Financial Stability in the EU

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Financial Stability in the EU

Financiële stabiliteit in de EU

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When still attending primary school, there was a bookshelf with old books in my room. In it was a book by Jan Tinbergen. At that time, it was hard to imagine that I would obtain my doctorate at the Tinbergen Institute in Rotterdam.

The completion of this doctoral thesis marks the end of some very instructive years. The masters degree in Financial Economics from Erasmus University Rotterdam and from the Université de Science Social in Toulouse, provided a good basis for studying financial sector regulation. Nevertheless, a good theoretical basis does not suffice for completing a Ph.D. Good guidance and wisdom of the supervisors makes the life of a Ph.D. student much easier. Moreover, the support from family, friends and colleagues was a prerequisite for me to complete this research.

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Finally, I want to express my gratitude for the love and moral support of my parents.

J. F. S., Rotterdam, December 2006.

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Chapter 1

Introduction

Most people in Europe take the soundness of their banks and insurers for granted. They can do so, because the risk management of these institutions is advanced and there are highly skilled regulators monitoring the institutions on our behalf. As a result, there were not many bankruptcies of financial institutions in the last decade in Western Europe. Nevertheless, the challenge for regulators to understand risk in the financial sector is growing.

The two most prominent trends in the financial sector are the increase in cross-border business by financial institutions and an increase of risk transfers between institutions. Numerous banks and insurers offer their products abroad and invest their assets in multiple countries. Improved risk pricing techniques, together with an advanced technological infrastructure, support the transfer of risks between institutions. Firms do so to diversify their risk exposure. However, these developments did increase the complexity of the risks underlying a bank or an insurer.

The bankruptcy of a financial institution results in losses for consumers and other stakeholders. Since losses incurred by an institution may have an impact on the stability of the financial system, the mutual dependence among firms in the financial sector is the focus of regulation to promote financial stability. This is of particular importance in the banking sector where the maintenance of its payment and clearing services crucially hinge on the stability of the entire network of banks. In addition, financial institutions are regulated to minimize the losses for consumers.

The primary focus of regulators is to prevent the bankruptcy of individual banks and insurers. Regulators are interested in the downside risk of the value of assets and in the unexpected large liabilities of these institutions. Statistically speaking, they are interested in the lower tail of the return distribution of banks and insurers. A statistical tool to study the tails of distributions, is known as extreme value theory (EVT). EVT can be used to estimate the probability of a loss in stock market value of a bank or insurer, beyond losses observed before.

The secondary focus of regulators is the soundness of the financial system. The mutual relation between institutions may make individual institutions prone to a failure of a competitor. Financial institutions can be exposed to similar risks, creating a dependence between losses. As a consequence, institutions suffer losses simultaneously. This may strain the provision of banking and insurance services during crises. The modeling of dependence between the downside risk of institutions adds additional insights into the risks facing the financial sector.

Since the expected losses of multiple banks or insurers are of interest, the downside risk of multiple institutions is investigated. The negative returns of two or more banks and insurers are modelled, to study the effect of risk diversification. This helps us to understand the observed dependence between losses of multiple companies.

The modelling of downside risk provides in itself interesting insights. However, it is even more interesting to compared these models with an empirical evaluation of the loss distribution of firms in the financial sector. Estimating the downside risk provides information on the best means to diversify downside risk. Moreover, it is evaluated whether country risk and sector risk are an important determinant of downside risk.

The mutual relations within the insurance industry are more limited than in the banking sector. However, the returns of insurers can also be dependent, because insurers may hold similar assets and liabilities, which creates a similar risk profile. Insurers can have the same liabilities because of an exposure to similar clients and regions. If insurers have invested in the same assets, this can also be a source of mutual risks. The reinsurance sector is well known for the ability to insure major catastrophes or the ability to provide cover to insurers against exceptionally large claims. This way insurers can protect themselves against catastrophic losses.

However, an exposure of insurers to the same reinsurer is a risk factor they have in common. The exposure of reinsurers to the same disasters is another source of common risk.

Dependence within the banking sector is a well known topic in the economic literature. Banks are the cornerstone of the financial sector. They maintain the payment system and provide short term liquidity to firms and households as well as longer term loans. Banks are important for economic growth, since they finance trade and investments and give people the opportunity to save. The banking sector has gone through some very serious crises, as for example the savings and loans crisis in the US. Because of the impact of a banking crisis for real economic activity, this sector is strictly regulated at the international level by the Basel Committee on Banking Supervision.

According to the traditional industrial organization view, the financial sector can be divided in the following subsectors: the banking sector, the insurance sector and the reinsurance sector. Moreover, financial conglomerates providing both banking and insurance services can be considered a subsector. The emergence of financial conglomerates raises interest in the degree of cross-sector dependence and this issue is discussed in Chapter 3. The dependence within the insurance sector during crises is of interest, since little is known about sector wide risk within this sector. Special attention is devoted in Chapter 4 to the differences between insurance and reinsurance risks. Mergers between banks in the EU raise the interest of policymakers in the downside risk dependence between banks across different countries in the EU. Dependence among banks is therefore the subject of Chapter 5.

In Chapter 3 the dependence between the downside risk of European banks and insurers is analyzed. Since the downside risk of banks and insurers differs, an interesting question from a supervisory point of view is the risk reduction that derives from diversification within large banks and financial conglomerates. The limited value of the normal distribution based correlation concept is discussed, and an alternative measure is proposed, which better captures the downside dependence given the fat tail property of the risk distribution. This measure is estimated and indicates better diversification benefits for conglomerates versus large banks. Chapter 3 is based on joint work with De Vries and Schoenmaker (Slijkerman et al., 2005).

In Chapter 4 the relation between insurers and reinsurers is studied. Simultaneous losses of the market value of insurers are modelled and measured, to understand the impact of shocks on the insurance sector. The downside risk of insurers is explicitly modelled by common and idiosyncratic risk factors. Because reinsurance is important for the capacity of insurers, the risk dependence among European insurers and reinsurers is measured. The results point to a relatively low insurance sector wide risk and indicate that the dependence among insurers is higher than among reinsurers.

In Chapter 5 the mutual relations among banks are investigated. The downside risk of multiple combinations of banks in the EU are modelled and their downside risk dependence is estimated. An explanation for the joint risks, based on macroeconomic developments, is provided. The results indicate that in general the dependence between banks based in the same country is higher and that the dependence did increase after the introduction of the euro. Evidence shows that the dependence can be explained by macroeconomic developments.

This thesis therefore offers a number of new insights on the risk diversification effects of mergers in the financial sector, from both a theoretical and an empirical perspective. The propositions in the different chapters are innovative, as is the use of the non-parametric estimator in this context. The use of this estimator and choice of European data provide us with new results. Moreover, different aspects of the methodology are explored in the following chapters. The robustness of the results is shown by sampling in Chapter 3. In Chapter 4, the dependence among more than two firms is investigated. In Chapter 5, it is shown how explanatory variables can be used in this context and it is investigated whether the dependence has changed over time. Moreover, in the chapters, a different policy question is addressed. The results are useful for the design of new regulatory policies and can be the input for future research on the diversification effects of downside risk. The framework to disentangle the common and idiosyncratic shocks, incurred by multiple firms, which is presented in Chapter 4, is well suited for future theoretical research. The non-parametric estimator, which is used to estimate the probability that two firms realize a simultaneous loss, can be used for future applied research.

The intention of this research is to formulate new theoretical propositions and present empirical results, which are of interest to policymakers. To keep this work concise and to make it accessible to non-academics, some choices have been made. For example, the degree of dependence between the returns of two firms will be represented by a probability measure and not by the parameter in a copula, which is in vogue in academics. Moreover, it is a deliberate choice not to redo a literature overview on e.g. systemic risk and extreme value theory, since excellent overviews exist. In this thesis, propositions related to extreme value theory are formulated and the dependence among firms is estimated in a similar way. Of course, there are other approaches to model the tails of the distribution of returns. However, the combination of the propositions and the empirical results, offers an interesting approach, because the propositions and empirical results are based on similar assumptions. In the following chapter, a short overview of the literature is given, to show how this research fits in the broader economic literature.

Chapter 2

Literature on systemic risk

The demise of the LTCM investment fund in 1998 posed a serious threat to the financial system. Many banks suffered losses because they where exposed to the fund through loans, investments or counterparty risk. Nowadays, regulators are much more aware of the risks to the financial system that result from an industry wide exposure to the same risks. The probability of simultaneous large losses incurred by multiple financial firms is the main topic of this thesis. This chapter discusses how this topic relates to the literature.

A natural starting point is the literature on systemic risk in the banking sector, which discusses the phenomenon of a bank run. To solve the problems associated with a bank run, deposit guarantee funds were installed and banks where supervised. However, there are still important questions to be answered regarding the stability of the financial system. Regulators and academics e.g. do not fully understand how risk is distributed within the financial system and there is insufficient knowledge about the effects and desirability of regulatory measures. When regulators know the risk exposure of the different firms, they can better assess the impact of shocks to the system. The perspective on financial stability taken in this research is therefore the risk that multiple institutions fail because of a common risk exposure. When financial institutions are exposed to similar risks, or depositors cannot identify the extent of the exposure to this risk, multiple institutions may be affected when this risk materializes. Often such crises are explained by contagion effects. After discussing systemic risk, the issues surrounding the estimation of contagion are introduced. Mergers between financial institutions change the distribution of risks within the financial system considerably. The risk diversification possibilities of mergers are therefore an important topic in this thesis and the question of efficiency gains following mergers is briefly touch upon. Next, our choice for a risk modeling approach which is unconditional on the current market environment is motivated. References are given to the vast literature on the modeling of dependence in the second moment of returns, the conditional approach. Since it is assumed in this work that dependence originates from similar risk factors and is therefore in part an asset side view, the relation of this research with the asset pricing literature is briefly discussed. However, regulators are not primarily interested in asset pricing but in the downside risk of institutions and the factors that cause this risk. Therefore the loss distribution of financial institutions is modeled and estimated. Not only the downside risk of institutions is of interest, but also the dependence among firms is modeled. This model provides a theoretic benchmark of the exposure of financial firms to large losses. It is shown that one can significantly underestimate the probability of multiple large losses, if an inappropriate statistical model is used. Before introducing the statistical theory, a broader perspective on systemic risk is given.

Systemic risk

The objective of supervision is to protect depositors and policyholders and more broadly to foster financial stability. To this end regulators promote the soundness of individual institutions and the stability of the financial system. Regulators are especially interested in the frequency and magnitude of extreme shocks to the system, which threaten the continuity of banks and insurers. Statistically speaking regulators are interested in the lower quantiles of the distribution of returns.

Most of the research on the stability of the financial system has a primary focus on the stability of the banking sector, due to the importance of the payment and clearing functions for the real economy. This activity comes as a joint product from the other banking activities and is a positive externality to the economy. A similar service does not derive from the insurance activities. Moreover, the type of contracts like a deposit makes that the banking sector is more fragile than the insurance sector. A survey of the issue of systemic risk can be found in De Bandt and Hartmann (2002). The Basel Committee on Banking Supervision (1999) provides a good overview of the empirical impact of banking regulation, specifically the 1988 Accord. The systemic aspects and the potential threat to the financial stability of insurers has not gained that much interest. One of the first studies raising this question was written by the Group of Thirty (1997). More recently Swiss Re (2003b) concluded that there is ample systemic risk in the reinsurance sector. Even though the stability of the insurance sector is perhaps of a lesser public concern than the fragility of the banking sector, the presence of financial conglomerates, nevertheless requires an assessment of the downside risk derived from both activities. Interestingly, the academic research on the prudential regulation of the insurance sector is still in its infancy.

De Nicolo and Kwast (2002) give the following definition of systemic risk: 'Systemic financial risk is the risk that an event (shock) will trigger a loss of economic value or confidence in, and attendant increases in uncertainty about, a substantial portion of the financial system that is large enough to, in all probability, have significant adverse effects on the real economy'. Underlying this definition is the idea that economic shocks may become systematic because of externalities associated with severe disruptions in the financial system. The authors distinguish direct and indirect channels through which financial firms are linked and which cause the firms to be interdependent. In the following chapters these dependencies will be investigated.

A classification of the literature on systemic risk can be found in Gorton (1988). He the discusses the possibility of a business cycle induced systemic crisis. 'A common view of panics is that they are random events, perhaps self-confirming equilibria in settings with multiple equilibria, caused by shifts in the beliefs of agents which are unrelated to the real economy. An alternative view makes panics less mysterious. Agents cannot discriminate between the riskiness of various banks because they lack bank specific information. Aggregate information may then be used to assess risk, in which case it can occur that all banks may be perceived to be riskier. .... This hypothesis links panics to occurrences of a threshold value of some variable predicting the riskiness of bank deposits.' According to Gorton, banking panics can be either random events or the result of the behavior of agents in the response to asymmetric information. In his research three causes of an increase in risk are given. Panics can be caused by extreme seasonal fluctuations, they can originate from the failure of a large financial institution or can be caused by a recession. According to Gorton, the causes are not mutually exclusive. A panic may for example be the result of a bank failure in an economic downturn.

Since the value of assets is related to the business cycle, the idea that a systemic crisis can be caused by a similar exposure to risks easily fits within this classification. In this research, the view is taken that crisis are predominantly caused by a similar exposure to risks, being e.g. risks relating to the macroeconomy and risks relating to the value of the assets and liabilities of institutions. However, if multiple banks realize a loss due to losses on their assets this does not necessarily constitute a panic. It is simply the result of a similar exposure to risk. De Vries (2005) explicitly models the dependence among banks, which is the result of a similar exposure to loans. For a discussion on the causes of interdependence between banks, see also De Nicolo and Kwast (2002).

The view that systemic risk is caused by a similar risk exposure may also explain why other financial institutions than banks are affected by a banking panic. The returns of non-bank financial institutions can be driven by the same risk factors that drive the risk in the banking sector. As mentioned above, the classic motivation for the introduction of banking supervision is consumer protection and the prevention of a bank run. However, there are other reasons for banking supervision since a bank failure may have negative externalities. A banking crisis may e.g. impact economic growth, which the government may want to avoid. Regulators can be seen as delegated monitors, supervising the bank on behalf of depositors and society at large. Freixas and Rochet (1997) elaborate on these views.

However, as e.g. Danielsson et al. (2002) show, regulation may also aggravate the risk of the financial system. Most regulations assume that the risk in the financial system is exogenous. The authors model the feedback effects of trading decisions on prices and show that risk regulations have the perverse effect of exacerbating financial instability. An similar approach is taken in Genotte and Leland (1990). They show that the trading effects of a portfolio insurance strategy may exacerbate a decline of stock prices. Moreover, the positive pay-off of momentum strategies may indicate herding behavior, which can be explained by asymmetric information. See Banarjee (1992) for a simple model on herd behavior. Another approach is taken by Allen and Gale (2000), who model the interaction of banks, in a setting with insufficient liquidity.

It is a deliberate choice in this thesis, not to model the interaction between agents, but to take a reduced form approach. With a reduced form approach the degree of dependence can be measured among different financial institutions. This is of interest to regulators. Moreover, the other approaches require to explicitly model the behavior of agents and thus knowledge about their information sets and preferences. A reduced form approach needs less assumptions and is easier to implement.

Contagion

There is a substantial literature examining the extent of contagion in financial markets. Simultaneous crashes of e.g. stock markets are estimated in this literature. Some researcher test whether the correlation coefficient during crisis is higher than during non-crisis times (see e.g. De Nicolo and Kwast (2002)), others apply probit (Eichengreen et al., 1996) or logistic models (Bae et al., 2003). However, much research is not precise in the definition of contagion, as is shown in Rigobon (2001) and Forbes and Rigobon (2002). They define contagion as a significant increase in cross-market linkages after a shock to one country (or group of countries). According to this definition there is only contagion if the cross-market comovement increases significantly after a shock. If there is no significant increase in the comovement, this suggests that the strong linkages exist in all states of the world. Forbes and Rigobon prefer to refer to interdependence for these situations. They show that findings based on an increase in the correlation coefficient during crises are often the result of heteroscedasticity. After applying a correction for this heteroscedasticity, most evidence for contagion disappears. However, this does not imply that there are no interdependencies during crises, it only implies that the linkages are not more severe during a crisis than during non-crisis times. An extensive discussion of the literature on contagion can be found in Hartmann et al. (forthcoming). They explicitly model simultaneous extreme losses, or interdependencies, in a similar vain as is done in the following chapters. In this research the interdependencies during crisis are studied, side-stepping the correlation coefficient. A reduced form approach is used and the frequency of multiple simultaneous crashes is investigated. The measure of systemic risk used (the failure measure) can be interpreted as the probability of joint crashes. When the probability of joint crashes is high, systemic risk is supposed to be high. The measure is not necessarily contagious in the sense of an influenza virus spreading around. It is assume that the cause of most simultaneous losses is a common exposure to risk, such as the broader macroeconomy or an exposure to similar assets. Since this research gives an explanation for dependence among banks based on a similar exposure to return factors and assets, a short overview of the broader literature on asset pricing is given. In this literature the factor approach is very common.

Asset pricing

When one takes the perspective that losses at multiple institutions are related because of a similar exposure to risk, there is a clear link with the asset pricing literature. The quantification of the relation between risk and return of assets is one of the main topics in finance. The main paper is the contribution by Markowitz (1952), who laid the foundations of the Capital Asset Pricing Model (CAPM). According to the CAPM, investors optimally diversify their assets (which results in the market portfolio) and choose their portfolio risk by a combination of an investment against the risk free rate and the market portfolio. The resulting optimal portfolio is said to be mean-variance efficient. Extensions of the CAPM were developed by Sharpe (1964) and Lintner (1965). Rochet (1992) models the effect of regulation in a CAPM framework and finds that solvency regulation may distort an efficient asset allocation.

In a way the CAPM helps to understand the dependence among financial institutions. If banks and insurers optimally diversify their assets and liabilities the characteristics of these institutions are highly related to the market portfolio. In Chapter 5 this is investigated more thoroughly. An alternative approach of modeling the relation between risk and return is given by Ross (1976). The so called Arbitrage Pricing Theorem (APT) provides a more general model than the CAPM and allows for multiple factors driving the returns of firms. The APT relates the expected returns of assets to a number of risk factors. However there is not a single way of identifying these factors. See e.g. Campbell et al. (1997), Brealey and Myers (2000) or Cochrane (2005) for an overview of the asset pricing literature.

