alpha}+o(t^{-\alpha}). \quad (5.4)$$

Since the explanation is identical to the one given for two banks, we avoid providing it repeatedly and refer a reader to the previous subsection.

5.4.3 Bank-to-Insurer

Having estimated tail dependence within sectors, i.e. for two banks and two insurance companies, we will now explore the cross-sectional dependence. It is enough to combine findings from the two previous subsections and one discovers that the probability of a single bank's and a single insurer's parallel crash is equal to:

$$P(B_k > t, I_m > t) = P(M+U+X_k > t, M+V+Y_m > t) = P(M > t) = t^{-\alpha}+o(t^{-\alpha}). \quad (5.5)$$

Getting back to our systemic risk measure (5.1), we can now simple estimate the downside risk in the respective sectors using the outcomes (5.3), (5.4) and (5.5). Following Slijkerman et al. (2005), probabilities that two institutions go bankrupt given that at least one is already bankrupt yield:

$$\begin{aligned} E[\tau|\tau \geq 1]_{Bank|Bank} &= \lim_{t\to\infty} \frac{P(B_k > t) + P(B_l > t)}{P(B_k > t) + P(B_l > t) - P(B_k > t, B_l > t)} \\ &= \frac{3t^{-\alpha} + 3t^{-\alpha}}{3t^{-\alpha} + 3t^{-\alpha} - 2t^{-\alpha}} = \frac{6}{4}, \end{aligned}$$

$$\begin{aligned} E[\tau|\tau \geq 1]_{Insurer|Insurer} &= \lim_{t\to\infty} \frac{P(I_m > t) + P(I_n > t)}{P(I_m > t) + P(I_n > t) - P(I_m > t, I_n > t)} \\ &= \frac{3t^{-\alpha} + 3t^{-\alpha}}{3t^{-\alpha} + 3t^{-\alpha} - 2t^{-\alpha}} = \frac{6}{4}, \end{aligned}$$

$$\begin{aligned} E[\tau|\tau \geq 1]_{Bank|Insurer} &= \lim_{t\to\infty} \frac{P(B_k > t) + P(I_m > t)}{P(B_k > t) + P(I_m > t) - P(B_k > t, I_m > t)} \\ &= \frac{3t^{-\alpha} + 3t^{-\alpha}}{3t^{-\alpha} + 3t^{-\alpha} - t^{-\alpha}} = \frac{6}{5}. \end{aligned}$$

To summmarize the above equations, the theoretical model uncovers a higher potential for systemic dependence within individual sectors than across them. Intuitively, it can be justified simply by the fact that companies operating in the same field are all subject to the same risks and as a result, it makes it easier for systemic breakdowns to emerge. In the empirical application we will find out, among others, whether the same conclusion follows from the analysis of real data.

5.5 Empirical Application

We now introduce a non-parametric estimator as defined in Slijkerman et al. (2005) and De Vries (2009), so that the conditional risk measure (5.1) can be put into practice. Following De Vries (2009), the estimation of the probability of a simultaneous failure of two institutions, given that at least one has already failed, can be obtained as a share of *"the number of minima and maxima that exceed the threshold t"*(De Vries 2009, p. 13). In fact, the numerator in (5.1) can be reformulated as

$$\begin{aligned} P(X_1 > t) + P(X_2 > t) &= 1 - P(X_1 \leq t, X_2 \leq t) + P(X_1 > t, X_2 > t) \\ &= P\big(max(X_1, X_2) > t\big) + P\big(min(X_1, X_2) > t\big) \end{aligned}$$

and the denominator in (5.1) is equal to

$$1 - P(X_1 \leq t, X_2 \leq t) = P\big(max(X_1, X_2) > t\big).$$

Eventually, the systemic risk estimator that we utilize has the form (De Vries 2009):

$$\widehat{SR}(\tau) = 1 + \frac{No.\ min(X_1, X_2)}{No.\ max(X_1, X_2)}.$$

We would like to remind a reader that we are interested in bivariate modelling, therefore we apply $\widehat{SR}(\tau) - 1$.

5.6 Results

We present the results of empirical estimation. The analysis of interdependencies is first carried out in each sector separately. Then we also estimate the level of interdependence across both sectors. We create all possible combinations of institutions so that every single institution is combined with the others in the sample. Our sample consisting of 20 banks and 20 insurance companies thus generates a total number of 190 combinations in the banking sector, 190 combinations in the insurance sector and 400 bank-to-insurer combinations.

We test dependencies in the two sample periods. The boundary line between them is December 31th, 2007. Our aim is to split data into the relatively calm period preceding the crisis times and the period marked by financial turbulences due to the crisis. We give several reasons for studying institution-to-institution interlinkages in the two separate periods. Firstly, we believe that systemic dependencies evolve in time and thus to some extent reflect the changing macroeconomic environment. Secondly, we believe that the development on the global financial systems has deepened interconnections between bank and insurance groups and as a result, the systemic risk increased.

The first period ranges from January, 1999 to December, 2007. The second sample period starts in January, 2008 and it continues up to April, 2014. Throughout the analysis we apply the threshold which corresponds to 3.5 standard deviations from the mean loss return. This threshold value stands for the amount of daily loss triggering the failure of institutions.

5.6.1 Pre-crisis Period

In Table 5.4 we summarize the average and median level of intra-sectoral and inter-sectoral dependencies in the period covering the span from January, 4th 1999 until December 31th, 2007.

Table 5.4: The overall sectoral dependence, pre-crisis period

Sectors	Average $SR(\tau) - 1$	Median $SR(\tau) - 1$	Threshold
Bank-to-Bank	0.085	0.063	t=3.5 st.d.
Insurer-to-Insurer	0.069	0.046	t=3.5 st.d.
Bank-to-Insurer	0.073	0.048	t=3.5 st.d.