In the early literature on portfolio construction the variance of the portfolio or risk factors is often a proxy for risk. However, regulators of the financial sector are primarily interested in the downside risk of institutions and not in the variance of the returns. The selection of optimal portfolios when the objective of an investor is to minimize the probability of large losses is discussed in the literature dealing with the safety first selection criterion, introduced by Roy (1952). It matters however how the risk of large losses is quantified, since e.g. the assumption that returns are normally distributed leads to an underestimation of risk.

A basic assumption behind both the CAPM and APT is that the returns of assets are normally distributed. However, this is often not the case as is described by Mandelbrot (1963), Campbell et al. (1997) and Jansen and De Vries (1991). In this research the fat tail characteristics of returns are explicitly modelled. This will help to understand the impact of large shocks to multiple institutions. Before discussing the dependence among multiple firms when their returns are not normally distributed, it is shown how to classify the tails of univariate return distributions with the use of extreme value theory.

Now that most of the economic context of this research is shown, we continue with the statistical context. First, however, the possible efficiency gains of mergers have to be addressed.

Mergers

In this research the downside risk of multiple financial institutions is investigated and therefore the risk diversification possibilities of mergers between financial firms. The question whether firms can improve efficiency by merging is another important question. It is a relevant topic when answering the question whether firms should merge. Firms should only merge if there are economies of scale and scope, though this is not the primary concern of regulators. In this thesis the perspective of a regulator is taken, whose objective it is to minimize the risk of institutions and of the financial system. The efficiency benefits of mergers are therefore left aside. See Brealey and Myers (1996) for a general discussion on the efficiency gains following a merger and e.g. Berger (2000) for a discussion on the benefits of mergers between banks and insurers. For a general industrial organization perspective on mergers see Tirole (1997). An interesting analysis of the benefits of internationalization strategies in the banking sector is given in Slager (2004).

Methodology

In the second part of this chapter, a short introduction to extreme value theory is given and references for further reading. First, the difference between the unconditional risk modeling approach and the conditional approach, is discussed.

Unconditional risk modeling approach

When modeling risk, a regulator may either choose to let the risk limit depend on the current market environment or choose a risk limit which is less prone to changes in volatility. Statistically speaking one can take a conditional modeling approach or an unconditional approach. In general an unconditional approach is appropriate for loss forecasts when the investment horizon is relatively long. An advantage of the unconditional approach is that the risk limits do not change frequently. The advantage of the conditional approach is that these models are well suited when there is dependence in the second moment. When studying monthly return series, conditional volatility is basically absent. The use of GARCH and Stochastic Volatility models are therefore particularly appropriate for short term risk forecast, as is needed for e.g. options traders. However, the conditional approach may be computationally difficult, since the large variance-covariance matrices can be complex. Primarily because regulators take a long term view when safe-guarding the financial system, an unconditional approach is followed in this research. A conditional approach can be linked to extreme value theory (EVT), as is shown in Poon et al. (2001). Moreover, as is shown in De Haan et al. (1989), an ARCH process, which is a time dependent process, can result in data with independently distributed extremes. This data can therefore be modelled by an unconditional approach. An overview on the literature on conditional approaches can be found in McNeil et al. (2005) or Campbell et al. (1997). Kole (2006) provides a discussion on the relation between bubbles and subsequent crashes.

Extreme value theory

Extreme value theory studies the limit distribution of the maxima and minima of return series. These limit distributions are informative about the tail shape of the underlying distribution. Consider the maximum of a stationary sequence $X_1, X_2, \ldots, X_n$ of independently and identically distributed random variables with a distribution function F, $M_n = max(X_1, X_2, \ldots, X_n)$. The probability that the maximum of the first n variables is below a threshold x is given by

$$P\{M_n \leq x\} = F^n(x).$$

EVT studies the limit distribution of M_n. One studies under what conditions there exist suitable normalizing constants $a_n > 0$, b_n, such that

$$F^n(\frac{x}{a_n} + b_n) \xrightarrow{w} G(x),$$

where $G(x)$ is one of three asymptotic distributions that are defined below and w stands for weak convergence. The three limiting distribution functions $G(x)$ are

$$\text{Type I} \qquad G(x) = \quad exp(-e^{-x}) \qquad -\infty < x < +\infty;$$

$$\text{Type II} \qquad G(x) = \begin{cases} 0 & x \leq 0, \\ exp(-x^{-\alpha}) & x > 0, \alpha > 0; \end{cases}$$

$$\text{Type III} \qquad G(x) = \begin{cases} exp(-(-x)^{\alpha}) & x < 0, \alpha > 0, \\ 1 & x \geq 0; \end{cases}$$

The distributions with a tail which is characterized by a Type III limiting distribution is said to have a bounded support. It is therefore unlikely that this is the appropriate limiting distribution to model log returns. When the tail is of Type I, the distribution is characterized by the existence of all moments and belongs to the type of distribution with exponentially declining tails, such as the normal distribution. When the higher moments of a distribution do not exist, the distribution is of Type II and is said to be fat tailed. De Haan (1976) gives a discussion of the conditions for the convergence of a distribution to a particular type of limiting distribution. In the following chapters, the sufficient condition for a distribution to be fat tailed is given, i.e. the property of regular variation. With the help of the limit distribution of heavy tailed random variables one can study the frequency of extreme losses without imposing a particular distribution a priori. If a distribution is of Type II, the tails can be approximated by a first order term identical to the Pareto distribution, which is well known by economists. The Student-t distribution with finite degrees of freedom has e.g. a limiting (stationary) distribution which is fat tailed. See Jansen and De Vries (1991) and McNeil et al. (2005) for an application of EVT to finance or Embrechts et al. (2003).

Bivariate EVT

In this thesis not only the downside risk of a single firm is modeled, but also the probability that multiple financial institutions realize a simultaneous loss. Consider a vector $(X_1, Y_1), (X_2, Y_2), \ldots, (X_n, Y_n)$ of i.i.d. random variables with a common distribution function $F(x, y)$. The i-th ascending order statistic of X (and Y respectively) is denoted with $X_{i,n}$ such that $X_{1,n} \leq \ldots \leq X_{n,n}$. The pair $(X_{n,n} Y_{n,n})$ of the sample of n random variables is below a certain threshold (x, y) with probability $P\{X_{n,n} \leq x, Y_{n,n} \leq y\} = F^n(x, y)$.

In a bivariate setting, EVT studies the limit laws for bivariate extremes. In line with the study of the extremes of a univariate stochastic sequence, one is interested under what conditions there exist suitable normalizing constants $a_n > 0, b_n$, such that

$$F^n(\frac{x_{n,n}}{a_n} + b_n, \frac{y_{n,n}}{c_n} - d_n) \xrightarrow{w} G(x, y),$$

where $G(x, y)$ is a multivariate extreme value distribution. If normalizing constants can be found such that $F^n(x, y)$ converges to a Type II limiting distribution, $F^n(x, y)$ is called a bivariate extreme value distribution. See Embrechts et al. (2003) or De Haan and Resnick (1977) for a more extensive overview of the literature.

Statistical analysis of bivariate random variables involves the modeling of the relation between the two random variables. The univariate tail of both X and Y and the bivariate dependence structure of X and Y have to be modeled. This can be done by using portfolio theory. According to the APT the returns of firms are a linear combination of independent risk factors. In this research a similar factor approach is taken. However, it is assumed that the return factors are fat tailed. Dependence among firms than originates from the exposure to the same factors. This characteristic of the economic process is used to validate the assumption of asymptotic dependence. Because of the heavy tail characteristics of the risk factors, the bivariate distribution $F^n(x, y)$, where x and y are the returns of two firms, is of Type II. Since this economic approach gives us the type of limiting distribution, one can start directly by studying the characteristics of $F^n(x, y)$ by using a non-parametric estimator. Moreover, the factor approach allows us to investigate the extent to which the tail dependence between pairs of firms differs as a result of a different exposure to the risk factors. De Vries (2005) uses a similar approach when discussing whether the potential for systemic risk is weak or strong. The degree of systemic risk depends on the tail characteristics of the investments made by banks.

The probability of multiple simultaneous losses is much higher when one takes into account the fat tail characteristics of returns. This becomes apparent when a different way to characterize heavy tails is used. In a sample of heavy tailed random variables, the maximum observation dominates all others, such that the sum and the maximum over a large threshold have approximately the same probability[1]). A

[1] One way to characterize heavy tails is by the fact that for a sample of n i.i.d. draws

$$\lim_{s\to\infty} P\left\{\max(X_1 ... X_n) > s\right\} \ / \ P(\sum_{i=1}^{n} X_i > s) = 1.$$

Thus the sum is almost entirely driven by the maximum of the observations.

well know result from e.g. the CAPM is, that the idiosyncratic risk factors diversify away. However, when the returns of the different portfolio items are independently drawn from the same distribution in the domain of attraction of the Type II extreme value distribution, this is not necessarily the case because the asset with the largest return is an important determinant of the return of the portfolio.

In Chapter 3 follows an analysis of the dependence among bank and insurers. In Chapter 4 the dependence among insurers in the EU is characterized, followed by an analysis of the dependence among banks in Chapter 5.

Chapter 3

Financial Conglomerates

Since the lifting of the regulatory barriers for mergers between banks and insurers in the US, there has been an ongoing discussion on the appropriate regulatory framework for financial conglomerates. If the risk profile of insurance activities of a newly formed conglomerate is different from the risk profile of banking activities, this gives scope for diversification. Regulators might then allow lower capital requirements for a conglomerate than for its individual constituent parts. If lower capital requirements are allowed, this reduces the cost of capital and hence increases profitability.

As an input for this discussion we investigate the dependence between the downside risk of European banks and insurers. If the downside dependence between a bank and an insurer is distinctly different from the dependence structure between two banks or between two insurers, financial conglomerates require less capital charges than large banks or insurance companies. Since we analyze risk from the perspective of a supervisor, we focus primarily on a measure of downside risk and do not use global risk measures like the variance. In the banking sector this focus on downside risk is evidenced by the emphasis on the Value at Risk (VaR) methodology. This perspective complements other research which takes the perspective from shareholders, investigating possible economies of scale and scope (e.g. Carow, 2001).

It is a stylized fact that the return series of financial assets are fat tailed distributed (Jansen and De Vries, 1991). The commonly maintained assumption that returns are normally distributed therefore underestimates the downside risk. Hence, given the focus on downside risk, we will not start from this premise and allow for fat tails to capture the univariate risk properties. For the multivariate question of downside risk diversification benefits, the normal distribution based correlation concept is also of limited value. For example, one can have multivariate Student-t distributed random variables, which exhibit fat tails, are dependent, but which are nevertheless uncorrelated. Research based on the correlation concept, to investigate the diversification benefits of banks into insurance activities, appears therefore inappropriate. To answer the question whether the capital requirements for conglomerates can be lower than the sum of requirements for large banks, we employ a downside risk measure which directly evaluates the systemic downside risk in terms of failure probabilities and losses. This measure is derived from Extreme Value Theory (EVT), and easily allows for the non-normality.

Financial conglomerates may exploit diversification possibilities between balance sheet items of banks and insurers. However, current regulation does not allow for cross hedging. The different entities of a conglomerate are supervised separately according to sector specific regulation. Since there is no common regulatory framework, capital has a distinct function in both banking and insurance. EU solvency requirements for insurers do e.g. not depend on credit risk. This makes it difficult to examine cross-sector risk transfers and may induce regulatory arbitrage. The current supervisory framework in banking is based on the Basle 1988 Capital Accord for the credit book and on the "Amendment to the capital accord to incorporate market risks" of 1996. The insurance regulation is based on the insurance directives in the EU and on the Risk Based Capital framework in the US. For the supervision of financial groups the financial conglomerates directive is in place. New regulation based on internal risk models for the banking sector is being implemented (Basle II Capital Accord). For the insurance sector the European Commission is working on a new regulatory framework, the so-called Solvency 2 project. The tendency is to tie regulatory capital more closely to Economic Capital models (e.g. Bikker and Lelyveld, 2002). These models enable financial institutions to allocate capital optimally, based on an economic concept of risk. If financial conglomerates face a lower risk, this validates lower capital requirements, which would boost return on investments.

The objective of supervision is to protect depositors and policyholders and more broadly to foster financial stability. To this end regulators promote the soundness of individual institutions and the stability of the financial system. Regulators are especially interested in the frequency and magnitude of extreme shocks to the system, which threaten the continuity of banks and insurers. Statistically speaking regulators are interested in the lower quantiles of the distribution of returns.

Most of the research on the stability of the financial system has a primary focus on the stability of the banking sector, due to the importance of the payment and clearing functions for the real economy. This activity comes as a joint product from the other banking activities and is a positive externality to the economy. A similar service does not derive from the insurance activities. Moreover, the type of contracts like a deposit makes that the banking sector is more fragile than the insurance sector. A survey of the issue of systemic risk can be found in De Bandt and Hartmann (2002). The Basel Committee on Banking Supervision (1999) provides a good overview of the empirical impact of banking regulation, specifically the 1988 Accord. The systemic aspects and the potential threat to the financial stability of insurers has not gained that much interest. One of the first studies raising this question was written by the Group of Thirty (1997). More recently Swiss Re (2003b) concluded that there is ample systemic risk in the reinsurance sector. Even though the stability of the insurance sector is perhaps of a lesser public concern than the fragility of the banking sector, the presence of financial conglomerates, nevertheless requires an assessment of the downside risk derived from both activities. Interestingly, the academic research on the prudential regulation of the insurance sector is still in its infancy.

In the empirical section we begin by measuring the riskiness of individual banks and insurers. We use the reduced form approach of the risk of financial institutions as analyzed by De Vries (2005) and employed in De Nicolo and Kwast (2002) and Hartmann et al. (2004). This involves estimating the probability of a crash by using daily stock price data. We employ estimators from statistical extreme value theory and avoid correlation based techniques which focus primarily on the central order statistics. The estimation results for individual firms provide information on the risk of individual institutions and allows for a cross-sector comparison of individual firm risk. Our main research question concerns whether the downside risk in the banking sector differs from the downside risk in the insurance sector. To this end we estimate the dependence between combinations of firms, both within a sector and across sectors. If the risk profile of both sectors is different, this creates risk diversification possibilities for financial conglomerates. To understand the possible differences in cross-sector risk, we develop an analytical model which helps us to interpret the tail dependence, in the theory section. This model provides an explanation for the differences in dependence between banks and insurers, compared to the dependence within the same sector.

The early work on the benefits of mergers between banks and insurers was done in light of the discussion on the abolishment of the Glass-Steagall act in the US (which forbid bank holding companies to perform insurance activities). For a literature overview see Laderman (1999) or Estrella (2001). Estrella (2001) applies option pricing theory to create a measure of failure for a firm and finds that banks and insurers are likely to experience diversification gains. The literature review of Berger (2000) suggests that most efficiency gains of mergers appear to be linked to benefits from risk diversification. A study by Oliver, Wyman & Company (2001) argues that there is scope for a reduction of 5-10% in capital requirements for a combined bank and insurance company. Carow (2001) analyses the Citicorp-Travelers Group merger by an event study approach and finds that investors expect significant benefits from the removal of regulatory barriers to bancassurance. However, in the meantime this merger is in the process of breaking up. Laderman (1999) finds that substantial investments in life insurance underwriting are optimal for reducing the risk of the return on assets for bank holding companies. Except for Gully et al. (2001) and Bikker and Lelyveld (2002), most studies focus on U.S. data, as in De Nicolo and Kwast (2002), and assume that the returns are normally distributed. Our research is focused on European data and applies extreme value theory, allowing for fat tails.

In the remainder of this paper we first describe the limited value of the correlation concept and provide another dependence measure. Next we provide an economic rational for dependence to exist, between different financial institutions. Thereafter, we explain the methodology, give a description of the data and present the results. Finally, we summarize our findings and draw some policy conclusions.

3.1 Dependence and correlation

To understand the dependence between two random variables which follow a normal distribution it is sufficient to know the mean, variance and correlation coefficient to characterize their joint behavior. The correlation measure itself, however, is often not an useful statistic for financial data for various reasons. First, economists are interested in the risk-return trade-off, to which the correlation measure is only an intermediate step. Boyer, Gibson and Loretan (1997), moreover, noticed that even

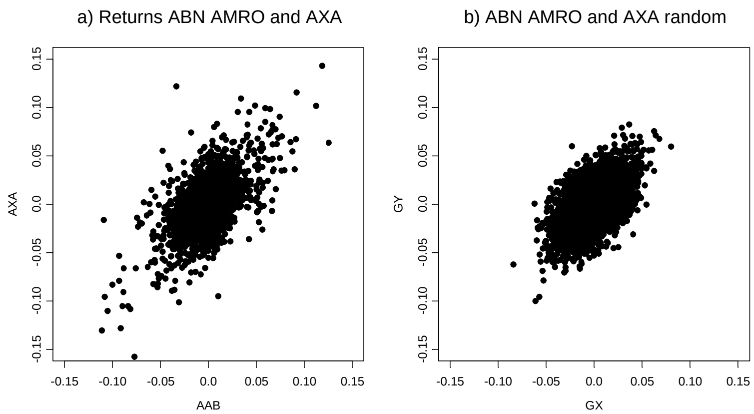


Figure 3.1: Normal distribution underestimates the risk

if the normal model applies, verifying the market speak of increased correlation coefficients in times of crisis can be illusory. Forbes and Rigobon (2002) show that not much of a correlation change can be identified around crisis times, by taking into account the simultaneous increase in variance of the return series.

A second reason for the failure of the normal based correlation measure is that the return series are clearly non-normal distributed. In Figure 3.1a we have depicted the daily stock returns of ABN AMRO Bank and AXA since 1992. We estimated the mean, variance and correlation of these returns and randomly generated returns with the same parameters assuming a bivariate normal distribution (Figure 3.1b). Project the observations along the two axes to obtain the univariate properties of the return series. The difference between the returns and the artificial returns is that in the latter sample there are no observations larger than 10 percent. The normal model, in fact, predicts that returns above the 10 per cent occur with a very low probability, while such returns are in reality quite common. Thus the return distributions exhibit fat tails. Since regulators are concerned with the extreme losses of value for banks and insurers, the assumption of normality therefore appears inappropriate.

The third reason as to why the multivariate normal based correlation measure is inappropriate for our analysis, is that it does not capture very well the dependency which one observes in the above plots. The true data have most of the extreme outcomes realized close to the diagonal, and thus occur jointly. In the normal remake, this is much less the case. To explain how this could be, we provide an example which is somewhat of an exaggeration, but which provides the key insight very well.

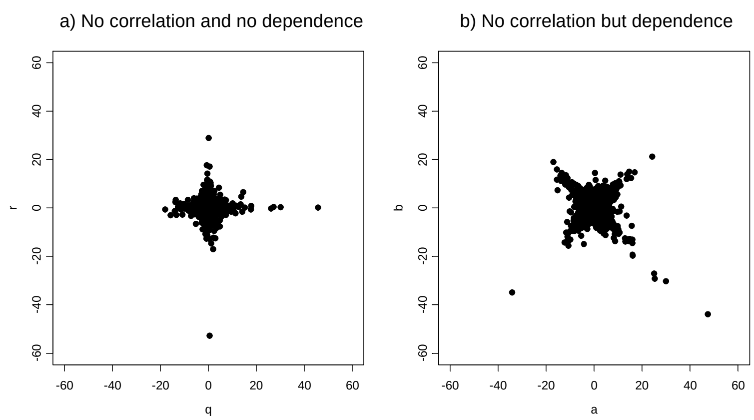


Figure 3.2: Two Student-t distributed variables

The example builds on the fact that if two random variables are dependent, the correlation between the variables may nevertheless be zero. In Figure 3.2a, two uncorrelated and independent random variables, q_i and r_i are shown (based on 10,000 randomly generated Student-t variables with 3 degrees of freedom). In contrast to Figure 3.2a, where two independent variables are plotted, the variables a_i and b_i in Figure 3.2b are made dependent. We formed two portfolio's, $a_i = q_i + r_i$ and $b_i = q_i - r_i$. On the x-axis on finds the sum $(a_i = q_i + r_i)$ of the two Student-t variables, on the y-axis one finds the difference $(b_i = q_i - r_i)$ between the two random variables; one can think of the second portfolio being short in the asset with return r_i. The correlation between a and b is zero, but note that there is dependence between the portfolios in Figure 3.2b as all extremes occur jointly along the two diagonals. In contrast, if q_i and r_i are drawn from a normal distribution, a_i and b_i are surely independent as they are uncorrelated. In that case a cross plot of a_i and b_i would generate a neat circle around zero. This illustrates that the characteristics of variables which are in the domain of the fat tailed Frechet extreme value distribution differ considerably from e.g. variables which follow a normal distribution. The sample maxima of these distributions all converge to the Frechet limit, when appropriately scaled. A typical feature of the Student-t distribution, which is in the domain of the Frechet, are the extremely high and low observations far away from the centre. In a sample of heavy tailed random variables, the maximum observation dominates all others (in such a way that the sum and the maximum over a large threshold have approximately the same probability[1]). This shows in Figure 3.2a as the larger observations appear along the two axes. In this figure the extreme observations are located alongside the axes since the probability of a pair of two large variables is so low. Therefore combinations $a_i = q_i + r_i$ and $b_i = q_i - r_i$ in Figure 3.2b far from the origin are almost entirely driven by either the q_i or the r_i, placing the largest observations on the two diagonals (which are essentially a rotation of the two axes from Figure 3.2a). In other words, the largest observation really dominates over the others and determines the scale and the dependence. Because of the shortcomings of the correlation measure, we want to use a measure that provides us with the probability of multiple extreme losses, taking into account that return series of stock prices are fat tailed.

3.1.1 The linkage measure

Instead of using the correlation measure to capture the dependence between two variables, we will directly study the probability of an extreme loss of a variable, conditional on the loss of another variable. Our indicator is therefore a conditional probability measure. The concern of regulators and risk managers is a simultaneous loss at the banking division and the insurance division of a financial conglomerate. More specifically, suppose a regulator wants to know the probability that $B > t$, given that $A > t$ and the probability that $A < t$ given that $B < t$, where A and B are the stochastic loss returns and t is the common high loss level. A high realization of a variable should be interpreted as a large loss, so we can focus on positive random variables for the study of our downside risk. Since we are interested in a crash of the banking division given the crash of the insurance division and vice versa, we will condition on either event. Let κ be the number of divisions which crash. We propose to use the linkage measure from Xin (1992) as the measure of systemic risk

$$E[\kappa|\kappa \geq 1] = \frac{P(A > t) + P(B > t)}{1 - P(A \leq t, B \leq t)}. \tag{3.1}$$

[1] One way to characterize heavy tails is by the fact that for a sample of n i.i.d. draws

$$\lim_{s \to \infty} \frac{P\{\max(X_1 ... X_n) > s\}}{P(\sum_{i=1}^{n} X_i > s)} = 1.$$

Thus the sum is almost entirely driven by the maximum of the observations.

This measure gives the expected number of divisions which crash, given that one division crashes. Hartmann et al. (2004) provide further motivation for this measure. Note that

$$E[\kappa|\kappa \geq 1] - 1 = \frac{P(A > t, B > t)}{1 - P(A \leq t, B \leq t)}$$

is the conditional probability that both divisions fail, given that there is a failure of at least one of the divisions. We will use either interpretation, depending on the context.

Unless one is willing to make further assumptions as in the options based distance to default literature, it is impossible to pin down the exact level at which a division fails, or at which supervisors consider the institution financially unsound. For this reason we do take limits and consider

$$\lim_{t \longrightarrow \infty} E[\kappa|\kappa \geq 1].$$

Extreme value theory then shows that even though the measure is evaluated in the limit, it nevertheless provides a reliable benchmark for the dependency at high but finite levels of t. We also like to note that the measure can be easily adapted in case failure levels at the divisions are different, in which case the measure is evaluated along a non 45^o line, in the A, B space.

Often a parametric approach is taken to describe dependence and there is a lot of interest in the use of copula to describe the joint behavior of random variables. However, when taking a parametric approach, an assumption has to be made on the appropriate copula. We therefore do not make use of an EVT copula and follow a non-parametric approach. The connection between the two concepts in the limit is as follows

$$\lim_{t \longrightarrow \infty} \frac{P(A > t) + P(B > t)}{1 - P(A \leq t, B \leq t)} = \lim_{p \uparrow 1} \frac{2(1-p)}{1 - C(p,p)},$$

where $P(A > t) = P(B > t) = 1 - p$ and $C(p,p)$ is the limit copula. Thus if the copula is known, the failure measure can be calculated. Kole (2006) discusses the use of different copulas in this context.

3.2 An economic rationale for dependence

To give a theoretical rationale for dependence between banks and insurers, we give a stylized representation of the insurance and banking risks, using an elementary factor model. The factors are assumed to follow a distribution with non-normal heavy tails. This provides us with a characterization of the level and degree of dependence. New financial products enhance the possibilities to transfer risk between and within financial institutions. We show this may lead to a convergence of the investment portfolios of banks and insurers. First, we will give examples of this convergence, followed by a short exposition on the approach taken by financial institutions to manage this risk. We conclude by capturing the characteristics in a theoretical model.

The investments of banks and insurers are to a certain degree similar. Both invest in syndicated loans, have proprietary investments in equity and both hold mortgage portfolios. This may cause similarities in the risk profile of banks and insurers. Moreover, the costs arising out of liabilities for banks and insurers are to some degree similar. Both, for example, sell products with a guaranteed interest rate. New financial instruments can transform insurance risk to financial investments (e.g. catastrophe bonds) or can transform default risk to insurance risk, via credit default swaps. Via securitization of bank loan portfolios, the scope of investments for insurers is widened.

There are also differences. The interest rate exposure for banks and insurers may differ, since banks profit from declining interest rates, while it may be more difficult for life insurers to maintain a healthy profit margin in a low interest rate environment. On the liability side of banks balance sheets, the deposit contract exposes the banks to the risk of immediate callability, while insurers do not have such a risk. If we find that cross-sector dependence is lower than dependence within the two sectors, this may provide an argument for cross-sector mergers. However mergers are not always necessary to exploit those advantages, since risks can be traded between firms. For some risks this might be difficult, since the seller of protection has less information about the risk it gets than the buyer has. As a starting point for the discussion on the benefits of cross-sector mergers, we model cross-sector dependence.

Banks and insurers develop risk management models to identify the risk of their institution. A study by the Basel Committee on Banking Supervision (2001) gives an overview of the different risk types that can be found in a financial conglomerate. Once the aggregate risk by risk type is known, one can look at the dependence between risk types. The concept of economic capital makes it possible to measure the degree of risk taking. Although the distribution function of the risk types differ, the economic capital framework sets a common standard in terms of a confidence interval in the cumulative loss distribution within a specific time horizon.

Findings by Oliver, Wyman & Company (2001) suggest that the largest benefits of diversification are obtained within a specific risk type, are smaller at the business line level and are getting even smaller across business lines. The current regulatory framework, which is designed for specific (sectoral) business lines, does not reflect possible diversification opportunities between banks and insurers. The predominant risk is often the primary focus of the current regulation. Internal risk models, which are increasingly used in modern regulation, are better fit to allow for diversification possibilities.

We focus on a semi-reduced form approach at the risk level of an institution. This implies that we do not form a complete structural model explaining the full strategy of agents, since we are primarily interested in the resulting risk. Of importance is the interdependency between institutions. We first model dependence theoretically and subsequently turn to an empirical evaluation. The model is related to the Arbitrage Pricing Theorem of Ross (1976). Suppose the risk of all firms in the financial sector can be decomposed into three elements. Firms face a common component of risk (macro risk), an insurance or bank sector specific risk (sector risk) and firm specific risk. We therefore assume total firm risk to be the sum of the financial market risk, F; risk within a sector, A and B; and firm specific risks, Y_i and Z_j. A high realization of a variable should be interpreted as a large loss, so we can focus on positive random variables for the study of our downside risk. This way we can turn the study of minima into the study of maxima, which permits a more expedient presentation.

The fat tail assumption for the loss distribution boils down to the assumption that the tails exhibit power like behavior, as in the case of the Pareto distribution. For ease of presentation we assume that the entire loss distribution is Pareto distributed. But we emphasize that the results carry over to all distributions which exhibit regular varying tails, such as the Student-t distribution. Assume that the downside risk of the independent stochastic portfolio items (A, B, F, Y_i, Z_j) are (unit scale) Pareto distributed on $[1, \infty)$

$$P(A > t) = P(B > t) = P(F > t) = P(Y_i > t) = P(Z_j > t) = t^{-\alpha}, \qquad (3.2)$$

where t is the threshold loss level which we are interested in. In the following we investigate the dependence between two financial firms or divisions, depending on the interpretation. We distinguish two cases, investigating dependence within a sector and across sectors. The analysis of the theoretical risk exposures helps us to interpret the dependence between the tail risk of the different firms. Understanding this downside risk is desirable from a policy perspective, since it points to the benefits and limits of cross-sector risk sharing.

3.2.1 Same sector dependence

Before we can proceed, we need to introduce some theoretical tools. The probability of a large loss for a combination of risk factors when these exhibit a power like distribution, is given by Feller's convolution theorem (1971, VIII.8). This theorem holds that if two independent random variables A and B satisfy (3.2), then for large t the convolution has probability

$$P(A+B>t)=2t^{-\alpha}L(t),$$

and where $L(t)$ is slowly varying (i.e. $\lim_{t\longrightarrow\infty} L(at)/L(t)=1$, for any $a>0$). The theorem implies that for large failure levels t, the convolution of A and B can be approximated by the sum of the univariate distributions of A and B. All that counts for the probability of the sum is the (univariate) probability mass which is located along the two axes from the points onward where the line $A+B=t$ cuts the axes. The probability that the convolution of A and B is larger than t, for large t, is therefore

$$P(A+B>t)=2t^{-\alpha}+o(t^{-\alpha}). \tag{3.3}$$

Consider the dependency from two financials within the same sector. We use a stylized model of the downside risk of banks and insurers to analyze the tail dependence between two companies. To this end define the equity returns of a company in the banking sector G_i or the insurance sector H_j as a portfolio of risk factors consisting of the following elements:

$$G_i=F+B+Y_i \text{ and } H_j=F+A+Z_j,$$

where F is broad financial market risk and A and B are the sector risks, which are similar for all firms within a sector. Bank and insurance specific risk is defined by Y_i and Z_j. Using Feller (1971, VIII.8), for sufficiently large t the probability that firm i has a return larger than t, $P(G_i>t)$, is the sum of the probabilities that the individual portfolio factors are larger than t. Since the portfolio consists of three items, the probability of a crash of an individual company therefore reads

$$P(F + B + Y_i > t) = 3t^{-\alpha} + o(t^{-\alpha}). \tag{3.4}$$

Suppose one is interested in the probability that two banks crash, simultaneously. The joint probability of a crash between two banks is equal to

$$P(G_1 > t, G_2 > t) = P(F + B + Y_1 > t, F + B + Y_2 > t) = 2t^{-\alpha} + o(t^{-\alpha}). \tag{3.5}$$

This result can again be obtained from Feller's convolution theorem by the following argument. Note that the two portfolio inequalities $F+B+Y_1 > t$ and $F+B+Y_2 > t$, when satisfied simultaneously, only have the points above t along the $F + B$ axis in the portfolio in common[2], but not any point along the Y_1 or the Y_2 axes. This implies that for large t

$$P(F + B + Y_1 > t, F + B + Y_2 > t) \approx P(F + B > t) = 2t^{-\alpha} + o(t^{-\alpha}) \tag{3.6}$$

where the last equality directly follows from Feller's theorem. The probability of a joint crash among two insurers is similar, $P(H_1 > t, H_2 > t) \approx 2t^{-\alpha}$. The relative magnitudes of these probabilities become clear in the empirical section, where we calculate the risk for cross-sector dependence.

3.2.2 Cross-sector dependence

In this paragraph we investigate the probability of a simultaneous crash in two different sectors. Since the sector risk for the two companies is different, there are less common components (factors) in the portfolio of the two firms. The probability of a joint crash of an insurer and a bank is lower, by the assumption that the sector specific portfolio items are independent,

$$P(G_1 > t, H_1 > t) = P(F + B + Y_1 > t, F + A + Z_1 > t) \approx t^{-\alpha} + o(t^{-\alpha}).$$

This probability can also be derived using Feller's convolution theorem. When the portfolio inequalities $F + B + Y_1 > t$ and $F + A + Z_1 > t$ hold simultaneously, there is only probability mass of order $t^{-\alpha}$ above t along the F axis in common, and no

[2]Note that sum of F and B can be treated as one variable.

	$P(G_i > t, G_j > t)$	$1 - P(G_i \leq t, G_j \leq t)$
$G_i = F + B + Y_i$ $G_j = F + B + Y_j$	$2t^{-\alpha}$	$4t^{-\alpha}$
	$P(G_i > t, H_j > t)$	$1 - P(G_i \leq t, H_j \leq t)$
$G_i = F + B + Y_i$ $H_j = F + A + Z_j$	$t^{-\alpha}$	$5t^{-\alpha}$
A, B, F, Y_i and Z are Pareto distributed		

Table 3.1: Cross-sector dependence

mass of this order along the $(B+Y_1)$ and $(A+Z_1)$ axes. This implies that for large t

$$P(F + B + Y_1 > t, F + A + Z_1 > t) \approx P(F > t) = t^{-\alpha} + o(t^{-\alpha}). \tag{3.7}$$

In Table 3.1 the probabilities of cross-sector and same sector risk are summarized. It is interesting to note that the probability of a joint crash of two companies differs considerably depending on cross-sector or within sector combinations.

To evaluate cross-sector dependence and dependence within the same sector analytically with the linkage measure, we need to substitute for the probabilities in the numerator and denominator of (3.1). The probabilities for the numerator are given in (3.4). By using our previous assumptions on the risk components of individual banks and insurers, we can calculate the denominator. The probability that both firms face a return smaller than or equal to t, i.e. $P(G_1 \leq t, G_2 \leq t)$ can be calculated by using the complement $1 - P(G_1 \leq t, G_2 \leq t)$. If we examine the complement, for sufficiently large t, we have the probability that at least one company has a return larger than t. A company has a return larger than t if F, A, B, Y_i or Z_j is larger than t. The complement $1 - P(G_1 \leq t, G_2 \leq t)$ is therefore equal to the sum of the probabilities that an individual portfolio component is larger than t. The complement $1 - P(G_1 \leq t, G_2 \leq t)$ is approximately equal to $4t^{-\alpha}$, since 4 different portfolio items (F, B, Y_1 and Y_2) each have the probability of $t^{-\alpha}$ to be larger than t. In Table 3.1 the complement $1 - P(G_1 \leq t, G_2 \leq t)$ for two firms from a similar sector and two firms from a different sectors are given.

To obtain the conditional risk of a crash of two firms, we substitute $1 - P(G_1 \leq t, G_2 \leq t)$ in the linkage measure. The conditional expectation of a crash of two firms in the same sector is given in (3.8)

$$\lim_{t\longrightarrow\infty} E[\kappa|\kappa \geq 1] = \lim_{t\longrightarrow\infty} \frac{P(G_i > t) + P(G_j > t)}{1 - P(G_i \leq t, G_j \leq t)} = \frac{6}{4}. \tag{3.8}$$

The conditional expectation is much higher in the case of same sector dependence than in the case of cross sector dependence. The conditional expectation of a crash of two firms in different sectors is only

$$\lim_{t\longrightarrow\infty} E[\kappa|\kappa \geq 1] = \lim_{t\longrightarrow\infty} \frac{P(G_i > t) + P(H_j > t)}{1 - P(G_i \leq t, H_j \leq t)} = \frac{6}{5}. \tag{3.9}$$

In the second part of this chapter we estimate the linkage measure. The dependence among financial institutions in the same sector and among institutions in different sectors, will be estimated. If the dependence estimates are higher within a sector than across sectors, this can be explained by the difference in risk between the insurance sector and banking sector, A and B. If cross-sector dependence is similar to the dependence within a sector than it is plausible that the risk in the banking sector is similar to the risk in the insurance sector, $A = B$.