Source: Author's computations

Our findings indicate that in the first examined period the banking sector exhibits slightly higher systemic dependencies than the insurance sector. The average probability of a single-bank crash resulting in a crash of another bank exceeds 8 %. To be more precise, it reaches 8.5 %. In comparison, the insurance sector appears to be more stable and posing even lower threat to the international financial stability. In the insurance industry the average probability that two insurance companies break down, given that at least one has already failed, amounts to 6.9 %, which is slightly less than in case of two banks. In other words, using a similar interpretation as in Slijkerman et al. (2005), while a joint failure of two banks on average occurs in one out of 11.7 times when there is a bank collapse, two insurance companies fall down together only in one out of 14.4 cases when there is an insurer's failure. There might exist several reasons for lower level of interdependence in the insurance sector. One possible explanation might be that insurance companies provide a wider range of services to their clients and it makes them less mutually dependent than lending-oriented banks. In addition, insurance companies are usually of much smaller size in comparison with banks. In Table A.2 in Appendix A one can notice that the size of the EU largest insurance company ING, measured according to the total volume of assets, corresponds to the size of the 9th largest bank Lloyds. Hence, it can be expected, for instance, that the insurance industry holds a lower portion of derivatives trading, which normally represents one of the most relevant sources of dependence. Eventually, in terms of the inter-sectoral dependencies, the average probability that a bank goes bankrupt provided that an insurance company is bankrupt or alternatively, the probability that an insurance company breakdowns in response to a breakdown of a bank, is 7.3 %. Contrary to the outcome of Slijkerman et al. (2005), the inter-sectoral systemic risk appears to be slightly above the systemic risk within the insurance industry.

Focusing now on individual pairs, we show the largest institution-to-institution dependencies in Table 5.5. Complete results for all combinations are presented in Appendix A. On the bank level, the highest probability of a joint failure has been identified between Svenska Handelsbank and its Swedish counterparty Skandinavska Enskilda Bank. The probability that both banks fail, conditionally on a failure of one of them, is 36.4 %. Other extraordinary dependencies are apparent in pairs Societe Generale and Royal Bank of Scotland, British banks Lloyds and Barclays, or BNP Paribas and Deutsche Bank. In all cases the level of mutual dependence exceeds 30 %, which is well above the sector average. The fact that we monitor strong dependencies between banks originating in the same country may refer to their common exposures to risks, which are specific to the given country. On the other hand, if ve focus on detailed results for bank-to-bank combinations in Table A.5 in Appendix A, we can see that for many combinations the conditional probability of a simultaneous failure is 0 %. For these pairs no simultaneous losses corresponding to the size of our threshold have been identified in the examined period, which means that a breakdown of one institution remains isolated with no systemic impact on the other institution in the pair.

Table 5.5: Largest individual dependencies, pre-crisis period

Bank	**Bank**	$SR(\tau)-1$	**Insurer**	**Insurer**	$SR(\tau)-1$	**Bank**	**Insurer**	$SR(\tau)-1$
SHBA	SEBA	0.364	AGN	CS	0.368	SAN	AGN	0.375
GLE	RBS	0.357	AGN	INGA	0.304	GLE	AGN	0.353
LLOY	BARC	0.357	AV	INGA	0.304	BNP	CS	0.353
BNP	DBK	0.313	AV	ALV	0.304	BNP	AGS	0.353
BBVA	GLE	0.313	MUV2	ALV	0.292	SAN	G	0.316
SEBA	BARC	0.308	AGS	INGA	0.280	DBK	ALV	0.294
GLE	BNP	0.294	CS	INGA	0.273	BNP	INGA	0.278
LLOY	RBS	0.286	MUV2	AV	0.273	DBK	MUV2	0.278

Source: Author's computations

Moving on to individual insurer-to-insurer dependencies, the largest systemic risk has been detected between Aegon and AXA. The conditional probability that Aegon crashes given that AXA has already crashed and vice versa amounts to 36.8 %. The other high systemic risk exposures are to be found between Aegon and ING, Aviva and ING or Aviva and Allianz, in which cases the conditional probabilities of joint crashes are slightly above 30 %. Taking a look at complete results for all insurer-to-insurer combinations in Table A.6 in Appendix A, it is interesting to notice that systemic risk exposures concentrate predominantly within the 10 largest insurance companies. For the rest of insurance companies in the sample, the conditional probability of a joint failure in most cases does not go beyond 10 %. Again, for many pairs no simultaneous crash has been detected. It applies for example to insurers Sampo, Uniqua and Nurnberger, in which cases the conditional probability of a joint crash only occassionally touches 6 % in pairs with other insurance companies, yet in most cases it is 0 %. At last, it remains to examine cross-sectoral systemic risk at the level of individual insitutions. Our results attribute the largest systemic dependence to Banco Santander and Aegon. The probability of the bank's failure provided that the insurance company has failed, and vice versa, is 37.5 %. The other high conditional probabilities about 35 % apply to pairs Societe Generale and Aegon, BNP Paribas and Aegon or BNP Paribas and Ageas. Therefore, it seems that cross-sectoral dependecies between some of the

EU largest banks and insurace companies also poses a potential threat to the international financial stability.

5.6.2 Post-crisis Period

Having examined systemic risk between the EU largest banks and insurance companies in the pre-crisis period, we now proceed to the estimation of systemic dependencies in the period characterized by turbulent times around the Lehman bankruptcy. The examined period also reflects the post-Lehman development. It starts in January, 2008 and continues up to April, 2014.

Table 5.6 offers results for the average and median of estimates of intra- and inter-sectoral dependencies.

Table 5.6: The overall sectoral dependence, post-crisis period

Sectors	Average $SR(\tau) - 1$	Median $SR(\tau) - 1$	Threshold
Bank-to-Bank	0.109	0.100	t=3.5 st.d.
Insurer-to-Insurer	0.104	0.077	t=3.5 st.d.
Bank-to-Insurer	0.123	0.071	t=3.5 st.d.

Source: Author's computations

Our findings indicate that compared to the pre-crisis period, the systemic risk increased in both examined industries. Furthermore, systemic dependencies across both sectors also increased. This is in line with our expectations about deepened interconnections between bank and insurance groups in recent years. This time, the average probability of a simultaneous breakdown of two banks, provided that one bank breakdowns, rose to 10.9 %. It represents an increase in the average level of interdependence in the banking industry amounting to 28 %. In comparison, the average probability that two insurance companies collapse, given that one has collapsed, is 10.4 %, which yields 50 % increase in the average level of interconnections in the insurance industry. At last, the average probability of a bank's collapse, provided that an insurer collapses and vice versa, rose to 12.3 %. Compared to 7.3 % in the pre-crisis period, the average level of interdependence across both sector increased even more relatively to the banking and insurance industries. Most interestingly, we find that in the second examined period inter-sectoral systemic dependencies pose higher threat to the international financial stability than systemic dependencies in the banking sector.