3.2.3 Dependence and the normal distribution

It is interesting to note that the dependence in the tail disappears if we assume that the factors, A, B, F, Y_i and Z_j are standard (independently) normally distributed. Note that normality immediately implies that G_i, G_j, H_i and H_j are all correlated. If we assume that the returns on the individual projects exhibit heavy tails as before, there is dependence in the tails and the linkage measure will be larger than one, even in the limit. However, even though there is positive correlation, if the returns of both G_i and H_i follow a bivariate normal distribution there is no dependence between firms for large values of t, or

$$\lim_{t\longrightarrow\infty} E[\kappa|\kappa \geq 1] = \lim_{t\longrightarrow\infty} \frac{P(G_i > t) + P(Gj > t)}{1 - P(G_i \leq t, G_j \leq t)}$$

$$= \lim_{t\longrightarrow\infty} \frac{P(G_i > t) + P(H_j > t)}{1 - P(G_i \leq t, H_j \leq t)} = 1.$$

The proof for this result is similar to the proof of proposition 2 in De Vries (2005) and follows directly from the general result by Sibuya (1960). Therefore, under the assumption of normality, there is asymptotic independence between all possible combinations of firms, being banks or insurers. This explains why Figure 3.1a differs so much from Figure 3.1b, especially in the North-East and South-West corner, since the remake in Figure 3.1b is based on the assumption of normality. The disappearance of the dependency in the tail area is not unique for the normal distribution. The same holds for the assumption of exponentially distributed portfolio items.

To study whether there is dependence in the limit, we will compare our dependence estimates with estimation results of a bivariate normal model for the returns of the two firms in the empirical section. First we present the univariate and bivariate estimators.

3.3 Estimators

3.3.1 Univariate estimators

Extreme value theory studies the limit distribution of the (joint) maxima or minima of (return) series, as the sample size increases without bound. To study the minimum, we change the sign of the returns. Suppose that X_i is an independent and identically distributed random variable with cumulative distribution function $F(x)$. This variable exhibits heavy tails if $F(x)$ far into the tails has a first order term identical to the Pareto distribution (see Appendix). We want to determine the probability that the daily stock return of a bank or insurer is lower than a prespecified loss level x_{var}, where the subscript refers to Value at Risk. To estimate this probability, we use the inverse quantile estimator from De Haan et al. (1994)

$$\widehat{p} = \frac{m}{n}\left(\frac{X_{m+1}}{x_{var}}\right)^{\widehat{\alpha_{(m)}}}, \ \widehat{\alpha}_{(m)} = \frac{1}{m}\sum_{j=0}^{m}\ln\left(\frac{X_j}{X_{m+1}}\right). \tag{3.10}$$

This probability estimate depends on the tail index α estimator (based on the m highest order statistics), the number of excesses m, the $m+1$-th order statistic X_{m+1}, the sample size n and the level x_{var}, which is the level which we estimate the return series to exceed. In our case x_{var} is determined at 25%. Estimation details are given in the Appendix. For the confidence interval of the quantile estimator we use the property that in the limit the estimator is normally distributed.

3.3.2 Multivariate estimation

In this paragraph we explain the estimator of the linkage measure (3.5). To develop an estimator for the linkage measure, note that

$$E[\kappa|\kappa \geq 1] = \frac{P(X_1 > t) + P(X_2 > t)}{1 - P(X_1 \leq t, X_2 \leq t)} = 1 + \frac{P(\min[X_1, X_2] > t)}{P(\max[X_1, X_2] > t)}, \tag{3.11}$$

where $P(\min[X_1, X_2] > t)$ is the probability that the minimum of X_1 and X_2 is above the threshold t, and $P(\max[X_1, X_2] > t)$ is the probability that the maximum of both random variables exceeds t. Both probabilities can be easily estimated. In the Appendix we show that this estimator captures the limiting dependence between two heavy tailed random variables. According to theory, the tail dependence between two dependent variables which follow a Student-t distribution is much higher than the dependence between two dependent variables which follow a normal distribution. Since we evaluate the limit behavior of (3.11), we take t close to the boundary of the sample and use $t = 0.075$. We obtain a confidence band by the Jackknife resampling procedure and show that our results do not change much if we omit a large number of observations (see Appendix).

3.3.3 Data

Our sample consists of the ten largest European banks and the ten largest European insurers. These firms were selected on the basis of balance sheet criteria such as the amount of customer deposits and life and non-life premium income. Insurers can provide both life insurance and non-life insurance (e.g. property and casualty insurance). We use daily data from January 1992 until December 2003. A precise description of the dataset is given in the Appendix.

3.4 Empirical results

In this section we present the estimates of the downside risk of individual firms and the dependence between firms. First we present the univariate risk for banks and insurers, next we present the dependency estimates between firms.

Banks	Probability (Xi < -0.25) * 260	Insurers	Probability (Xi < -0.25) * 260
HSBC	0.0037	ROYAL & SUN	0.0482
RBS	0.0064	AEGON	0.0584
UBS	0.0142	AVIVA	0.0161
BARCLAYS	0.0068	PRUDENTIAL	0.0237
BSCH	0.0081	LEGAL & GENERAL	0.0020
BBVA	0.0186	ALLEANZA	0.0070
DEUTSCHE BANK	0.0089	SKANDIA	0.0501
ABN AMRO	0.0072	GENERALI	0.0121
UNICREDITO	0.0150	AXA	0.0153
STD CHARTERED	0.0168	ZFS	0.1073
Average	0.0106		0.0340
Median	0.0085		0.0199

Table 3.2: Univariate loss probabilities

3.4.1 Univariate results

Suppose one is interested in the probability of a loss of market value of 25% or more in a single day. Since these probabilities are very small, we scaled these up by a factor of 260, so that the probabilities can be interpreted as the probability that in a year there is a day with a loss of 25%. The estimated probabilities are given in Table 3.2. From the averages of the different sectors it is clear that insurers are more risky than banks. The average in the banking sector is 0.0106, in the insurance sector the average probability is 0.034. In other words, about once per thirty years there is a day on which an insurer loses 25% of its equity value. For banks this is only once per century. Within the different groups there are however large deviations from the sector means. The results for the banking sector range from 0.0037 to 0.0186. The results for the insurance sector are between 0.0020 and 0.1073. We formally test our null-hypothesis that both groups have the same general distribution by using the Wilcoxon/Mann-Whitney signed ranks test. The probability that the equality hypothesis is valid is 0.064. We therefore reject the null-hypothesis and conclude that insurers are more risky than banks. Further evidence for this result can be found in Table 3.8 in de Appendix. Although the normal model underestimates risk, the results also indicate that insurers are more risky than banks.

Using (3.14) from the Appendix, one can calculate a confidence band. Results are given in Table 3.3. In this table we use a threshold loss of 15%[3]. Given the limited

[3] Here we do not multiply the probabilites with 260, so as to guarantee that the probabilities are between 0 and 1.

Firms	Lower Bound	Probability Xi < -0.15	Upper Bound	Hill
HSBC	0.00005	0.00012	1.00000	4.14
RBS	0.00010	0.00020	1.00000	4.06
UBS	0.00015	0.00028	0.00478	3.23
BARCLAYS	0.00009	0.00019	1.00000	3.89
BSCH	0.00012	0.00024	0.01360	3.98
BBVA	0.00020	0.00037	0.00304	3.23
DEUTSCHE BANK	0.00012	0.00023	0.01908	3.75
ABN AMRO	0.00011	0.00023	0.04766	4.09
UNICREDITO	0.00018	0.00033	0.00346	3.43
STD CHARTERED	0.00020	0.00038	0.00297	3.49
ROYAL & SUN	0.00055	0.00092	0.00276	3.14
AEGON	0.00059	0.00097	0.00281	2.86
AVIVA	0.00021	0.00038	0.00297	3.57
PRUDENTIAL	0.00027	0.00049	0.00263	3.28
LEGAL & GENERAL	0.00004	0.00009	1.00000	4.85
ALLEANZA	0.00010	0.00019	1.00000	3.87
SKANDIA	0.00078	0.00125	0.00309	3.66
GENERALI	0.00012	0.00024	0.01274	3.21
AXA	0.00022	0.00042	0.00281	3.82
ZFS	0.00095	0.00148	0.00334	2.50

Table 3.3: Loss probabilities and confidence bands

amount of data, even at this loss level several upper bounds of the confidence bands are equal to 1. The difference between the point estimator and the upper bound of the interval is larger than the difference between the point estimator and the lower bound. This is also a result of a relatively small sample size (n).

The estimates are derived by assuming that the tails of the return distributions are heavy tailed. Since we study events that have a high impact, but which materialize at a very low frequency, our estimated probabilities may at first sight appear very small. To put these probabilities in perspective, recall the Figures (3.1a) and (3.1b), which showed a huge discrepancy between the normal distribution and the empirical distribution. Suppose one calculated the loss probabilities for HSBC and ZFS (respectively the first and last company) from Table 3.3 under the assumption of normality. This gives $1.5 * 10^{-15}$ and $8.6 * 10^{-11}$ for respectively HSBC and ZFS. These figures are much lower than 0.00012 and 0.00148. The entire Table 3.3 is recalculated under the assumption of normality and is given in the Appendix in Table 3.8.

	Mean		Median	
	Bank	Insurer	Bank	Insurer
Bank	0.1038	0.0744	0.095	0.069
Insurer	0.0744	0.1170	0.069	0.107
	$E[\kappa \mid \kappa \geq 1] - 1$			

Table 3.4: Summary non-parametric estimation results

3.4.2 Multivariate results

Is cross-sector dependence between banks and insurers lower than dependence between two firms within the same sector? Since we have 10 banks and 10 insurers in our dataset, we have results for 45 possible combinations of banks, 45 possible combinations of insurers and 100 possible combinations between banks and insurers. In Table 3.4 the estimation results for the 190 possible combinations are summarized. The results for all 190 combinations are given in the Tables 3.9, 3.10 and 3.11, in the Appendix. The results of the multivariate estimation in Table 3.4 indicate that cross-sector dependence between banks and insurers is lower than dependence between two firms within the same sector. The average probability that two banks crash, given that one crashes is 10.3%. For insurers this probability is 11.7%, which is not very different. The probability that an insurer crashes given that a bank crashes or that a bank crashes, given that an insurer crashes is 7.4%. This is much lower than the 10.3% in the banking sector. This indicates that in general dependence is lower for cross-sector combinations. We formally test the null-hypothesis that cross-sector dependence is similar to the dependence within the same sector, by using the Wilcoxon/Mann-Whitney signed ranks test. The probability that the hypothesis is not rejected is 0.004% if we test whether dependence among banks is similar to dependence between banks and insurers. We conclude that the risk profile of the two groups is different. Using the same test procedure, we can also find that the probability that the risk for combinations of insurers is equal to combinations of insurers and banks is only 0.003%. Thus the dependence between banks and insurers is also lower than the combinations of insurers.

On the firm level, there are sizable deviations from the average risk within the sector. Results for specific combinations of firms given in the Tables 3.9, 3.10 and 3.11. The largest conditional probability of a crash of two firms is 37.5% and it involves two Spanish banks (Table 3.9). Since 37.5% is much higher than the sector average of

	Mean	
	Bank	Insurer
Bank	0.0082	0.0063
Insurer	0.0063	0.0133
$E[\kappa \mid \kappa \geq 1]-1$		

Table 3.5: Estimation results (bivariate normal model)

10.3%, it makes considerable difference which firms merge. A possible explanation for this high probability are the common exposure of the two Spanish banks to risks in Spain and Latin America.

We have also calculated (3.1), assuming a bivariate normal distribution function for the returns. The results are given in the Tables 3.12, 3.13 and 3.14. A summary is given in Table 3.5. The results indicate that the dependence between banks and insurers is also lower than the dependence among other combinations. This indicates that our main empirical result is robust. However, once again it is clear that the assumption of a normal distribution function for the returns underestimates the downside risk. The conditional probability of a second crash for the combination of HSBC and RBS is 0.083, while estimation based on normality gives 0.0044. Our measure therefore predicts that the conditional probability of a double crash is approximately 20 times higher for this combination than the normality based measure. For the pair Aviva and AEGON, the estimate based on normality gives 0.0134. This is a factor 8 lower than 0.111. Thus the normal based measure gives a completely different view on the tail dependence and essentially rules out the possibility of a joint crash. Estimates taking into account the fat tails are of an entirely different order and appear to be more in line with the facts, since we do observe joint failures repeatedly.

To illustrate the dimension of the result of 37.5% conditional crash probability for the two Spanish banks, one can also calculate the conditional expected number of failures κ in (3.1) under the assumption of independence

$$E[\kappa \mid \kappa \geq 1] = \frac{P(F_1 > t) + P(F_2 > t)}{1 - (P(F_1 \leq t) * P(F_2 \leq t))} = 1 + \frac{1}{\frac{1}{0.0038} + \frac{1}{0.0035} - 1} = 1.0018.$$

The number 1.0018 is considerably smaller than 1.375. It is therefore clear that there is quite a bit of dependence in the tails. This exercise delivers similar results for other combinations of firms.

	ROYAL & SUN - AEGON	
1.194	1.225	1.257
	AEGON - AVIVA	
1.097	1.111	1.125
	RBS - STD CHARTERED	
1.056	1.091	1.100
	RBS - LEGAL & GENERAL	
1.000	1.000	1.000
	BSCH - BBVA	
1.357	1.375	1.400
	BSCH - LEGAL & GENERAL	
1.063	1.063	1.071

Left and right the bounds of the 90% confidence interval are given, in the central column the point estimator.

Table 3.6: Multivariate results and 90% confidence bands

Table 3.6 reports the confidence bands for a number of the linkage measure estimates. The bounds of the confidence interval do not deviate considerably from the point estimator and are of the same order. The Jackknife procedure behind the confidence bands is given in the Appendix. In the central column one finds the point estimator of (3.15). In the left and right column one finds the 90% confidence interval. In the case of the combination of BSCH and Legal and General, the point estimator of (3.15) hits the lower bound. This is the result of the quite limited sample, of only 12 years of daily data, which is small if one studies bivariate dependence. Another interesting observation is that the conditional expectation of a combined crash for the combination of RBS and Legal and General is zero. This stems from the fact that there are no joint losses of 7.5% or larger for these companies. In this case the point estimator defaults to the lower bound and the resampling based construction of the confidence bands collapses.

3.5 Conclusion

The downside risk dependence between insurance and banking risks investigated in this paper is indicative for the risk of a financial conglomerate. A financial conglomerate may provide scope for risk diversification across the banking and insurance books. This may lower capital requirements and enhance the efficiency of the financial services sector. Alternatively, one could also imagine that the downside risk of a conglomerate is actually larger, due to diseconomies of scope.

To measure the scope for diversification, we first investigated the uses of the normal distribution. We showed that the normal distribution strongly underestimates the downside risk, since the return series of financial assets are fat tailed distributed. Given the focus on downside risk, we therefore allow for fat tails. Both for the univariate risks and the multivariate downside risks this gives a much better description of the downside risk than the normal approximation.

To understand the possible differences in cross-sector risk, we develop an analytical model in the theory section, which helps to interpret the tail dependence between banking and insurance risks. It provides an explanation for the dependence structure between banking and insurers. Given this structure, the model explains the differences between the dependence among firms within an industry and the dependence among firms from different sectors.

In the empirical section we first measure the riskiness of individual banks and insurers. This involves estimating the probability of a crash by using daily stock price data. The estimation results for individual firms provide information on the risk of individual institutions and allows for a cross-sector comparison of individual firm risk. The estimation results for individual firms point to the conclusion that banks are less risky than insurers. If we take into account the low probability of a crash, both banks and insurers may be considered as safe.

The main research question concerns whether the downside risk in the banking sector differs from the downside risk in the insurance sector. To this end we examine the dependence between combinations of firms, both within a sector and across sectors. We find that risk dependence between a bank and an insurer is significantly different from the dependence structure between two banks or between two insurers. The average probability that two banks crash, given that one crashes is 10.3%. For insurers this probability is 11.7%, which is not very different. The probability that an insurer crashes given that a bank crashes or that a bank crashes, given that an insurer crashes is 7.4%. This is much lower than the 10.3% in the banking sector. This indicates that in general dependence is lower for cross-sector combinations.

The theoretical model gives an explanation for the lower dependence between banks and insurers. Apparently, there is a different downside risk for the sector specific risks for insurance and banking. This relatively low cross-sector dependence implies a smaller impact of financial conglomerates on systemic risk. It follows that capital requirements for financial conglomerates could be set below the sum of the capital requirements for the banking and insurance parts.

The Basle II capital framework does not take into account these diversification benefits. We recommend to explore the properties of risk diversification by financial conglomerates in future work on capital requirements (the Basle III agenda). If lower capital requirements can be justified from a prudential point of view, this may enhance social welfare.

3.6 Appendix

3.6.1 Data selection

Since it is common for financial companies in Europe to exploit a broad portfolio of activities in banking and insurance, it is difficult to construct a dataset of companies pursuing pure banking or insurance strategies. Moreover, some activities as for example the provision of mortgages, are common for all companies in both banking and insurance. In this section we will explain when we define a company being a bank or an insurer.

We distinguish three different categories: banks, insurers (combining property&casualty and life insurance business) and financial conglomerates. The dataset contains companies from Europe (the EU and Switzerland). First, we have taken the largest firms by market capitalization in the following sectors from Datastream: banking, life insurance, insurance and other financial. Since we could not find the Datastream criteria for sector selection, we made our own classification of these companies based on their annual accounts over 2002.

To be able to make a distinction between insurers and banks, we collected the following balance sheet items: ‘customer deposits’, ‘technical provisions’ and ‘life-insurance risk born by the policy holder’. We suppose that those broad items are unique for specific sectors. The item ‘customer deposits’ is typical for banks, since they borrow money from the public. The item ‘technical provisions’ is typical for insurers, since it represents the size of provisions for future insurance claims. Another item typical for life insurance is ‘life-insurance risk born by the policy holder’, which represents provisions for future claims of life insurance policies. The three items were added up and we represented the customer deposits as a percentage of this sum of balance sheet items. When the percentage of deposits is larger than 90% we define a firm as a bank. When the sum of ‘technical provisions’ and ‘life-insurance risk born by the policy holder’ represented as a percentage of the sum of all three items is larger than 90%, we define a firm as an insurer.

Furthermore we want to get an indication of the main activity of the insurers. We made a distinction between property and casualty insurers and life insurers and collected data on the net premium income of insurers. The net premiums are the gross premiums written minus reinsurance cover. Since an insurer might choose to

	Bank (%)	Insurer (%)	Life (%)	Non-life (%)
Bank				
HSBC	0.98	0.02		
RBS	0.96	0.04		
UBS	1.00	0.00		
BARCLAYS	0.95	0.05		
BSCH	1.00	0.00		
BBVA	1.00	0.00		
DEUTSCHE BANK	0.98	0.02		
ABN AMRO	0.97	0.03	0.78	0.22
UNICREDITO	1.00	0.00		
STD CHARTERED	1.00	0.00		
Insurer				
GENERALI	0.00	1.00	0.65	0.35
AXA	0.00	1.00	0.70	0.30
AEGON	0.03	0.97	0.96	0.04
AVIVA	0.00	1.00	0.75	0.25
PRUDENTIAL	0.06	0.94	0.98	0.02
ZFS	0.00	1.00	0.30	0.70
LEGAL & GENERAL	0.00	1.00	0.94	0.06
ALLEANZA	0.00	1.00	1.00	0.00
ROYAL & SUN	0.00	1.00	0.82	0.18
SKANDIA	0.08	0.92	0.99	0.01

Table 3.7: Selected data

	P(Xi<-0.15)	P(Xi<-0.15)*260
HSBC	0.00000000000000	0.00000000000040
RBS	0.00000000000113	0.00000000029305
UBS	0.00000000000000	0.00000000000000
BARCLAYS	0.00000000000030	0.00000000007759
BSCH	0.00000000000041	0.00000000010585
BBVA	0.00000000000002	0.00000000000468
DEUTSCHE BANK	0.00000000000001	0.00000000000167
ABN AMRO	0.00000000000001	0.00000000000277
UNICREDITO	0.00000000004858	0.00000001263127
STD CHARTERED	0.00000000006859	0.00000001783248
ROYAL & SUN	0.00000000503413	0.00000130887418
AEGON	0.00000000003063	0.00000000796488
AVIVA	0.00000000000205	0.00000000053240
PRUDENTIAL	0.00000000000330	0.00000000085795
LEGAL & GENERAL	0.00000000000096	0.00000000024929
ALLEANZA	0.00000000000434	0.00000000112779
SKANDIA	0.00000116611496	0.00030318989027
GENERALI	0.00000000000000	0.00000000000000
AXA	0.00000000004009	0.00000001042234
ZFS	0.00000000008602	0.00000002236395

Table 3.8: Univariate probability assuming normal cdf

buy reinsurance cover for some lines of business, we argue that the net premium income gives the best information whether an insurer is active in life insurance or in property and casualty insurance. The life-insurance premium income was represented as a percentage of the total premium income.

We use data from 1992-2003, since in 1992 Basle I came into effect and because of data availability. Data is on a daily basis. Firms which are part of a larger conglomerate, like Winterthur which is a holding of Credit Suisse, are excluded. Some firms are omitted because the available data series is too short.

3.6.2 Assuming normality

To highlight the limits of the assumption of normality for the return distribution, we have calculated the risk of a loss of more than 15% on a given day for the different firms by using the normal distribution. The results can be found in Table 3.8. These normal based probabilities are way below the corresponding extreme value distribution based fat tail hypothesis estimates from Table 3.3.

3.6.3 Univariate estimation

Extreme value theory studies the limit distribution of the maximum or minimum of a single return series. To study the minimum, we change the sign of the returns. Let X_i be an independent and identically distributed random variable with cumulative distribution function $F(x)$. This variable exhibits heavy tails if $F(x)$ far into the tails has a first order term identical to the Pareto distribution, i.e.

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

where $L(x)$ is a slowly varying function such that

$$\underset{t \longrightarrow \infty}{Lim} \frac{L(tx)}{L(t)} = 1, \; x > 0.$$

It can be shown that the two previous conditions are equivalent to

$$\underset{t \longrightarrow \infty}{Lim} \frac{1 - F(tx)}{1 - F(t)} = x^{-\alpha}, \, \alpha > 0, \, t > 0.$$

The coefficient α is known as the tail index and gives the number of bounded moments of the distribution. When a distribution has finite endpoints or exponentially decaying tails (like the normal and lognormal distributions), it fails the property of regular variation and all moments are bounded.

We estimate α with the Hill (1975) estimator:

$$\widehat{\gamma} = 1/\widehat{\alpha} = \frac{1}{m} \sum_{j=0}^{m} \ln \left(\frac{X_j}{X_{m+1}} \right), \tag{3.12}$$

where the parameter m equals the number of highest order statistics. The number m has to be selected such that the Pareto approximation of the tail is appropriate. We select the threshold by the bootstrap method proposed in Danielsson et al. (2001), which is also based on the Hill estimator. An alternative estimator can be found in Huisman et al. (2001). In Figure 3.3 the Hill plots for four firms are given. In a Hill plot one varies the threshold s or alternatively m, and plots $\widehat{\gamma}$ from (3.12) against s (or m). In the Hill plots of Figure 3.3, where $\widehat{\gamma}$ is plotted against m, one sees considerable variation if one uses only the very top order statistics. Subsequently using more order statistics one notices some plateaus. Increasing m even further, the Hill plots all appear to be moving down. This is a result of the bias which kicks in when one uses too many central order statistics. Using too few order statistics causes the variance to dominate. Somehow one has to sail between these two vices.

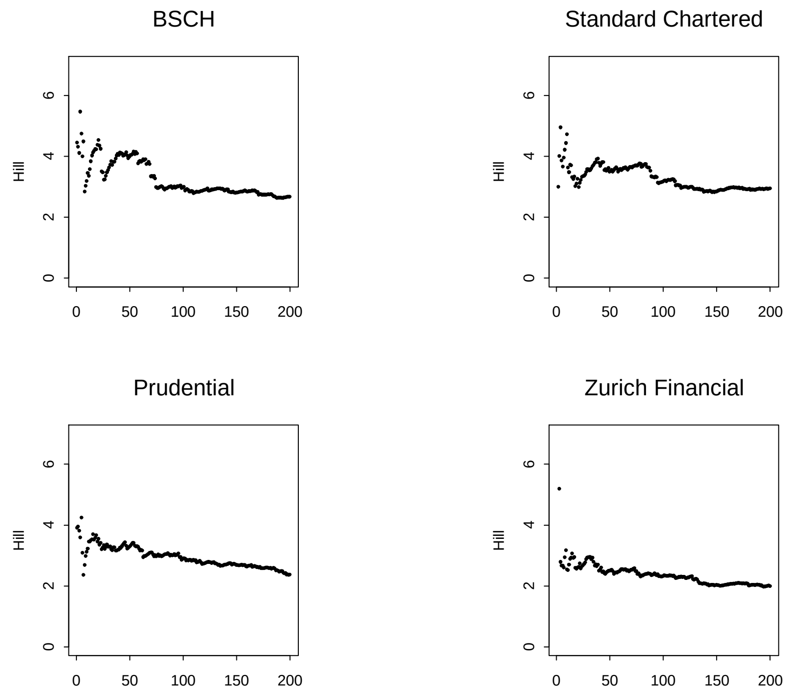


Figure 3.3: Hill plots for 4 firms

The next question is which threshold s (or m) should be selected? We choose m in such a way as to minimize the mean square error (mse), following Danielsson et al. (2001). This involves creating elaborate subsample bootstraps. Mean square error plots for four firms are given in Figure 3.4. The plots indicate that a minimum is reached around $m = 50$. Since similar plots appear for all the series, we fixed m at 50 for all our $\widehat{\gamma}$ estimates.

The objective of our investigation is to determine the probability that the daily stock return of a bank or insurer is lower than a prespecified probability level, x_{var}. To estimate this probability, we use the inverse quantile estimator from De Haan et al. (1994),

$$\widehat{p} = \frac{m}{n} \left(\frac{X_{m+1}}{x_{var}} \right)^{\widehat{\gamma_{(m)}}}. \tag{3.13}$$

This estimator depends on the inverse tail index γ, the number of higher order statistics m, the $m+1$-th order statistic X_{m+1}, the sample size n and the level x_{var}. In our case x_{var} is chosen at 25%.

For the calculation of the confidence interval of this estimator we use the property of convergence of the estimator to normality in large samples. To calculate the 90% confidence interval for equation (3.13), we use the following from De Haan et al. (1994),

$$\frac{m^{1/2}}{\log(\frac{x_t}{x_p})}(\frac{\widehat{p}}{p} - 1) \sim N(0, \alpha^2). \tag{3.14}$$

We rewrite this to obtain the lower bound and the upper bound of the 90% confidence interval for p

$$\frac{\widehat{p}}{\frac{1.65\widehat{\alpha}f}{\sqrt{M}} + 1} < p < \frac{\widehat{p}}{-\frac{1.65\widehat{\alpha}f}{\sqrt{M}} + 1} \text{ where } f = \log(\frac{x_t}{x_p}).$$

The 90% confidence intervals for $x_{var} > 0.15$ are given in Table 3.3, in the main text.

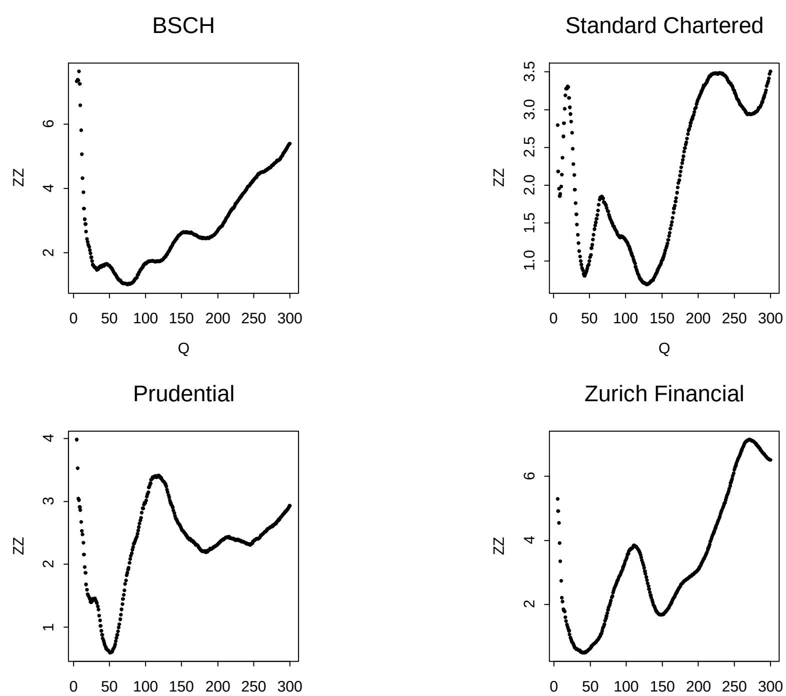


Figure 3.4: MSE 4 firms

3.6.4 Multivariate estimation

In this section we elaborate on the bivariate estimation technique employed in the paper. We first rewrite the linkage measure, turn it into an estimator and subse-

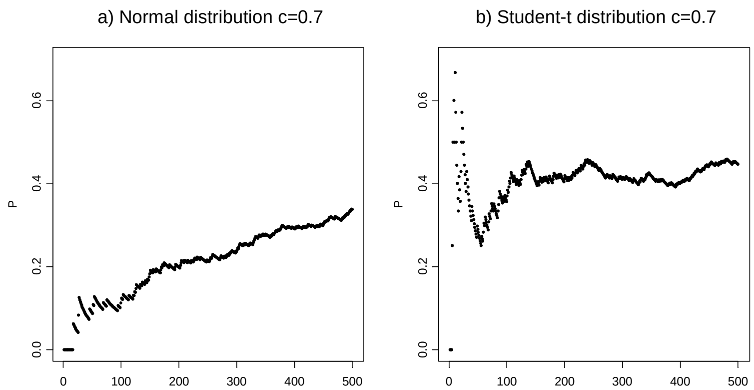


Figure 3.5: Conditional expectation, simulated data

quently show how the estimator performs on simulated data en real data.

From elementary probability theory we know that $P(X_1 \leq t, X_2 \leq t) = 1 - P(\max[X_1, X_2] > t)$ and $P(X_1 > t) + P(X_2 > t) = P(\max[X_1, X_2] > t) + P(\min[X_1, X_2] > t)$. One can therefore rewrite the conditional expectation as follows

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

The estimation of the probability of multiple crashes can thus be reduced to the estimation of two univariate probabilities. This greatly facilitates the empirical analysis, since one can proceed on basis of the previously described univariate estimation methods for the minimum and maximum return series. We use the notation P_{min} for $P(\min[X_1, X_2] > t)$ and the corresponding notation for the maximum. If the tail index α is identical for the minimum (α_i) and maximum (α_a) series, we obtain the following non-parametric estimator[4]

$$E[\kappa|\kappa \geq 1] = 1 + \frac{\widehat{P}_{\min}}{\widehat{P}_{\max}}. \tag{3.15}$$

In the following we show that this estimator captures the low dependence of a bivariate normal distribution, in comparison to the high dependence in the tails of a bivariate Student-t distribution. To this end we generate two times 5000 observations, based on the normal and Student-t distribution, with 3 degrees of freedom.

[4] Using $E[\kappa|\kappa \geq 1] = 1 + \frac{\frac{M_{\min}}{n}\left(\frac{X_{M+1}}{x_p}\right)^{\widehat{\alpha_i(m)}}}{\frac{M_{\max}}{n}\left(\frac{X_{M+1}}{x_p}\right)^{\widehat{\alpha_a(m)}}} = 1 + \frac{M_{\min}}{M_{\max}}$, which shows that the estimator reduces to a simple counting procedure for the minima and maxima.

We draw q and z from a normal distribution and define $a = q + 0.7z$. The correlation between a and z is therefore 0.7. This correlation pattern corresponds to the correlation which is present in Figure 3.1. However, the dependence in the tails between a and z is non-existent. This is also what the estimator (3.15) indicates, as can be seen in Figure 3.5a. The threshold t is depicted on the x-axis, the linkage estimator is on the y-axis. High values for t are on the left side. On sees that the dependence is low in the tails, i.e. for high values of t, but increases while going into the center of the distribution, when t decreases.

Next, we generate q and z from a Student-t distribution, with 3 degrees of freedom and define $a = q + 0.7z$. The estimation results for the dependence between a and z can be found in Figure 3.5b. Contrary to the normal distribution, for large values of t (on the left side of the Figure), there is dependence. This is exactly what one would expect on basis of the theory.

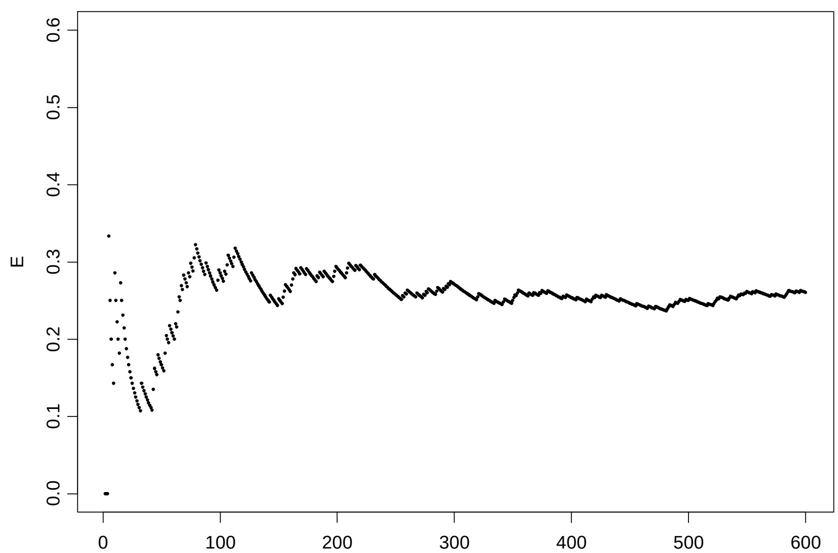


Figure 3.6: $E[\kappa|\kappa \geq 1]$ for ABN AMRO Bank and AXA

In Figure 3.6 we show the estimation results for real empirical data. The results of estimator (3.15) for the combination of ABN AMRO Bank and AXA looks very similar to the results of the Student-t simulation in Figure 3.5. $E[\kappa|\kappa \geq 1]$ is depicted at the y-axis. The threshold t is on the x-axis. Large t are on the left, where t is taken from the sorted, joint set of returns of AXA and ABN AMRO Bank. The value at the x-axis is the rank of t in this joint sample. On the left side of the graph the variance is high, because there are few extremely large returns. The other side of the graph is relatively stable and there is not much variation. The interesting feature of this graph is however that for large t, $E[\kappa|\kappa \geq 1]$ is not zero. This is exactly what is in the generated graph for the bivariate Student-t distribution. The conditional probability of a simultaneous crash in normal distributed data is zero, for large t.

The calculation of the confidence interval is based on resampling. We use a Jack-knife procedure. To this end we divided the data in 20 blocks of 156 observations. We then apply estimator (3.15) 20 times, each time leaving one block of 156 observations out of the time series. To obtain the confidence band, the highest and lowest estimation results were removed, the next highest and lowest provide the 90% confidence interval. The point estimator is estimated using the full sample.