Let us now move on to individual pairs. Starting with banks, the largest holders of systemic risk in the post-crisis period are French banks Societe Generale, Credit Agricole and BNP Paribas. The highest conditional probability of a simultaneous failure has been identified between Societe Generale and Credit Agricole, which is then followed by pairs Societe Generale and BNP Paribas and Credit Agricole and BNP Paribas. Their conditional probabilities amount to 45.5 %, 30.8 % and 30 %, respectively. The other strong relationship is found between Spanish banks Banco Bilbao and Banco Santander with the conditional probability as much as 30 %. If we look at the complete results for all bank-to-bank combinations in Table A.8 in Appendix A, one may notice that systemic risk has spread and expanded in the post-crisis period, as conditional probabilities of a joint failure approaching 30 % concern a greater number of banks. However, it is hardly possible to identify "hotspots" of systemic dependencies, as it is rather dispersed across the sample. On the contrary, Belgian Dexia bank exhibits a very weak potential for systemic risk as in pairs with other banks, the conditional probability of a simultaneous crash only seldom exceeds 5 %. Focusing on insurers, it is interesting that with some exceptions, stronger sys-

Table 5.7: Largest individual dependencies, post-crisis period

Bank	**Bank**	SR(tau)-1	**Insurer**	**Insurer**	SR(tau)-1	**Bank**	**Insurer**	SR(tau)-1
GLE	ACA	0.455	AGN	INGA	0.438	SAN	CS	0.455
GLE	BNP	0.308	ALV	CS	0.429	NDA	AGN	0.455
ACA	BNP	0.300	AGN	LGEN	0.412	SHBA	SAN	0.417
BBVA	SAN	0.300	MED	ALV	0.400	BNP	CS	0.364
ISP	GLE	0.286	ALV	INGA	0.353	HSBA	ALV	0.333
STAN	BBVA	0.286	CS	INGA	0.313	DBK	ALV	0.333
STAN	DBK	0.278	SAMAS	AGN	0.313	HSBA	LGEN	0.308
UCG	ACA	0.267	AV	INGA	0.294	RBS	AV	0.308

Source: Author's computations

temic dependencies are clustered predominantly among the 8 largest insurance companies. The remaining insurers in most cases do not exhibit any excessively high conditional probabilities of a simultaneous collapse. We discover the highest potential for systemic failure between ING and Aegon with the conditional probability being 43.8 %. The other high probabilities above 40 % are to be found in pairs Allianz and AXA, Aegon and Legal&General Group, or Mediolanum and Allianz. Examining individual bank-to-insurer dependencies, we find some evidence that the 8 largest insurance companies are also prone to systemic breakdowns in tandem with banks. The largest exposures are uncovered between Banco Santander and AXA and Nordea bank and Aegon. For both pairs the conditional probability is very high and exceeds the level of 45 %.

5.6.3 Testing Significance

Once intra-sectoral and inter-sectoral systemic risk has been explored, we need to look for statistical evidence that systemic dependencies in the examined sectors are statistically different in both examined periods. Hence, following Slijkerman et al. (2005), we use the Wilcoxon-Signed Rank test.[3] Since this non-parametric test is often used for comparing matched samples in which the assumption about normality might not be satisfied, it seems to be well suited for our data. It tests the null hypothesis that the mean difference between two related samples is equal to zero. In this manner, we test for the difference between the systemic dependence in the banking and insurance sectors in the pre-crisis and post-crisis periods. Subsequently, we also test whether the difference in bank-to-insurer dependence in both examined periods statistically differs from zero.[4] Since in all cases the p-value is equal to 0, we reject the null hypothesis at 5 % and 1 % significance level and may conclude that systemic dependencies in the banking sector are stronger and statistically different from systemic dependencies in the insurance sector in both pre-crisis and post-crisis periods. Similarly, the post-crisis period exhibits higher and statistically different bank-to-bank, insurer-to-insurer and bank-to-insurer dependencies than the pre-crisis period.

5.7 Discussion and Policy Implications

In this thesis we explore a potential for systemic risk in the international financial systems through investigating systemic dependencies between bank and insurance groups. Our results indicate an increase in the level of systemic dependencies in all examined relationships in recent years. Hence, there is no dispute that nowadays systemic risk inseparably belongs to the main issues associated with modern financial systems. The question is how this relatively new form of risk will be treated by regulatory authorities and whether it will be reflected in regulatory actions taken by regulators. The current financial regulation goes rather towards the protection of individual financial institutions against extreme market shocks while not taking into account the fact that interdependencies among financial institutions are a hidden threat to the financial system as a whole. Therefore, should systemic risk be taken into consideration

[3]For more information and references, see for example Chlass and Krueger (2007).
[4]Computations has been made in the statistical software SPSS.

for setting regulatory requirements, large systemically important and highly interconnected financial institutions might be a subject of higher capital charges than institutions with only a minor systemic impact. On the level of insurance companies, for instance, we have identified clustering of systemic risk mainly among the 10 largest insurance companies, suggesting that these may belong to the institutions due to which the current regulation might be redesigned in the future.

Chapter 6

Conclusion

In recent decades financial systems all over the world have undergone a rapide wave of expansion and enhancements. Major purpose of such development can be attributed to the efforts of financial authorities to promote accelerating execution of financial transactions, eliminating transaction costs, facilitating cross-border capital flows, and all together thus lead towards the global economic growth. One of direct consequences of the process of financial liberalization is that national financial systems have somewhat disappeared and they rather transformed into a huge global financial ecosystem, where financial institutions are free to closely cooperate. On one hand, this process carries numerous positives, yet it is necessary to emphasize new forms of risks it is connected with. Most importantly, deepened cooperation leads to the formation of various sources of dependence due to which financial institutions can easily transfer risk exposures from one to another. This risk gains in importance during crisis times, when breakdowns of individual institutions no longer remain an issue of those institutions, but they concern other entities even beyond national borders.

The risk of occurrence of extreme market situations is ubiquitous in finance industry and one of the major tasks for risk management is the ability to effectively handle it. Extreme events receive lots of attention particularly in response to the recent crisis, which showed its power and opened wide discussions regarding interconnectedness of financial systems. The crisis also uncovered imperfections of models applied for analysis of institutional risks and in many cases it led to the reshaping of current risk management frameworks. To ensure that financial institutions, or rather the entire financial systems, are able to withstand extreme market situations, it is crucial that extreme returns are modelled precisely and accurately.