	HSBC	RBS	UBS	BARCLAYS	BSCH	BBVA	DEUTSCHE BANK	ABN AMRO	UNICREDITO	STD CHARTERED
	1	2	3	4	5	6	7	8	9	10
1	2.000	1.083	1.083	1.077	1.000	1.000	1.083	1.071	1.000	1.056
2	1.083	2.000	1.125	1.188	1.056	1.050	1.125	1.053	1.059	1.091
3	1.083	1.125	2.000	1.118	1.118	1.167	1.125	1.111	1.059	1.091
4	1.077	1.188	1.118	2.000	1.111	1.100	1.056	1.167	1.118	1.042
5	1.000	1.056	1.118	1.111	2.000	1.375	1.056	1.167	1.267	1.136
6	1.000	1.050	1.167	1.100	1.375	2.000	1.050	1.095	1.235	1.125
7	1.083	1.125	1.125	1.056	1.056	1.050	2.000	1.111	1.000	1.091
8	1.071	1.053	1.111	1.167	1.167	1.095	1.111	2.000	1.111	1.130
9	1.000	1.059	1.059	1.118	1.267	1.235	1.000	1.111	2.000	1.143
10	1.056	1.091	1.091	1.042	1.136	1.125	1.091	1.130	1.143	2.000

Table 3.9: Banks vs Banks, t=0.075, Real data

	ROYAL & SUN	AEGON	AVIVA	PRUDENTIAL	LEGAL & GENERAL	ALLEANZA	SKANDIA	GENERALI	AXA	ZFS
	11	12	13	14	15	16	17	18	19	20
1	1.037	1.036	1.056	1.053	1.000	1.125	1.019	1.143	1.045	1.030
2	1.100	1.097	1.043	1.087	1.000	1.077	1.055	1.083	1.167	1.147
3	1.100	1.063	1.143	1.087	1.000	1.077	1.074	1.083	1.167	1.083
4	1.097	1.094	1.190	1.130	1.000	1.154	1.113	1.077	1.160	1.111
5	1.063	1.061	1.042	1.040	1.063	1.000	1.035	1.000	1.074	1.081
6	1.091	1.028	1.038	1.037	1.000	1.063	1.034	1.067	1.069	1.050
7	1.138	1.063	1.091	1.087	1.000	1.077	1.074	1.083	1.077	1.083
8	1.167	1.161	1.238	1.227	1.059	1.067	1.071	1.071	1.111	1.108
9	1.065	1.030	1.043	1.042	1.067	1.077	1.036	1.000	1.037	1.054
10	1.083	1.053	1.034	1.069	1.048	1.111	1.016	1.056	1.063	1.071

Table 3.10: Banks vs Insurers, t=0.075, Real data

	ROYAL & SUN 11	AEGON 12	AVIVA 13	PRUDENTIAL 14	LEGAL & GENERAL 15	ALLEANZA 16	SKANDIA 17	GENERALI 18	AXA 19	ZFS 20
11	2.000	1.225	1.182	1.143	1.107	1.074	1.106	1.037	1.229	1.125
12	1.225	2.000	1.111	1.242	1.032	1.034	1.138	1.036	1.333	1.196
13	1.182	1.111	2.000	1.192	1.100	1.111	1.143	1.056	1.097	1.154
14	1.143	1.242	1.192	2.000	1.150	1.105	1.140	1.053	1.207	1.122
15	1.107	1.032	1.100	1.150	2.000	1.000	1.018	1.000	1.040	1.057
16	1.074	1.034	1.111	1.105	1.000	2.000	1.038	1.286	1.091	1.061
17	1.106	1.138	1.143	1.140	1.018	1.038	2.000	1.019	1.172	1.179
18	1.037	1.036	1.056	1.053	1.000	1.286	1.019	2.000	1.095	1.030
19	1.229	1.333	1.097	1.207	1.040	1.091	1.172	1.095	2.000	1.195
20	1.125	1.196	1.154	1.122	1.057	1.061	1.179	1.030	1.195	2.000

Table 3.11: Insurers vs Insurers, t=0.075, Real data

	HSBC 1	RBS 2	UBS 3	BARCLAYS 4	BSCH 5	BBVA 6	DEUTSCHE BANK 7	ABN AMRO 8	UNICREDITO 9	STD CHARTERED 10
1	2	1.0044	1.0032	1.0074	1.0039	1.0051	1.0036	1.0064	1.0012	1.0096
2	1.0044	2	1.0016	1.0241	1.0061	1.0045	1.0044	1.0069	1.0036	1.0088
3	1.0032	1.0016	2	1.0026	1.0033	1.0054	1.0086	1.0097	1.0010	1.0011
4	1.0074	1.0241	1.0026	2	1.0057	1.0054	1.0045	1.0083	1.0039	1.0105
5	1.0039	1.0061	1.0033	1.0057	2	1.0793	1.0098	1.0181	1.0057	1.0059
6	1.0051	1.0045	1.0054	1.0054	1.0793	2	1.0104	1.0188	1.0046	1.0037
7	1.0036	1.0044	1.0086	1.0045	1.0098	1.0104	2	1.0178	1.0032	1.0033
8	1.0064	1.0069	1.0097	1.0083	1.0181	1.0188	1.0178	2	1.0049	1.0042
9	1.0012	1.0036	1.0010	1.0039	1.0057	1.0046	1.0032	1.0049	2	1.0049
10	1.0096	1.0088	1.0011	1.0105	1.0059	1.0037	1.0033	1.0042	1.0049	2

Table 3.12: Banks vs Banks, t=0.075, Bivariate normal

	ROYAL & SUN 11	AEGON 12	AVIVA 13	PRUDENTIAL 14	LEGAL & GENERAL 15	ALLEANZA 16	SKANDIA 17	GENERALI 18	AXA 19	ZFS 20
1	1.0013	1.0023	1.0032	1.0033	1.0030	1.0014	1.0007	1.0013	1.0026	1.0024
2	1.0075	1.0073	1.0131	1.0100	1.0091	1.0033	1.0024	1.0012	1.0094	1.0093
3	1.0007	1.0025	1.0016	1.0019	1.0014	1.0012	1.0005	1.0024	1.0031	1.0038
4	1.0081	1.0079	1.0140	1.0139	1.0126	1.0032	1.0020	1.0017	1.0105	1.0082
5	1.0044	1.0130	1.0077	1.0072	1.0054	1.0063	1.0038	1.0024	1.0187	1.0126
6	1.0028	1.0100	1.0051	1.0052	1.0040	1.0051	1.0021	1.0046	1.0126	1.0083
7	1.0022	1.0081	1.0040	1.0049	1.0035	1.0036	1.0020	1.0028	1.0092	1.0073
8	1.0034	1.0204	1.0088	1.0087	1.0060	1.0053	1.0027	1.0045	1.0158	1.0105
9	1.0063	1.0081	1.0049	1.0052	1.0034	1.0183	1.0061	1.0036	1.0112	1.0095
10	1.0120	1.0084	1.0090	1.0098	1.0073	1.0034	1.0065	1.0007	1.0114	1.0096

Table 3.13: Banks vs Insurers, t=0.075, Bivariate normal

	ROYAL & SUN 11	AEGON 12	AVIVA 13	PRUDENTIAL 14	LEGAL & GENERAL 15	ALLEANZA 16	SKANDIA 17	GENERALI 18	AXA 19	ZFS 20
11	2	1.0175	1.0200	1.0175	1.0112	1.0047	1.0158	1.0007	1.0190	1.0249
12	1.0175	2	1.0134	1.0184	1.0095	1.0092	1.0117	1.0022	1.0465	1.0399
13	1.0200	1.0134	2	1.0317	1.0221	1.0050	1.0041	1.0016	1.0147	1.0128
14	1.0175	1.0184	1.0317	2	1.0321	1.0063	1.0048	1.0019	1.0214	1.0131
15	1.0112	1.0095	1.0221	1.0321	2	1.0030	1.0024	1.0012	1.0114	1.0091
16	1.0047	1.0092	1.0050	1.0063	1.0030	2	1.0033	1.0166	1.0119	1.0088
17	1.0158	1.0117	1.0041	1.0048	1.0024	1.0033	2	1.0004	1.0128	1.0146
18	1.0007	1.0022	1.0016	1.0019	1.0012	1.0166	1.0004	2	1.0027	1.0019
19	1.0190	1.0465	1.0147	1.0214	1.0114	1.0119	1.0128	1.0027	2	1.0442
20	1.0249	1.0399	1.0128	1.0131	1.0091	1.0088	1.0146	1.0019	1.0442	2

Table 3.14: Insurers vs Insurers, t=0.075, Bivariate normal

Chapter 4

Insurance Sector Risk

The financial stability of the global insurance sector was a major concern for regulators following the losses of the September 2001 WTC collapse. At the same time, the investment income arising out of the assets of insurers declined, due to low interest rates and a declining stock market during the recession at the time. In this chapter the downside risk dependence of multiple insurers is studied. Similarities in sector wide risk exposure are measured using daily stock price returns of European insurers and reinsurers.

An explanation for a similar exposure to very large losses is provided, based on the idea that multiple insurers carry similar risks. Insurance companies can e.g. be exposed to similar insurance risk on the liability side, due to reinsurance practices which spread the same risk across companies. This common exposure can also arise because of an exposure to similar macroeconomic variables, like interest rates or inflation on the asset side. The effect of risk diversification on downside risk is modelled and estimated for individual companies and for the sector as a whole.

Risk diversification may reduce the risk of individual insurance companies, but the risk profiles of multiple insurers becomes more similar due to this diversification. Hence, systemic risk may increase due to risk sharing. For the design of optimal regulation, it matters if regulators have to deal with sector wide risk or firm specific risk. When firms are exposed to the same risks, during a crisis all insurers realize losses on either their assets or liabilities. The capacity of the insurance sector can therefore be at risk and may need to be enhanced. Moreover there is an increasing interest in the effects of a loss of insurance capacity on real economic activity. A better understanding of sector wide downside risk can contribute to this impact assessment.

Since insurers want to limit and diversify their risk exposure they protect themselves by reinsurance contracts. Reinsurers provide insurers protection against major losses and the bankruptcy of a reinsurer might expose insurers to unforeseen losses. Reinsurance can be provided by both reinsurance companies, by other insurers and by the capital markets. It is the primary responsibility of insurers to have a sound reinsurance risk management strategy. Regulators are interested in the mutual relations between insurers and reinsurers. The Financial Stability Forum (2002) e.g. is concerned about the impact of the collapse of a major reinsurer on insurance companies. The degree of such dependence between insurers and reinsurers is therefore measured.

The banking sector is also exposed to problems within the insurance sector. Insurers may sell credit protection to banks, via credit default swaps. In practice the reverse occurred more frequently and contributed to the woes of the insurance sector during the last recession, while the banking sector was more or less unaffected. The dependence between banks and insurers is investigated in detail in Slijkerman et al. (2005). Systemic concerns for the banking sector have a higher relevance than for the insurance sector. Bank failures have a public externality because of the maintenance of the payment system by banks. The specificity of the deposit contract also creates a (negative) public externality, due to the possibility of a drain of liquidity due to a bank failure. The stability of the reinsurance sector is nevertheless of a public concern, since the bankruptcy of a major reinsurer may reduce the capacity of the insurance sector and therefore have real consequences. However, the literature on systemic risk in the insurance sector is still in its infancy. Geluk and De Vries (2005) analyze the asymptotic dependence among reinsurers. This interdependency not withstanding, the insurance sector is less fragile and does not have the same importance to the real economy as the banking sector.

The OECD (2004) writes that the insurance sector has an important role to play in the real economy. For a lot of economic activities insurance is mandatory or necessary to contain the investment risk. Airlines, for example, have to insure their airplanes. Construction companies want to insure their property. A possible shortage of the capacity to provide insurance is therefore a concern of regulators. In this chapter the impact of insufficient insurance cover on real economic activity is not explicitly quantified, but the possibility of sector wide losses in the insurance sector is analyzed. The consequences of a loss in insurance cover are briefly discussed in the following.

Before the collapse of HIH Insurance in March 2001, it was the second biggest insurer in Australia. According to Buchanan et al.(2003), the collapse of HIH made reinsurance premiums rise globally. Moreover, housing construction in Australia was affected, since builders where deprived of insurance cover at HIH Insurance and had to find replacement coverage. (See Vaughan, 2004) Approximately half of the doctors in Australia lost malpractice insurance and thousands of small businesses lost liability coverage.

The WTC attack also caused problems with insurance cover for e.g. property damage, aviation liability, business interruption and life liability. This had the strongest impact on aviation and transport, but also on manufacturing, energy, real estate and construction. The OECD (2004) reports that according to the Bond Market Association, 10 per cent of the commercial mortgage-backed securities market has been suspended or cancelled due to issues of terrorism insurance. These examples highlight the importance of the insurance sector for the broader economy. Interestingly, the academic research on the prudential regulation of the insurance sector is still in its infancy. Apart from policy papers and research by risk managers and actuaries, there is little economic theory on the optimal regulation of this sector. In this chapter a possible explanation for joint losses of insurance companies is given, as a start.

In this work the tail dependence between stock returns of insurers and reinsurers is studied and the extent of sector wide downside risk is investigated. The observation that the distribution of stock prices for insurers is fat tailed is explicitly taken into account and the relative importance of market risk is modelled. The model helps to understand the impact of adverse shocks which negatively affect multiple insurers. Finally, the breadth of downside risk in the insurance sector and in the reinsurance sector is measured. If the downside risk of a loss in market value in the two sectors is the same, this points to similarities in the risks exposure, possibly resulting from similar assets or similar liabilities holdings across insurance firms.

If sector risk is important, the dependence between companies will be high. During crisis, multiple insurers may realize losses on their assets or liabilities. Losses in insurance capacity during crises can cause insufficient supply of insurance cover.

This lack of insurance capacity may have an adverse impact on economic activity. It is therefore important that new capital can easily enter the insurance sector. Capacity can, for example, be enhanced by increasing the use of the capital markets as a source of insurance cover, or through institutional arrangements in which governments provide part of the insurance cover, when private insurance cover is not available.

In the remainder of the paper the EU insurance sector is described. Next, an intuitive explanation for the mutual dependence between insurance companies is provided and subsequently this dependence is explicitly modelled. Finally, the degree of dependence between the different sectors is estimated and conclusions are drawn from the empirical investigation.

4.1 EU insurance

The European insurance market is the second largest in the world, after the US and accounts for 30% of world premium income. Moreover, the two largest reinsurers (Swiss Re and Munich Re) are European based. Therefore it is interesting to take a European perspective. The market share of the largest companies is increasing, as the result of consolidation. The five largest insurers in EU countries hold on average close to 50% of life insurance income and close to 40% of non-life insurance income, according to the CEA (2004). Most insurance companies offer both life and non-life products. In 1991 collected premiums for life and non-life were balanced, but nowadays the life insurance sector is relatively larger. Most European companies are mixed insurers and offer both life and non-life insurance. Some companies like AEGON, ING, Zurich Financial Services and Prudential have a sizeable US business, or have a large banking business, like ING and Allianz. This fits in the trend of the emergence of insurance companies with a global presence and insurers with multiple business lines, to make use of economies of scale and scope. The insurance sector is growing due to new products and demand for additional pension products. The expectation is that the life insurance market in most countries will grow, because most countries reform their pension systems. Notably the UK and the Netherlands already have large life insurance markets. It is also likely that there will be more cross border business in the EU, due to the integration of the financial markets because of the introduction of the euro and an increasing harmonization of regulation.

Before September 11 insurance markets were characterized by low prices for reinsurance and excess capacity. Investment income was driving the results of insurers. In 2001 the insurance sector was hit on both the asset side, due to falling stock prices, and the liability side, due to the costs of September 11. According to Swiss Re (2005) European insurers made larger investments in equity than American insurers, but the investments in equity by insurers were lower in 2004 than in 1999. This indicates that insurers have become less willing to take investment risk on their balance sheets.

The importance of the capital markets for the provision of insurance is growing. In some cases it may be difficult for firms to buy insurance cover, since it is hard for insurers to estimate the expected losses. This may be due to a lack of information on the number of accidents and the costs which are incurred by the firms, but also to moral hazard, leading to higher claims than expected. With the help of the capital markets large firms can self insure their risks with the use of insurance captives. Firms pay premiums to a separate legal entity, owned by the firm (the captive), and create a financial buffer for insurance losses. Capital markets or insurers may provide liquidity if losses occur before the firms made sufficient savings.

Besides the capital market, governments can also help to alleviate the impact of (natural) catastrophes. In a lot of countries governments recognized the difficulties to obtain insurance cover for certain types of risks. They have set up public private insurance schemes to insure e.g. natural catastrophes and terrorism risk, as is described by the OECD (2004).

The EU insurance sector is regulated with separate directives for life and non-life insurance. The most important elements of this regulation are the requirements on the technical provisions, investment rules, solvency requirements, accounting rules and criteria for home country control and the provision to provide cross border business. There is a proposal for new regulation for the EU reinsurance sector. The Solvency II project aims to modernize insurance regulation, taking into account actual risks of insurers in the calculation of solvency requirements, similar to the revamp of the Basle accords for banks. However, insurance sector regulation does not explicitly take into account the need for sufficient insurance capacity during crisis times. In the following it is explained why this capacity may be at risk.

4.2 Risk diversification and financial fragility

In this section an explanation for downside risk dependence between insurers is given. A reduced form approach is followed to determine this downside risk. Following the Efficient Market Hypothesis, the stock price of insurers should reflect the value of companies. Changes in stock prices are therefore the result of changes in value of assets and liabilities. In a competitive environment it stands to reason that firms with similar assets and liabilities, make similar profits and show similar returns. At the level of our study, these returns are random. Therefore, the degree of dependence one finds between the different returns, depends on the specific nature of the shocks and the economic structure of the assets and liabilities. A presumption of normality gives e.g. quite a different result than the presumption that the returns of assets and liabilities follow a Student-t distribution. But the specific network structure of the insurance sector is also a contributing factor.

4.2.1 Explaining dependence

The intuition for the existence of dependence among insurers is provided in the following. The mutual dependence among insurance companies may originate from a similar exposure to similar assets and to similar liabilities. Swiss Re (2003b) gives an description of the main assets of insurers. These include the following items: shares, investments in bonds and investment funds, real estate and technical reserves held by reinsurers. If companies have similar assets, they will have a similar risk profile. If insurance companies invest e.g. in the same stocks and bonds or (credit) derivatives, they are exposed to the same shocks which adversely affect the value of investments. However, little is known about the exact assets insurers invest in. This may indicate a lack of transparency in the European insurance sector. Since insurers started to act as sellers of credit protection, this gained special attention of supervisors and the issue is studied extensively by the Joint Forum (2005).

Insurers do not only invest in similar assets, but may also participate in similar liabilities, insurance risk in particular. It is possible for insurers to provide reinsurance and in this way participate (proportionally) in the insurance portfolio of other insurers. Another important development is the securitization of insurance risk (IAIS, 2003). Insurers can transfer their insurance portfolio and expected premium income to a legal entity which manages these liabilities. In this way other investors can participate in the same insurance risks. Catastrophe bonds are an example of insurance risk which is transferred to the capital market. Another possible source of risk is the long term interest rate. A particular problem for life insurers is that their profitability depends for an important part on the long term interest rate developments. A decreasing long term interest rates poses problems for the non-hedged liabilities. A low long term interest rate environment poses problems for new production. When the level of the short term interest rate is close to the long term interest rate, the benefits for customers of long term insurance contracts over short term savings are limited. Since the interest rate risk might be similar for all life insurers, one may expect that most life insurers are affected by an interest rate move in a similar way. On the contrary, if it is found that there is a low dependence between insurers, this indicates that the firms invest in different assets and liabilities.

Other risks which may be similar for insurers are the risk of changes in the legal and regulatory environment and fraud. New jurisprudence can increase the unexpected liabilities for insurers and new regulation may increase costs on a sector wide basis.

By modelling the dependence among firms explicitly, new insights are obtained on the degree of similarities in downside risk. Before the model and the estimation results are presented, the univariate firm risk is investigated. The distributions of the stock price returns of individual insurers exhibit fat-tails. This characteristic is explicitly taken into account when modelling and estimating dependence among firms.

4.2.2 Heavy tails and dependence

It is a stylized fact that stock returns are heavy tailed, rather than exhibiting an exponential type tail as under normality. This is e.g. extensively documented by Jansen and De Vries (1991). Moreover there is considerable evidence that the risk exposure of non-life insurers is even heavier tailed, see e.g. Embrechts et al. (1997). First an introduction to the heavy tail characteristics of the univariate return series is given, because this theory is the basis for our multivariate modelling.

Extreme Value Theory (EVT) studies the limit distribution of the maxima or minima of return series. These limit distributions are informative about the tail shape of the underlying distribution. With the help of this limit distribution, one can study the frequency of extreme losses without imposing a particular distribution a priori (like a Student-t or Pareto). Our approach is therefore semi-parametric (as only the tail area of the distribution is parametrized). For ease of presentation, we work with positive variables and take the negative of the minima. It is assumed that X_i is an independent and identically distributed random variable with cumulative distribution function $F(x)$. This variable exhibits heavy tails if $F(x)$ far into the tails has a first order term identical to the Pareto distribution, i.e.

$$F(x) = 1 - x^{-\alpha} L(x) \text{ as } x \rightarrow \infty,$$

where $L(x)$ is a slowly varying function such that

$$\underset{t \longrightarrow \infty}{Lim} \frac{L(tx)}{L(t)} = 1, x > 0.$$

It can be shown that the two previous conditions are equivalent to

$$\underset{t \longrightarrow \infty}{Lim} \frac{1 - F(tx)}{1 - F(t)} = x^{-\alpha}, \ \alpha > 0, \ t > 0.$$

The coefficient α is known as the tail index and gives the number of bounded moments of the distribution. When a distribution has finite endpoints or exponentially decaying tails (like the normal and lognormal distributions), it does not fit the property of regular variation and all moments are bounded. Because of the Pareto characteristics of the tails of the empirical return distribution, our theoretical model is based on the Pareto law. Before we model dependence, we will first present the measure of dependence which we will use.

4.2.3 A measure of dependence

The most frequently used measure of dependence is the correlation measure. However, regulators are interested in the likelihood of losses and the correlation measure does not provide information on probabilities, without knowledge of the marginal distributions. The correlation measure is only an intermediate step in the calculation of probabilities given a specific multivariate distribution. If two variables e.g. follow a bivariate normal distribution, their joint behavior can be characterized by using the correlation measure. One disadvantage of the correlation measure is that there can be dependence in the data, while the correlation is zero (see Slijkerman et al., 2005). Forbes and Rigobon (2002) moreover, show that changes in the correlation measure over time are difficult to interpret if the variance of variables is not constant over time.

The correlation measure is therefore bypassed and a measure is used which is based on the probability of multiple shocks to the financial system. Our indicator is a conditional probability measure. Regulators and risk managers are concerned with a simultaneous loss at multiple insurers, given the losses at one insurer. More specifically, suppose a regulator wants to know the probability that $F_1 > t$, given that $F_2 > t$ and the probability that $F_2 > t$ given that $F_1 > t$, where F_1 and F_2 are the stochastic loss returns and t is the common high loss level. Since we are interested in a crash of an insurer given the crash of another insurer and vice versa, we will condition on either event. Let κ denote the number of insurers which crash. We propose to use the failure measure of Xin (1992) as the measure of systemic risk. In two dimensions it reads

$$E[\kappa|\kappa \geq 1] = \frac{P(F_1 > s) + P(F_2 > s)}{1 - P(F_1 \leq s, F_2 \leq s)}. \tag{4.1}$$

The failure measure is the conditional expectation of the number of insurance companies that crash, given that there is at least one crash. Hartmann et al. (2004) give a further motivation for this measure. Note that

$$E[\kappa|\kappa \geq 1] - 1 = \frac{P(F_1 > t, F_2 > t)}{1 - P(F_1 \leq s, F_2 \leq s)} \tag{4.2}$$

is the conditional probability that both firms fail, given that there is a failure of at least one of the firms. We will use either interpretation, depending on the context.

Unless one is willing to make further assumptions, as in the options based distance to default literature, it is impossible to pin down the exact level at which a firm fails, or at which supervisors consider the institution financially unsound. For this reason we do take limits and consider

$$\lim_{t \longrightarrow \infty} E[\kappa|\kappa \geq 1].$$

Extreme value theory shows that even though the measure is evaluated in the limit, it nevertheless provides a useful benchmark for the dependency at high but finite levels of t. We also like to note that the measure can be easily adapted in case failure levels at the companies are different. In that case the measure is evaluated along a non 45^o line.

4.3 Modelling dependence

By making different assumptions regarding the distribution of the returns of the firms, we can study how the conditional failure probability (4.1) changes as a result of an increasing exposure of firms to common risks. We present a model of tail dependence, assuming that the returns of insurers follow a heavy tailed multivariate distribution. If the returns follow a process with innovations which have a distribution with exponentially declining tails, large shocks occur with very low frequency and a large loss of multiple insurers is highly unlikely. However, if the stochastic process of losses is fat tailed, large losses may occur more often and may be difficult to diversify away. De Vries (2005) provides a detailed analysis of the differences between exponentially distributed returns and returns which follow a fat tailed distribution.

We already provided potential explanations for simultaneous losses at insurance companies. Because of a similar exposure to some risks, we suppose that all insurers carry sector risk. We do not model the individual sources of this risk explicitly, but investigate a reduced form model, which is basic to many models in finance. The returns of individual firms are partly driven by the stochastic variable A, which captures sector risks, both on the asset side as well as on the liability side. Different factors contribute to this sector risk. The variable A is the sum of possible common shocks, such as changes in interest rates and the exchange rate and common insurance risk exposures.

The returns by firms are also driven by a firm specific factor I_i, which is not related to the sector risk. Our model is therefore related to the factor model of Ross (1976). We assume total firm risk to be the sum of industry specific risk, A and firm specific risk, I_i. Firm specific risk arises out of losses on assets and liabilities for firm i, which are not incurred by other firms in the industry. For now, it is assumed that the downside risk of the common stochastic variable A and firm specific variable I_i are independently Pareto distributed with unitary scale

$$P(A > t) = P(I_i > t) = t^{-\alpha},\ t \in [1, \infty), \tag{4.3}$$

where t is the loss quantile of interest. A high realization of a variable should be interpreted as a large loss, so we can focus on positive random variables for the study of our downside risk. In the following we first investigate how the dependence between two firms changes if we change the relative importance of the common component A. We thus analyze the effect of an increase in the importance of common factors. Secondly, a model with multiple firms is analyzed.

4.3.1 Downside risk and dependence

We start by calculating the downside risk of an individual insurer, which is needed in the numerator of our risk measure (4.1). The returns of the insurance companies follow the sum of the common factor A and the idiosyncratic factor I_i in the following way

$$F_1 = A + I_1 \text{ and } F_2 = A + I_2. \tag{4.4}$$

The probability of a large loss for a combination of risk factors when these exhibit a power like distribution, is given by Feller's convolution theorem (1971, VIII.8). This theorem holds that if two independent random variables A and I_i satisfy (4.3), then for large t the convolution has probability

$$P(A + I_i > t) = 2t^{-\alpha} L(t),$$

and where $L(t)$ is slowly varying (i.e. $\lim_{t \longrightarrow \infty} L(at)/L(t) = 1$, for any $a > 0$). The theorem implies that for large failure levels t, the convolution of A and I_i can be approximated by the sum of the univariate distributions of A and I_i. All that counts for the probability of the sum is the (univariate) probability mass which is located along the two axes from the points onward where the line $A + I_i = t$ cuts the axes. The probability that the convolution of A and I_i is larger than t, for large t, is therefore

$$P(A + I_i > t) = 2t^{-\alpha} + o(t^{-\alpha}). \tag{4.5}$$

If the returns of a firm follow (4.5), the numerator in (4.1) is therefore approximately equal to $4t^{-\alpha}$.

To obtain the denominator of (4.1), we have to determine the probability that the firms do not all have a return smaller than t. The probability that all firms have a return smaller than t is denoted by $P(F_1 \leq t, F_2 \leq t)$. If we examine the complement $1 - P(F_1 \leq t, F_2 \leq t)$, this gives the probability that at least one firm realizes a return exceeding t. Since the returns of firms follow the specification in (4.4), common or idiosyncratic shocks can cause the returns of one of the firms or both firms to be large. Following the convolution theorem, we can approximate the probability of a large loss by the sum of the probabilities of a common shock or an idiosyncratic shock. Since we have two firms, we can take the sum of the probability that $A > t$, the probability that $I_1 > t$ and the probability that $I_2 > t$ (t being large). For two firms which follow the specification in (4.4) this sum of probabilities is equal to $3t^{-\alpha} + o(t^{-\alpha})$, or

$$\lim_{t \longrightarrow \infty} \frac{1 - P(F_1 \leq t, F_2 \leq t)}{3t^{-\alpha}} = 1.$$

We can now make our measure of systemic risk (4.1) operational. The conditional expectation of a crash of two firms, given that one firm crashes, follows once we substitute the theoretical probabilities in the failure measure (4.1). For large t,

$$\underset{\lim\ t\to\infty}{E[\kappa|\kappa \geq 1]} = \lim_{t \longrightarrow \infty} \frac{P(F_1 > t) + P(F_2 > t)}{1 - P(F_1 \leq t, F_2 \leq t)} = \frac{2t^{-\alpha} + 2t^{-\alpha}}{3t^{-\alpha}} = \frac{4}{3}. \tag{4.6}$$

As a point of reference, note that the value of the failure measure ranges between 1 and 2. The measure equals 1 under complete independence while it equals 2 in case of complete dependence. The measure therefore gives the expected number of firms that crash, conditional on at least one crash. In a bivariate setting we can derive the probability of two crashes, given one crash, by subtracting 1 of the failure measure. Note that one firm crashes for sure, since we condition on this.

The result 4/3 indicates that given a loss of one of the two firms, the expected probability of two crashes is 33% (= 4/3 − 1). In this example either one or two firms crash, but if one firm crashes, on average 1 out of 3 times both firms crash.

We provide some other stylized examples in the Appendix and show that dependence increases if an extra common risk component is added. We also calculate dependence in a stylized example with three firms to understand the dependence among multiple firms. In a setting with more than two firms ($n > 2$) the failure measure can range from 1 to n. However, we show in the following that it is highly unlikely that the failure measure will be equal to n. First, we calculate that the assumption of normally distributed risk factors gives different results.

4.3.2 Dependence and normality

In the previous section we investigated the tail dependence in case the common and idiosyncratic risk factors are fat tailed distributed. Under this assumption we find a higher dependence than under the assumption of normally distributed risk factors. In a bivariate normal setting, there is no dependence between extreme losses of two insurers, even if the returns of the two companies are correlated. This is interesting, since the assumption of normality is frequently made. If A and I_i in (4.4) follow independent standard normal distributions the failure measure will converge to 1, for large t

$$\lim_{t\longrightarrow\infty} E[\kappa|\kappa \geq 1] = \lim_{t\longrightarrow\infty} \frac{P(F_i > t) + P(F_j > t)}{1 - P(F_i \leq t, F_j \leq t)} = 1.$$

The proof is similar to proposition 2 in De Vries (2005). A high correlation between two return series is therefore not equivalent to high tail dependence. Note that the correlation coefficient is often not an useful statistic for financial data. The correlation measure is used as an intermediate step in the calculation of a bivariate conditional probability. If two random variables follow a normal distribution it is sufficient to know the mean, variance and correlation coefficient to characterize their joint behavior. However, the measure is not appropriate to describe the joint behavior of two fat-tailed distributed variables.

4.3.3 Downside risk and the market model

So far we have relied on specific examples to show the extent of downside risks among multiple firms, depending on the number of firms and the number of market shocks. We now present a more general form of firm returns in which we let the number of firms approach infinity. Similar to the market model of Sharpe (1964), where the risk of a firm is determined by market risk and idiosyncratic risk, a factor model is specified. The common risk factor A is premultiplied by a constant β, which denotes the relation between the returns of a firm and market risk. Downside risk of a firm is driven by the common risk factor and idiosyncratic risk in the following way

$$F_j = \beta_j A + I_j, \tag{4.7}$$

where β determines the relative impact of sector risk on the risk of a firm. If β is low or close to zero, this indicates that the risk of a firm is not driven by sector risk but by idiosyncratic risk factors. A high β, indicates that the risk of firms is to a large extend driven by the common factor.

We examine the probability that a firm faces a shock arising out of common risk factors. If the probability of a market shock follows a unit Pareto distribution i.e. $P(A > t) = t^{-\alpha}$, where $t \, \epsilon \, [1, \infty)$, the probability that an individual firm is hit by a shock, for large t, is equivalent to

$$\Pr(\beta_j A > t) = \Pr(A > \frac{t}{\beta_j}) = \beta_j^\alpha t^{-\alpha}.$$

We assume that the probability of an idiosyncratic shock I_j follows a Pareto distribution scaled with a factor i_j,

$$P(I_j > t) = i_j t^{-\alpha}$$

Since the risk of a large loss for a single firm is the sum of the risk of a market shock and the firm specific shock, following Feller's convolution theorem, this is equal to

$$\Pr(F_j > t) = (i_j + \beta_j^\alpha)t^{-\alpha}.$$

This is still pretty much like (4.5), except that we now have risk factors with non unitary scales. We extend the analysis to n firms, where the returns of each firm is driven by market risk and idiosyncratic risk. In this way the limit behavior of the failure measure can be studied for a large number of firms. We present a general form of the failure measure for multiple firms

$$\lim_{t\longrightarrow\infty} E[\kappa|\kappa \geq 1] = \lim_{t\longrightarrow\infty} \frac{(P(F_1 > t) + ... + P(F_n > t))}{1 - P(F_1 \leq t, ..., F_n \leq t)}. \tag{4.8}$$

First, we evaluate (4.8) assuming a stylized form of the firm returns. We assume $\beta_1 = \beta_2 = ... = \beta_n = 1$ and $i_1 = i_2 = ... = i_n = 1$. In this case, the failure measure converges to two, for a large number of firms and for large shocks.

Proposition 4.1 *Suppose the returns of the firms follow* $F_j = \beta_j A + I_j$, *where* $P(\beta_j A > t) = P(I_j > t) = t^{-\alpha}$, $t \epsilon [1, \infty)$. *If* $\beta_j = 1 \ \forall \ j$, $i_j = 1 \ \forall \ j$, *then, for* t *large, the failure measure (4.8) converges to* 2, *as* n *increases.*

Proof. To derive the numerator of the failure measure, the individual firm risk can be premultiplied by the number of firms. The denominator can be decomposed as the sum of the different factors which determine the returns of the firms, according to Feller (1971). Examine $1 - P(F_1 \leq t, ..., F_n \leq t)$, which is the probability that at least one firm realizes a return larger than t. The factors which can cause a loss at a firm are the idiosyncratic risk factors and the common risk factor. The probability on at least one firm with a large loss can be approximated by the sum of the probabilities of a large idiosyncratic shock (which gives the probability that at least one firm experiences such a shock), and the market shock. An individual firm faces a large market shock with probability $\beta_j^{\alpha} t^{-\alpha}$ and a large idiosyncratic shock with probability $i_j t^{-\alpha}$. The probability of the market shock inducing one of the firms to fail is equal to $(\max[\beta_1, ..., \beta_n])^{\alpha}) t^{-\alpha}$, since the market risk of the firm with the highest β has the most effect on violation of $F_i \leq t$, $i = 1, .., n$. The probability that one of the firms is affected by an idiosyncratic shock is equal to $(i_1 + ... + i_n) t^{-\alpha}$. The denominator of (4.1) thus reads

$$1 - P(F_1 \leq t, ..., F_n \leq t) = ((i_1 + ... + i_n) + (\max[\beta_1, ..., \beta_n])^{\alpha}) t^{-\alpha}.$$

If we substitute these probabilities in the failure measure (4.1) we find that for large t

$$\lim_{t \longrightarrow \infty} E[\kappa | \kappa \geq 1] = \frac{(i_1 + ... + i_n) + (\beta_1^{\alpha} + ... + \beta_j^{\alpha})}{(i_1 + ... + i_n) + \max[\beta_1^{\alpha}, ..., \beta_n^{\alpha}]}. \tag{4.9}$$

Now use the assumption that $\beta_j = 1 \ \forall \ j$ and $i_j = 1 \ \forall \ j$ and let the number of firms become unbounded to conclude the proof

$$\begin{aligned} \underset{\lim t \to \infty}{E[\kappa | \kappa \geq t]} &= 1 + \frac{\beta_1^{\alpha} + ... + \beta_n^{\alpha} - \max[\beta_1^{\alpha}, ..., \beta_n^{\alpha}]}{(i_1 + ... + i_n) + \max[\beta_1^{\alpha}, ..., \beta_n^{\alpha}]} \\ &= 1 + \frac{n-1}{n+1} \approx 2, \text{ for } n \text{ large.} \end{aligned} \tag{4.10}$$

■

We have thus proved that if one firm realizes a large loss, at most the loss of one other firm is expected, even though the number of firms is large. The failure measure will only be equal to the number of firms in the absence of idiosyncratic risk. If β_j $\forall \ j$ is equal to 1 and there is no idiosyncratic risk, i.e. $i_j = 0 \ \forall \ j$, the measure equals n. If the parameter i_j denoting the idiosyncratic risk of the firms is equal to a 1 for all firms and there is no market risk, *i.e.* $\beta_j = 0$, the measure converges to 1. A value of 1 for the failure measure indicates that the returns of the insurers are asymptotically independent. In these last, stylized examples there is either no dependence or full dependence.

The focus of this paper is the degree of sector risk in the insurance sector. The dependence is determined by the relative impact of common and idiosyncratic shocks. The previous assumption of β_j and i_j being equal to 1 is very stylized. We therefore rewrite (4.9) for the average of the betas raised to the power α, $\bar{\beta^{\alpha}} = \frac{1}{n} \sum_{j=1}^{n} \beta_j^{\alpha}$ and average idiosyncratic risk, $\bar{i} = \frac{1}{n} \sum_{j=1}^{n} i_j$. In the following proposition we investigate the degree of dependence after rewriting (4.9) for average market risk and average idiosyncratic risk.