Hence, we apply method which disregards ordinary financial returns and deals only with outlying observations located in tail areas of distribution of returns. We study dependencies in extremes between bank and insurance groups in order to investigate the eventuality of simultaneous crashes that could threaten the stability of the international financial system. For the analysis we collected data on stock prices of the 20 EU largest banks and insurance companies from January, 1999 until April, 2014. We split data into two shorter time ranges and examine dependencies in the pre-crisis as well as in the post-crisis period.

Our results suggest that in both examined periods the banking sector exhibits a higher potential for systemic risk than the insurance sector. With this respect, our findings are compatible with the outcome of Slijkerman et al. (2005) and De Vries (2009). In the pre-crisis period the average probability of a simultaneous crash of two banks is 8.5 %, whereas for insurers it yields 6.9 %. In the post-crisis period the average conditional probabilities in both sectors converged, yet the risk of simultaneous breakdowns is still slightly higher between banks (10.9 %) than between insurers (10.4 %). Secondly, we find that dependencies evolve in time and under different market conditions. In all examined relationships systemic dependencies prove to be higher in the post-crisis period than in the pre-crisis period. In the banking sector we record 28% increase in the average level of dependence, in the insurance sector it amounts to 50 %, and an increase in the average level of dependence between a bank and an insurer reaches 68 %. The latter uncovers another important fact, which is a necessity to promote monitoring of dependencies across the respective sectors. Before crisis the average probability of a joint collapse of a bank and an insurer amounts to 7.3 % and this probability jumped to 12.3 % in the post-crisis period. Compared to 10.9 % in the banking sector and 10.4 % in the insurance sector, it seems that bank-to-insurer interconnections are becoming increasingly important issue in terms of systemic risk and stability of the international financial system. Therefore, the findings of this thesis are relevant mainly to regulatory authorities, as it can familiarize them with the changing pattern of dependencies between most systemically important institutions.

If we compare our results with the outcomes of theoretical model presented in Chapter 5, we may conclude that at least in crisis times the effect of sector-specific risks is outweighed by a new form of risks emerging between bank and insurance sectors. The efforts to determine what particular risks these are can form the basis for further research in this field.

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Appendix A

Tables

[1]

Table A.1: Detailed information about the sample banks

Equity	**Assets ($bn)**	**Category**	**Country**	**Stock Exchange**	**Obs.**
HSBA	2 684.1	Major	UK	London	3865
DBK	2 652.6	Major	Germany	Germany	3892
BNP	2 504.2	Major	France	Euronext Paris	3909
ACA	2 431.4	Major	France	Euronext Paris	3160
BARC	2 422.5	Major	UK	London	3865
RBS	2 133.1	Major	UK	London	3865
GLE	1 648.9	Major	France	Euronext Paris	3908
SAN	1 647.8	Major	Spain	Spain	3871
LLOY	1 495.9	Major	UK	London	3865
UCG	1 221.9	Major	Italy	Borsa Italiana	3882
NDA	892.6	Regional	Sweden	Stockholm	3842
BBVA	840.8	Major	Spain	Spain	3871
CBK	838.3	Major	Germany	Germany	3891
ISP	813.8	Major	Italy	Borsa Italiana	3883
KN	658.0	Major	France	Euronext Paris	3907
STAN	636.5	Major	UK	London	3865
DANSKE	615.6	Major	Denmark	Copenhagen	3830
DEXB	534.9	Major	Belgium	Euronext Brussels	3903
SEBA	376.8	Major	Sweden	Stockholm	3842
SHBA	367.0	Major	Sweden	Stockholm	3842

Source: Author

[1] All data and computations are available on demand at the author.

Table A.2: Detailed information about the sample insurers

Equity	**Assets ($bn)**	**Category**	**Country**	**Stock Exchange**	**Obs.**
INGA	1 533.7	Life&Health	Netherlands	Euronext Amsterdam	3911
CS	1 005.4	Diversified	France	Euronext Paris	3910
ALV	915.8	Diversified	Germany	Germany	3892
G	582.4	Diversified	Italy	Borsa Italiana	3882
LGEN	562.9	Life&Health	UK	London	3865
AV	512.7	Life&Health	UK	London	3865
PRU	489.4	Life&Health	UK	London	3865
AGN	483.2	Diversified	Netherlands	Euronext Amsterdam	3910
CNP	466.1	Diversified	France	Euronext Paris	3910
MUV2	340.6	Diversified	Germany	Germany	3892
AGS	128.0	Diversified	Belgium	Euronext Brussels	3894
UNI	109.7	Diversified	Italy	Borsa Italiana	3882
MAP	69.2	Diversified	Spain	Spain	3872
VIG	50.0	Diversified	Austria	Vienna	3650
MED	43.7	Life&Health	Italy	Borsa Italiana	3883
SCR	43.0	Diversified	France	Euronext Paris	3910
SAMAS	41.4	Diversified	Finland	Helsinky	3839
UQA	37.0	Diversified	Austria	Vienna	3566
NBG6	28.9	Diversified	Germany	Germany	3892
CASS	23.2	Diversified	Italy	Borsa Italiana	3404

Source: Author

Equity	t-statistics	p-value
HSBA	21988.60	0
DBK	8743.59	0
BNP	9390.10	0
ACA	4895.71	0
BARC	182659.00	0
RBS	1096520.00	0
GLE	5789.98	0
SAN	5514.20	0
LLOY	172472.00	0
UCG	7799.18	0
NDA	4447.22	0
BBVA	4743.51	0
CBK	9701.77	0
ISP	4820.18	0
KN	42493.20	0
STAN	17271.50	0
DANSKE	4710.92	0
DEXB	55467.00	0
SEBA	15296.40	0
SHBA	5253.31	0

Table A.3: JB normality test for banks

Equity	t-statistics	p-value
INGA	25318.20	0
CS	7093.91	0
ALV	688.73	0
G	1559.92	0
LGEN	30775.90	0
AV	50256.20	0
PRU	14985.40	0
AGN	19596.50	0
CNP	1550.89	0
MUV2	7678.67	0
AGS	1703140.00	0
UNI	178558.00	0
MAP	4210.91	0
VIG	21028.10	0
MED	1373.78	4.9E-299
SCR	85586.30	0
SAMAS	10039.90	0
UQA	11452.10	0
NBG6	17138.40	0
CASS	3527.73	0

Table A.4: JB normality test for insurers

Table A.5: Bank-to-bank dependence, pre-crisis period

	HSBA 1	DBK 2	BNP 3	ACA 4	BARC 5	RBS 6	GLE 7	SAN 8	LLOY 9	UCG 10	NDA 11	BBVA 12	CBK 13	ISP 14	KN 15	STAN 16	DANSKE 17	DEXB 18	SEBA 19	SHBA 20
1	1.000	0.056	0.111	0.111	0.125	0.133	0.176	0.125	0.118	0.125	0.105	0.111	0.100	0.059	0.000	0.214	0.000	0.050	0.125	0.000
2	0.056	1.000	0.313	0.000	0.059	0.059	0.105	0.000	0.056	0.118	0.048	0.000	0.136	0.100	0.000	0.059	0.048	0.095	0.056	0.000
3	0.111	0.313	1.000	0.133	0.053	0.118	0.294	0.056	0.111	0.111	0.095	0.167	0.200	0.100	0.000	0.118	0.045	0.095	0.176	0.133
4	0.111	0.000	0.133	1.000	0.000	0.067	0.071	0.091	0.071	0.077	0.067	0.071	0.077	0.067	0.000	0.000	0.000	0.000	0.125	0.200
5	0.125	0.059	0.053	0.000	1.000	0.214	0.176	0.063	0.357	0.063	0.053	0.125	0.050	0.063	0.000	0.063	0.000	0.176	0.063	0.000
6	0.133	0.059	0.118	0.067	0.214	1.000	0.357	0.067	0.286	0.063	0.111	0.063	0.167	0.063	0.056	0.067	0.000	0.053	0.308	0.077
7	0.176	0.105	0.294	0.071	0.176	0.357	1.000	0.053	0.250	0.053	0.095	0.313	0.143	0.100	0.048	0.118	0.000	0.045	0.176	0.063
8	0.125	0.000	0.056	0.091	0.063	0.067	0.053	1.000	0.056	0.056	0.000	0.267	0.000	0.000	0.000	0.133	0.050	0.050	0.056	0.000
9	0.118	0.056	0.111	0.071	0.357	0.286	0.250	0.056	1.000	0.059	0.050	0.176	0.100	0.059	0.000	0.059	0.000	0.105	0.125	0.071
10	0.125	0.118	0.111	0.077	0.063	0.063	0.053	0.056	0.059	1.000	0.050	0.053	0.048	0.111	0.053	0.133	0.000	0.050	0.056	0.000
11	0.105	0.048	0.095	0.067	0.053	0.111	0.095	0.000	0.050	0.050	1.000	0.000	0.136	0.050	0.000	0.053	0.043	0.091	0.235	0.200
12	0.111	0.000	0.167	0.071	0.125	0.063	0.313	0.267	0.176	0.053	0.000	1.000	0.045	0.105	0.000	0.125	0.045	0.048	0.118	0.067
13	0.100	0.136	0.200	0.077	0.050	0.167	0.143	0.000	0.100	0.048	0.136	0.045	1.000	0.091	0.043	0.050	0.000	0.087	0.158	0.056
14	0.059	0.100	0.100	0.067	0.063	0.063	0.100	0.000	0.059	0.111	0.050	0.105	0.091	1.000	0.048	0.000	0.000	0.048	0.118	0.071
15	0.000	0.000	0.000	0.000	0.000	0.056	0.048	0.000	0.000	0.053	0.000	0.000	0.043	0.048	1.000	0.056	0.000	0.095	0.053	0.000
16	0.214	0.059	0.118	0.000	0.063	0.067	0.118	0.133	0.059	0.133	0.053	0.125	0.050	0.000	0.056	1.000	0.000	0.053	0.133	0.077
17	0.000	0.048	0.045	0.000	0.000	0.000	0.000	0.050	0.000	0.000	0.043	0.045	0.000	0.000	0.000	0.000	1.000	0.091	0.105	0.059
18	0.050	0.095	0.095	0.000	0.176	0.053	0.045	0.050	0.105	0.050	0.091	0.048	0.087	0.048	0.095	0.053	0.091	1.000	0.167	0.059
19	0.125	0.056	0.176	0.125	0.063	0.308	0.176	0.056	0.125	0.056	0.235	0.118	0.158	0.118	0.053	0.133	0.105	0.167	1.000	0.364
20	0.000	0.000	0.133	0.200	0.000	0.077	0.063	0.000	0.071	0.000	0.200	0.067	0.056	0.071	0.000	0.077	0.059	0.059	0.364	1.000

Source: Author's computations

Table A.6: Insurer-to-insurer dependence, pre-crisis period

	INGA	CS	ALV	G	LGEN	AV	PRU	AGN	CNP	MUV2	AGS	UNI	MAP	VIG	MED	SCR	SAMAS	UQA	NBG6	CASS
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
1	1.000	0.273	0.231	0.217	0.000	0.304	0.211	0.304	0.000	0.250	0.280	0.000	0.100	0.000	0.095	0.107	0.000	0.000	0.000	0.217
2	0.273	1.000	0.167	0.263	0.063	0.182	0.267	0.368	0.056	0.227	0.217	0.048	0.059	0.000	0.000	0.174	0.059	0.063	0.000	0.120
3	0.231	0.167	1.000	0.167	0.050	0.304	0.150	0.154	0.000	0.292	0.185	0.000	0.048	0.000	0.045	0.069	0.048	0.000	0.000	0.143
4	0.217	0.263	0.167	1.000	0.000	0.227	0.176	0.238	0.000	0.238	0.174	0.048	0.059	0.000	0.056	0.174	0.000	0.000	0.000	0.200
5	0.000	0.063	0.050	0.000	1.000	0.056	0.091	0.056	0.000	0.056	0.000	0.071	0.000	0.000	0.000	0.053	0.000	0.000	0.000	0.045
6	0.304	0.182	0.304	0.227	0.056	1.000	0.235	0.120	0.000	0.273	0.115	0.000	0.118	0.000	0.100	0.160	0.056	0.000	0.045	0.154
7	0.211	0.267	0.150	0.176	0.091	0.235	1.000	0.167	0.000	0.105	0.100	0.000	0.083	0.000	0.250	0.100	0.000	0.000	0.000	0.143
8	0.304	0.368	0.154	0.238	0.056	0.120	0.167	1.000	0.050	0.167	0.250	0.000	0.050	0.000	0.050	0.074	0.000	0.053	0.000	0.160
9	0.000	0.056	0.000	0.000	0.000	0.000	0.000	0.050	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.083	0.000	0.045
10	0.250	0.227	0.292	0.238	0.056	0.273	0.105	0.167	0.000	1.000	0.154	0.000	0.053	0.000	0.000	0.200	0.053	0.000	0.000	0.103
11	0.280	0.217	0.185	0.174	0.000	0.115	0.100	0.250	0.000	0.154	1.000	0.000	0.053	0.000	0.000	0.107	0.000	0.000	0.000	0.074
12	0.000	0.048	0.000	0.048	0.071	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.053	0.000	0.042	0.000	0.063	0.000	0.115
13	0.100	0.059	0.048	0.059	0.000	0.118	0.083	0.050	0.000	0.053	0.053	0.000	1.000	0.000	0.000	0.048	0.000	0.000	0.000	0.048
14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.053	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000
15	0.095	0.000	0.045	0.056	0.000	0.100	0.250	0.050	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.091
16	0.107	0.174	0.069	0.174	0.053	0.160	0.100	0.074	0.000	0.200	0.107	0.042	0.048	0.000	0.000	1.000	0.000	0.000	0.000	0.103
17	0.000	0.059	0.048	0.000	0.000	0.056	0.000	0.000	0.000	0.053	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000
18	0.000	0.063	0.000	0.000	0.000	0.000	0.000	0.053	0.083	0.000	0.000	0.063	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000
19	0.000	0.000	0.000	0.000	0.000	0.045	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000
20	0.217	0.120	0.143	0.200	0.045	0.154	0.143	0.160	0.045	0.103	0.074	0.115	0.048	0.000	0.091	0.103	0.000	0.000	0.000	1.000

Source: Author's computations

Table A.7: Bank-to-insurer dependence, pre-crisis period

	B1	**B2**	**B3**	**B4**	**B5**	**B6**	**B7**	**B8**	**B9**	**B10**	**B11**	**B12**	**B13**	**B14**	**B15**	**B16**	**B17**	**B18**	**B19**	**B20**
I1	0.045	0.150	0.278	0.154	0.095	0.045	0.211	0.278	0.150	0.150	0.095	0.211	0.000	0.045	0.000	0.045	0.095	0.278	0.150	0.095
I2	0.000	0.211	0.353	0.250	0.095	0.095	0.353	0.211	0.095	0.095	0.150	0.095	0.095	0.211	0.000	0.000	0.100	0.278	0.278	0.095
I3	0.000	0.294	0.150	0.154	0.095	0.045	0.150	0.095	0.095	0.045	0.150	0.095	0.095	0.095	0.000	0.000	0.100	0.211	0.211	0.095
I4	0.048	0.150	0.211	0.250	0.048	0.100	0.150	0.316	0.000	0.211	0.095	0.211	0.045	0.150	0.000	0.048	0.048	0.211	0.150	0.150
I5	0.045	0.150	0.095	0.154	0.150	0.150	0.095	0.048	0.045	0.000	0.048	0.048	0.045	0.048	0.045	0.045	0.048	0.095	0.000	0.048
I6	0.000	0.095	0.150	0.071	0.150	0.045	0.150	0.100	0.150	0.100	0.100	0.100	0.045	0.048	0.000	0.000	0.100	0.150	0.158	0.100
I7	0.095	0.278	0.045	0.250	0.150	0.211	0.095	0.158	0.045	0.100	0.100	0.158	0.045	0.158	0.045	0.045	0.100	0.211	0.048	0.100
I8	0.045	0.211	0.211	0.250	0.150	0.150	0.353	0.375	0.211	0.211	0.095	0.150	0.045	0.095	0.000	0.045	0.095	0.211	0.150	0.095
I9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
I10	0.000	0.278	0.211	0.250	0.045	0.095	0.211	0.211	0.045	0.045	0.150	0.095	0.045	0.095	0.000	0.000	0.100	0.278	0.211	0.095
I11	0.000	0.211	0.353	0.250	0.150	0.045	0.278	0.211	0.150	0.211	0.150	0.095	0.045	0.095	0.000	0.045	0.100	0.278	0.211	0.095
I12	0.000	0.000	0.045	0.000	0.000	0.000	0.000	0.045	0.000	0.095	0.000	0.000	0.000	0.045	0.045	0.000	0.000	0.000	0.000	0.000
I13	0.048	0.045	0.000	0.071	0.000	0.048	0.000	0.045	0.000	0.095	0.000	0.045	0.045	0.045	0.000	0.048	0.048	0.000	0.000	0.000
I14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
I15	0.048	0.150	0.095	0.154	0.048	0.100	0.095	0.150	0.000	0.211	0.045	0.150	0.150	0.095	0.000	0.048	0.048	0.095	0.095	0.045
I16	0.000	0.095	0.045	0.071	0.045	0.045	0.045	0.045	0.000	0.045	0.045	0.045	0.095	0.045	0.000	0.000	0.000	0.045	0.045	0.045
I17	0.000	0.000	0.048	0.071	0.000	0.048	0.048	0.048	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.048	0.000	0.000
I18	0.000	0.000	0.053	0.000	0.000	0.000	0.053	0.000	0.053	0.000	0.053	0.000	0.000	0.000	0.000	0.000	0.053	0.000	0.053	0.000
I19	0.045	0.000	0.045	0.000	0.000	0.045	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.045	0.045	0.000	0.000	0.000	0.045
I20	0.0000	0.0000	0.0000	0.0714	0.0000	0.0000	0.0000	0.0588	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0588	0.0000	0.0000	0.0000	0.0000	0.0000

Source: Author's computations

Table A.8: Bank-to-Bank dependence, post-crisis period

	HSBA	DBK	BNP	ACA	BARC	RBS	GLE	SAN	LLOY	UCG	NDA	BBVA	CBK	ISP	KN	STAN	DANSKE	DEXB	SEBA	SHBA
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
1	1.000	0.118	0.250	0.154	0.167	0.143	0.056	0.200	0.111	0.100	0.071	0.273	0.063	0.063	0.111	0.222	0.125	0.000	0.167	0.059
2	0.118	1.000	0.063	0.231	0.100	0.063	0.111	0.059	0.105	0.095	0.143	0.071	0.200	0.059	0.167	0.278	0.056	0.042	0.222	0.111
3	0.250	0.063	1.000	0.300	0.125	0.083	0.308	0.154	0.063	0.176	0.091	0.091	0.071	0.071	0.000	0.056	0.000	0.000	0.125	0.067
4	0.154	0.231	0.300	1.000	0.125	0.083	0.455	0.077	0.063	0.267	0.000	0.100	0.273	0.167	0.133	0.118	0.071	0.000	0.125	0.000
5	0.167	0.100	0.125	0.125	1.000	0.267	0.158	0.050	0.211	0.136	0.214	0.063	0.111	0.053	0.095	0.087	0.111	0.000	0.095	0.176
6	0.143	0.063	0.083	0.083	0.267	1.000	0.214	0.067	0.200	0.053	0.182	0.091	0.154	0.071	0.059	0.111	0.143	0.000	0.118	0.067
7	0.056	0.111	0.308	0.455	0.158	0.214	1.000	0.125	0.050	0.150	0.333	0.071	0.200	0.286	0.105	0.095	0.118	0.000	0.222	0.111
8	0.200	0.059	0.154	0.077	0.050	0.067	0.125	1.000	0.000	0.050	0.000	0.300	0.000	0.067	0.000	0.158	0.133	0.000	0.111	0.000
9	0.111	0.105	0.063	0.063	0.211	0.200	0.050	0.000	1.000	0.091	0.063	0.067	0.118	0.000	0.158	0.091	0.053	0.040	0.150	0.111
10	0.100	0.095	0.176	0.267	0.136	0.053	0.150	0.050	0.091	1.000	0.000	0.059	0.105	0.105	0.043	0.130	0.100	0.000	0.042	0.150
11	0.071	0.143	0.091	0.000	0.214	0.182	0.333	0.000	0.063	0.000	1.000	0.000	0.077	0.077	0.063	0.056	0.067	0.000	0.125	0.231
12	0.273	0.071	0.091	0.100	0.063	0.091	0.071	0.300	0.067	0.059	0.000	1.000	0.000	0.182	0.067	0.286	0.071	0.000	0.308	0.071
13	0.063	0.200	0.071	0.273	0.111	0.154	0.200	0.000	0.118	0.105	0.077	0.000	1.000	0.067	0.267	0.105	0.214	0.045	0.111	0.000
14	0.063	0.059	0.071	0.167	0.053	0.071	0.286	0.067	0.000	0.105	0.077	0.182	0.067	1.000	0.056	0.105	0.133	0.000	0.176	0.125
15	0.111	0.167	0.000	0.133	0.095	0.059	0.105	0.000	0.158	0.043	0.063	0.067	0.267	0.056	1.000	0.143	0.111	0.040	0.211	0.000
16	0.222	0.278	0.056	0.118	0.087	0.111	0.095	0.158	0.091	0.130	0.056	0.286	0.105	0.105	0.143	1.000	0.100	0.037	0.316	0.158
17	0.125	0.056	0.000	0.071	0.111	0.143	0.118	0.133	0.053	0.100	0.067	0.071	0.214	0.133	0.111	0.100	1.000	0.000	0.100	0.053
18	0.000	0.042	0.000	0.000	0.000	0.000	0.000	0.000	0.040	0.000	0.000	0.000	0.045	0.000	0.040	0.037	0.000	1.000	0.038	0.000
19	0.167	0.222	0.125	0.125	0.095	0.118	0.222	0.111	0.150	0.042	0.125	0.308	0.111	0.176	0.211	0.316	0.100	0.038	1.000	0.222
20	0.059	0.111	0.067	0.000	0.176	0.067	0.111	0.000	0.111	0.150	0.231	0.071	0.000	0.125	0.000	0.158	0.053	0.000	0.222	1.000

Source: Author's computations

Table A.9: Insurer-to-Insurer dependence, post-crisis period

	INGA **1**	CS **2**	ALV **3**	G **4**	LGEN **5**	AV **6**	PRU **7**	AGN **8**	CNP **9**	MUV2 **10**	AGS **11**	UNI **12**	MAP **13**	VIG **14**	MED **15**	SCR **16**	SAMAS **17**	UQA **18**	NBG6 **19**	CASS **20**
1	1.000	0.313	0.353	0.000	0.333	0.294	0.222	0.438	0.125	0.176	0.200	0.048	0.071	0.067	0.067	0.111	0.167	0.056	0.048	0.118
2	0.313	1.000	0.429	0.091	0.167	0.118	0.267	0.250	0.071	0.214	0.077	0.056	0.091	0.083	0.083	0.063	0.059	0.067	0.056	0.231
3	0.353	0.429	1.000	0.077	0.150	0.158	0.222	0.294	0.063	0.188	0.143	0.000	0.077	0.188	0.071	0.188	0.222	0.048	0.050	0.200
4	0.000	0.091	0.077	1.000	0.000	0.077	0.000	0.000	0.000	0.000	0.000	0.083	0.000	0.000	0.400	0.000	0.000	0.000	0.000	0.000
5	0.333	0.167	0.150	0.000	1.000	0.200	0.263	0.412	0.056	0.176	0.188	0.000	0.071	0.125	0.067	0.000	0.050	0.167	0.158	0.125
6	0.294	0.118	0.158	0.077	0.200	1.000	0.294	0.222	0.063	0.188	0.000	0.000	0.077	0.200	0.071	0.118	0.105	0.050	0.050	0.063
7	0.222	0.267	0.222	0.000	0.263	0.294	1.000	0.222	0.063	0.188	0.133	0.050	0.167	0.125	0.071	0.118	0.105	0.050	0.105	0.133
8	0.438	0.250	0.294	0.000	0.412	0.222	0.222	1.000	0.063	0.188	0.250	0.000	0.167	0.200	0.154	0.118	0.313	0.105	0.050	0.200
9	0.125	0.071	0.063	0.000	0.056	0.063	0.063	0.063	1.000	0.077	0.000	0.000	0.125	0.182	0.000	0.000	0.000	0.143	0.067	0.083
10	0.176	0.214	0.188	0.000	0.176	0.188	0.188	0.188	0.077	1.000	0.071	0.000	0.222	0.154	0.091	0.067	0.000	0.059	0.059	0.154
11	0.200	0.077	0.143	0.000	0.188	0.000	0.133	0.250	0.000	0.071	1.000	0.067	0.111	0.091	0.000	0.077	0.143	0.071	0.000	0.200
12	0.048	0.056	0.000	0.083	0.000	0.000	0.050	0.000	0.000	0.000	0.067	1.000	0.000	0.000	0.077	0.000	0.000	0.000	0.000	0.000
13	0.071	0.091	0.077	0.000	0.071	0.077	0.167	0.167	0.125	0.222	0.111	0.000	1.000	0.250	0.167	0.000	0.000	0.083	0.083	0.111
14	0.067	0.083	0.188	0.000	0.125	0.200	0.125	0.200	0.182	0.154	0.091	0.000	0.250	1.000	0.091	0.071	0.063	0.063	0.063	0.083
15	0.067	0.083	0.071	0.400	0.067	0.071	0.071	0.154	0.000	0.091	0.000	0.077	0.167	0.091	1.000	0.000	0.071	0.071	0.000	0.000
16	0.111	0.063	0.188	0.000	0.000	0.118	0.118	0.118	0.000	0.067	0.077	0.000	0.000	0.071	0.000	1.000	0.125	0.000	0.000	0.071
17	0.167	0.059	0.222	0.000	0.050	0.105	0.105	0.313	0.000	0.000	0.143	0.000	0.000	0.063	0.071	0.125	1.000	0.053	0.000	0.133
18	0.056	0.067	0.048	0.000	0.167	0.050	0.050	0.105	0.143	0.059	0.071	0.000	0.083	0.063	0.071	0.000	0.053	1.000	0.111	0.067
19	0.048	0.056	0.050	0.000	0.158	0.050	0.105	0.050	0.067	0.059	0.000	0.000	0.083	0.063	0.000	0.000	0.000	0.111	1.000	0.063
20	0.118	0.231	0.200	0.000	0.125	0.063	0.133	0.200	0.083	0.154	0.200	0.000	0.111	0.083	0.000	0.071	0.133	0.067	0.063	1.000

Source: Author's computations

Table A.10: Bank-to-insurer dependence, post-crisis period

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13	B14	B15	B16	B17	B18	B19	B20
I1	0.143	0.143	0.231	0.231	0.143	0.231	0.143	0.231	0.333	0.231	0.333	0.143	0.067	0.231	0.231	0.143	0.143	0.000	0.067	0.231
I2	0.231	0.231	0.364	0.231	0.067	0.067	0.231	0.455	0.143	0.143	0.385	0.333	0.143	0.333	0.231	0.333	0.231	0.000	0.333	0.261
I3	0.333	0.333	0.143	0.067	0.143	0.231	0.143	0.333	0.333	0.067	0.067	0.231	0.143	0.143	0.067	0.231	0.067	0.000	0.143	0.231
I4	0.067	0.000	0.143	0.143	0.143	0.143	0.231	0.231	0.143	0.143	0.143	0.231	0.067	0.231	0.143	0.143	0.067	0.000	0.067	0.067
I5	0.308	0.067	0.143	0.067	0.143	0.143	0.067	0.231	0.143	0.000	0.231	0.231	0.067	0.143	0.067	0.231	0.071	0.000	0.143	0.231
I6	0.231	0.067	0.231	0.143	0.231	0.308	0.067	0.231	0.295	0.067	0.143	0.143	0.143	0.067	0.067	0.143	0.000	0.000	0.231	0.333
I7	0.231	0.333	0.143	0.067	0.143	0.333	0.067	0.333	0.333	0.067	0.333	0.143	0.067	0.143	0.067	0.143	0.071	0.000	0.300	0.417
I8	0.231	0.231	0.231	0.231	0.143	0.143	0.143	0.143	0.333	0.231	0.455	0.067	0.000	0.143	0.143	0.067	0.231	0.000	0.333	0.313
I9	0.000	0.000	0.067	0.067	0.000	0.000	0.143	0.000	0.000	0.143	0.000	0.000	0.067	0.143	0.000	0.000	0.067	0.038	0.000	0.000
I10	0.333	0.143	0.143	0.143	0.067	0.143	0.143	0.333	0.231	0.067	0.143	0.231	0.143	0.231	0.000	0.231	0.143	0.000	0.067	0.231
I11	0.000	0.000	0.067	0.067	0.067	0.143	0.143	0.067	0.067	0.067	0.067	0.067	0.000	0.067	0.067	0.067	0.067	0.000	0.143	0.067
I12	0.067	0.000	0.000	0.000	0.067	0.000	0.000	0.067	0.000	0.000	0.000	0.067	0.000	0.067	0.000	0.067	0.067	0.000	0.000	0.000
I13	0.143	0.067	0.143	0.067	0.000	0.000	0.067	0.333	0.067	0.143	0.231	0.231	0.000	0.231	0.067	0.067	0.143	0.000	0.067	0.231
I14	0.071	0.143	0.143	0.231	0.071	0.154	0.231	0.143	0.250	0.143	0.333	0.067	0.067	0.067	0.143	0.154	0.000	0.000	0.143	0.333
I15	0.067	0.067	0.143	0.231	0.143	0.000	0.143	0.143	0.067	0.067	0.067	0.231	0.067	0.261	0.067	0.143	0.231	0.000	0.067	0.000
I16	0.143	0.143	0.143	0.067	0.067	0.067	0.067	0.143	0.067	0.067	0.067	0.143	0.231	0.143	0.067	0.143	0.143	0.000	0.143	0.067
I17	0.143	0.143	0.231	0.231	0.231	0.000	0.143	0.143	0.143	0.067	0.231	0.231	0.067	0.333	0.067	0.143	0.231	0.000	0.067	0.067
I18	0.000	0.000	0.067	0.067	0.071	0.000	0.067	0.067	0.000	0.067	0.067	0.067	0.067	0.067	0.067	0.071	0.154	0.000	0.067	0.000
I19	0.000	0.067	0.000	0.067	0.000	0.000	0.000	0.000	0.000	0.000	0.067	0.000	0.067	0.000	0.000	0.000	0.067	0.000	0.067	0.067
I20	0.143	0.067	0.067	0.067	0.067	0.067	0.067	0.231	0.143	0.067	0.067	0.067	0.143	0.143	0.067	0.143	0.143	0.000	0.067	0.143

Source: Author's computations