Proposition 4.2 *Suppose the returns of the firms follow* $F_j = \beta_j A + I_j$*, where* $P(\beta_j A > t) = \beta_j^\alpha t^{-\alpha}$*,* $P(I_j > t) = i_j t^{-\alpha}$*,* $t \in [1, \infty)$*, then, for* t *large, the failure measure (4.8) converges to* $1 + \frac{\bar{\beta}^\alpha}{\bar{i}}$ *as* n *increases, where* $\bar{\beta}^\alpha = \frac{1}{n}\sum_{j=1}^{n} \beta_j^\alpha$ *and* $\bar{i} = \frac{1}{n}\sum_{j=1}^{n} i_j$ *(assuming the* β_j *and* i_j *are bounded).*

Proof. Rewrite the failure measure (4.9) for the average common factor, β_j, and average idiosyncratic risk factor, $\bar{i}$. For a large number of firms and for large shocks this reads

$$\lim_{n \longrightarrow \infty} \left(\underset{\lim t \to \infty}{E[\kappa | \kappa \geq t]} \right) = \lim_{n \longrightarrow \infty} \frac{\bar{i} + \bar{\beta}^\alpha}{\bar{i} + \max[\beta_1^\alpha, ..., \beta_n^\alpha]/n} = 1 + \frac{\bar{\beta}^\alpha}{\bar{i}}. \tag{4.11}$$

■

The ratio of $\bar{\beta}^\alpha / \bar{i}$ gives the relative importance of market risk and idiosyncratic risk for the occurrence of multiple large losses. If the average idiosyncratic risk is relatively small, the dependence among firms will be high. If the average beta is small, the failure measure will converge to a 1, which implies asymptotic independence. If the failure measure returns a 1, the returns of the firms are asymptotically independent. A value for the failure measure around 2 (when estimated for a large number of firms) implies that a firm is exposed to idiosyncratic shocks and common shock with roughly the same order, i.e. for large n and t, $E[\kappa | \kappa \geq t] = 1 + \bar{\beta}^\alpha / \bar{i} \approx 2$ and therefore $\bar{\beta}^\alpha = \bar{i}$, following (4.11). If the returns of the firms are highly dependent, the failure measure is larger than 2. This corresponds with a large $\bar{\beta}^\alpha$ and a comparatively small $\bar{i}$ in (4.11). A value between 1 and 2 implies that idiosyncratic shocks are more frequent than common shocks. A value larger than 2 implies that common shocks are more frequent.

We show in the following section that the measure provides information on the relative importance of common risk factors and idiosyncratic risk factors for the riskiness of the sector.

4.3.4 Model interpretation

Regulators of the insurance sector are concerned with the stability of the financial sector. They are therefore interested in the degree of dependence among insurers.

If insurers carry the same risks, it is likely that multiple insurers are affected by large losses and that losses in their market value are dependent. We discuss how the model relates to high or low dependence between the losses of the insurers.

If insurers hold different assets and liabilities, the dependence among insurers will be low, since it is unlikely that multiple firms are hit by a loss on shared liabilities or assets. In this case idiosyncratic risk is the most important source of risk. If the idiosyncratic risk dominates over market risk, the failure measure will be between 1 and 2.

Vice versa, if most of the assets and liabilities of insurers are the same, the dependence among insurers is high. The exposure to market risk is high and the common risk factor is the most important source of risk. The failure measure will therefore be larger than 2, as was shown in (4.11). A high dependence may be the result of risk diversification. Because of risk diversification, insurers are exposed to the same risks. Implicitly, the failure measure gives information on similarities in the risk exposure between insurers. This is interesting, since the risk exposure can be regulated to reduce the industry wide dependence.

If the estimation of the dependence indicates that the failure measure (4.8) is smaller than two, this implies that idiosyncratic risk is the most important source of risk. If the failure measure estimates indicate that dependence is high, i.e. larger than two, market risk is the dominant risk factor. This framework can therefore help to understand the impact of market risk on the downside risk of multiple insurers. An improved understanding of the impact of market risk can help to design appropriate regulatory policy, as is argued in the following.

When risk in the insurance industry is largely driven by common risk factors, regulators may deem the dependence among insurers as being too high. They can reduce the dependence by reducing the common exposures of insurers. The benefit of a lower dependence is that, more often, losses will be isolated to single firms. The probability of multiple simultaneous losses of insurers is therefore reduced. Losses will be contained to single insurers, since the insurers have a different risk profile. If an individual insurer goes bankrupt, other insurers may remain solvent. They can take over the clients of the bankrupt insurer, reducing the economic impact of a bankruptcy. However, a disadvantage of reducing the common exposure is a reduction of risk diversification possibilities for insurers. If regulators want insurers to be exposed to different risks, insurers are constraint in the investment and insurance risks they take. The probability that an individual firm faces a large loss can therefore be increased by this policy, since the exposure to specific risk factors may be higher. When the exposure to common factors is reduced, risks are less often shared by multiple insurers, with the benefit of a reduced industry wide risk.

If there is a high sector risk, the capacity of the insurance sector during crises can be a concern. As mentioned before, the insurance industry had a shortage of capacity following the terrorist attacks on the Twin Towers in 2001. Following such events, the capacity of the insurance sector has to be augmented. There are two sources of insurance cover outside the commercial insurance sector: the capital market and public insurance pools.

A straightforward way to increase the capacity of the insurance sector is to make an extensive use of the capital market. An important element of insurance products is the provision of liquidity. When the insured suffers losses, capital is needed to repair the damage. This liquidity can be provided by capital markets via innovative products. The idea behind these products is that investors provide liquidity in exchange for a predetermined number of payments from the insured to investors. The insured can use this liquidity in case of predescribed events. The reinsurance industry has a broad range of solutions to transform insurance risk to investment products. The capital markets can e.g. be used by firms which have difficulties finding insurance cover. These firms can create a separate insurance entity to which they pay premiums. The capital markets provide liquidity in the case of an event, for which they receive a return, paid for by the premiums. In this way firms reduce their dependence on external insurance companies. See Swiss Re (2003a) for a more extensive discussion on risk transfers. If there is a high degree of sector risk, i.e. the failure measure is larger than two, regulators may encourage firms to exploit the capital markets for their insurance needs. By being less dependent on insurance companies, firms are less exposed to fluctuations in the premiums they pay, which can be the result of the changing capacity of the insurance industry.

Following the 9/11 disaster insurers and other investors realized huge losses on their investments. Insurers where at the time not able to raise sufficient funds to restore the capacity of the insurance sector immediately. Moreover, insurers had difficulties to estimate the future impact of terrorism. Since the exclusion of terrorism risk from insurance policies was not desirable, the insurance industry in The Netherlands asked the government to join an initiative for a terrorism insurance pool, which would provide insurance cover against terrorism risk of up to 1 billion euros. The advantage of such a pool is that it gives certainty on the level of insurance to residents and firms. An advantage for the government is that it receives insurance fees and that the maximum loss for the government is clear up-front. This way the impact on the government budget of disasters is limited. See Schilperoort (2002/2003) for a more extensive discussion.

If the common exposure of insurers is low, the sector wide dependence among insurers is relatively low. A low dependence corresponds to a relatively high idiosyncratic risk of insurers. A high idiosyncratic risk for insurers can be a reason to study the prudential regulation at the firm level. Regulators may e.g. want to reduce the risk of individual insurers, by encouraging them to diversify their exposure, or by demanding a higher solvency at the firm level.

4.4 Measuring dependence

For our estimation approach we follow the approach of Hartmann et al. (forthcoming). The empirical return series for each firm i are denoted with $X_{i,t}$, where the subscript t denotes the t^{th} element of the sample of returns. We take the negative of the empirical observations. Let $Q_{i,t}$ represent the t-th ascending order statistic of $X_{i,t}$, with $t = 1, ..., T$, such that $X_{i,1} > ... > X_{i,T}$ and $p = t/T$, where p is the probability corresponding to the empirical loss quantile $Q_{i,t}$. We are interested in the losses occurring with a small probability. This probability p corresponds to a high threshold $Q_{i,var}$ (the Value at Risk or stress test level) for each firm i, above which losses occur with the probability p. We derive the extreme loss quantile $Q_{i,var}$ corresponding to the probability p using the empirical distribution of the returns $X_{i,t}$. Since the empirical distribution is firm specific, the stress test level $Q_{i,var}$ corresponding to the probability p differs for each firm

$$p = P\left\{X_{1,t} > Q_{1,var}\right\} = ... = P\left\{X_{i,t} > Q_{i,var}\right\} = ... = P\left\{X_{n,t} > Q_{n,var}\right\}. \quad (4.12)$$

We are interested in the expected number of firms that crash, conditional on the crash of at least one firm,

$$E[\kappa|\kappa \geq 1] = \frac{np}{1 - P(X_1 \leq Q_{1,var}, ..., X_n \leq Q_{n,var})}. \quad (4.13)$$

If $n = 2$ this measure reduces to the bivariate measure in (4.1). The measure gives us the expected number of institutions that crash (κ) given that at least one institution crashes, i.e., has a return exceeding $Q_{i,var}$, where $Q_{i,var}$ is the quantile from the empirical distribution corresponding to the probability p in (4.12). In the denominator of (4.13) we therefore have different thresholds $\{Q_{1,var}, ..., Q_{n,var}\}$. For estimation purposes it is convenient if we premultiply the empirical returns with $Q_{1,var}/Q_{i,var}$,

$$\begin{aligned} p &= P\{X_i > Q_{i,var}\} = P\left\{\frac{Q_{1,var}}{Q_{i,var}}X_i > \frac{Q_{1,var}}{Q_{i,var}}Q_i\right\} \\ &= P\{Q_{1i,var}X_i > Q_{1,var}\}, \end{aligned} \tag{4.14}$$

where $Q_{1i,var} = (Q_{1,var}/Q_{i,var})$. This way we can rewrite the denominator of (4.13) as

$$1 - P(Q_{1i,var}X_1 \leq Q_{1,var}, ..., Q_{1n,var}X_n \leq Q_{1,var}).$$

This is equivalent to

$$P(max[Q_{1i,var}X_1, ..., Q_{1i,var}X_n] > Q_{1,var}).$$

This probability corresponds to the quantile $Q_{1,var}$ of the empirical distribution function of the maxima, which is equivalent to $max[Q_{1i,var}X_1, ..., Q_{1n,var}X_n]$. Since we evaluate the limit behavior of (4.13), we take $Q_{1,var}$ close to the boundary of the sample and use the 10^{th} largest order statistic of the return series X_i. As a result, the probability in (4.12) corresponds to 10 divided by the sample size, N. In the Appendix we indicate the robustness of the procedure, using a higher or lower number of order statistics.

We consider the dependence among pairs of firms and the dependence among blocks of 4 and 8 firms, i.e. $n = 2, 4$ and 8. In the bivariate setting we apply a different estimation approach. The probability that two firms realize a large loss on a given day is estimated. For the bivariate estimates, the variables are not scaled according to 4.14. The advantage of this approach is that the estimates are straightforward to interpret, since the estimates return the probability that the second firm of a pair realizes a large loss. We deem a daily loss larger than 7.5% as being a large loss. In the bivariate setting, the failure measure returns the probability that two firms realize a loss larger than 7.5%, given that one firm realizes a loss of 7.5%. For the multivariate estimates we have to scale the variables as in (4.14) to be able to take the maximum in the denominator. See the Appendix for estimation details for the bivariate estimation.

4.5 Empirical results

In this section the dependence among insurance firms is measured. We estimate dependence between firms within the insurance sector and within the reinsurance sector. As a benchmark, we estimate dependence between large oil companies and the dependence between firms from entirely different sectors. The motivation for these benchmarks is given in the following. We present the estimated dependence among pairs of firms and the dependence among multiple firms.

4.5.1 Empirical benchmark

A benchmark is needed to interpret the estimated degree of dependence between insurers. We need a benchmark for dependence among firms in a sector with a high degree of dependence and a benchmark for the dependence among firms which are unrelated. The value of oil firms depends heavily on the price of oil. We therefore expect to find a high degree of dependence among oil firms. This sector is therefore the benchmark for a sector with high dependence. If dependence within the insurance sector is of the same magnitude, it is plausible that the returns of insurers are driven by a common factor, which is comparable to the price of oil in the oil sector.

We also estimate the dependence among firms from different sectors. This gives the value for the failure measure in case the returns of the firms are not driven by sector risks. This way we can compare the estimation results for the insurance sector with estimation results for a sector with high dependence and with results for firms from different sectors. The firms used for the estimation of the dependence across the different sectors are given in Table 4.5 in the Appendix.

4.5.2 Independence

Suppose that the marginal returns of two insurers are independently distributed and rewrite the failure measure (4.1) under this assumption. Under the assumption of independently distributed returns for the firms, the denominator of the failure measure is equal to $1 - (P(F_1 \leq t) * P(F_2 \leq t))$. The failure measure for independently distributed returns then reads

$$E[\kappa|\kappa \geq 1] = \frac{P(F_1 > t) + P(F_2 > t)}{1 - (P(F_1 \leq t) * P(F_2 \leq t))}. \tag{4.15}$$

By estimating the univariate probabilities $P(F_i > t)$, and calculating (4.15) as if the returns are unrelated, we obtain yet another benchmark to judge the amount of dependency. Note that

$$\lim_{t \longrightarrow \infty} = \frac{P(F_1 > t) + P(F_2 > t)}{1 - (P(F_1 \leq t) P(F_2 \leq t))} = 1,$$

but at finite loss levels this measure is larger than 1 since $\frac{2(1-p)}{1-p^2} = \frac{2(1-p)}{(1-p)(1+p)} = \frac{2}{1+p} > 1$, where $p = P(F_1 \leq t)$.

The univariate probability of an extreme loss in (4.12) can be derived from the empirical distribution function. This probability is substitute for in the failure measure

$$E[\kappa|\kappa \geq 1] = \frac{P(F_1 > t) + P(F_2 > t)}{1 - (P(F_1 \leq t) * P(F_2 \leq t))} = \frac{20/2739}{1 - ((2729/2739)^2)} = 1.0018.$$

If the marginal returns of two insurers are independently distributed, the conditional probability of a simultaneous crash is close to 0 $(1.0018 - 1)$. Hence the 0.0018 probability provides a lower bound benchmark.

4.5.3 Data

The dataset starts in January 1995 and ends in June 2005, because of data availability. The sample size N of daily data is equal to 2739. In the EU there are 4 reinsurers with stock price data available for the full sample. The selected 8 insurers, independent firms and oil firms are given in Table 4.5. For the estimation of the dependence among 4 firms, only the first 4 firms in Table 4.5 are used.

4.5.4 Dependence among pairs of firms

The failure measure in a bivariate setting provides the conditional probability of a crash of two firms. We estimate the bivariate conditional probabilities of all possible combinations of insurers, all combinations of reinsurers and combinations of insurers and reinsurers. In Table 4.1 we report the averages of the estimates, the pair wise

	Insurers	Reinsurers
Insurers	0.18	0.13
Reinsurers	0.13	0.12

Table 4.1: Average bivariate dependence (no scaling)

estimates can be found in Table 4.6 in the Appendix. From Table 4.1 we see that the average probability that two insurers realize an extreme loss, given the extreme loss of one of the two insurers is on average 18%. The probability that two reinsurers realize a large loss, given the large loss of one of the two reinsurers is equal to 12%. The dependence among insurers is thus higher than the dependence among reinsurers. The dependence among insurers and reinsurers is 13% and lower than the dependence among insurers. All values are much larger than the benchmark lower bound of 0.0018, indicating that there is considerable asymptotic dependence. Since the value for the insurance companies is much larger, we therefore conclude that the systemic risk in the insurance sector differs from the systemic risk in the reinsurance sector.

Even though both sectors deal with insurance, the interdependencies are higher in the insurance sector. This is somewhat surprising, given that the reinsurers take on risk from the different insurers. These risks are concentrated at reinsurance companies. Apparently, the connectedness stems from other sources of risk, such as investment risk, which may be more similar among insurers. Since most insurers invest in cash and equities, large movements in interest rates or equity prices should have an impact on the investment portfolio of insurance companies. An alternative explanation may be that the idiosyncratic risk of reinsurers is higher than the idiosyncratic risk of insurers. It is likely that the insurance liabilities of the four reinsurers is different. Losses caused by e.g. a natural catastrophe will therefore have a different impact on the reinsurance companies. If the stock price of a reinsurer reacts to this large insurance loss, the stock price decline is unrelated to the stock price movement of other reinsurers.

Apart from the average dependence within the different sectors, the average dependence for an individual company is given below. For individual firms, the conditional probability of a loss, given the loss of another firm, differs considerably from the sector averages. Since there are 8 insurers and 4 reinsurers in the dataset, we can es-

Firm	mean prob.	Firm	mean prob.
ALLIANZ	0.17	MUNICH RE	0.16
ING	0.23	SWISS RE	0.13
GENERALI	0.08	HANNOVER RE	0.13
AXA	0.18	SCOR	0.10
AEGON	0.17		
AVIVA	0.14		
PRUDENTIAL	0.16		
ZFS	0.14		

Table 4.2: Bivariate dependence (no scaling)

Insurers	Insurance/Reinsurance	Firms
1.905	1.739	1.290
	$1 \leq E[\kappa \mid \kappa \geq 1] \leq 8$	
	Jan. 1995 - June 2005	

Table 4.3: Dependence among 8 companies

timate the bivariate conditional failure probability for each firm in combination with 11 other firms. This bivariate dependence is estimated and the average probability of a loss for a firm is reported in Table 4.2.

The interpretation of the bivariate probabilities is the probability that one of the two firms crash, given that the other crashes. If e.g. an insurer or reinsurer realizes a large loss, the probability that ING also realizes a loss is on average 23%, which is the highest probability in the table. If an insurer or reinsurer realizes a large loss, the probability that Generali also realizes a loss is low, on average 8%. A possible explanation for this result is that ING has more risk factors in common with other insurers than Generali. These common risk factors can be related to e.g. country risk and the riskiness of individual business lines.

4.5.5 Dependence among multiple firms

Our main research question concerns the sector wide dependence between insurance and reinsurance companies. We therefore do not only estimate the downside risk dependence among pairs of firms, but also among multiple firms. First, we estimate the dependence among eight firms. However, there are only four reinsurers and four oil firms in the dataset. Secondly, we therefore estimate the dependence among four firms to obtain the dependence among reinsurers and oil firms.

Dependence among eight firms

Recall that the failure measure returns the expected number of firms that crash, given the crash of one firm and is not smaller than 1. If there are eight firms, the failure measure can be at most equal to eight. The failure measure is estimated among 8 insurers and 8 firms from different sectors. Moreover, we are interested in the dependence between reinsurers. Since we have only 4 reinsurers, we estimate the dependence measure among a set of 4 reinsurers and 4 insurers, together a set of 8 firms. The results are presented in Table 4.3.

The dependence among the eight insurance firms is higher (1.905) than the dependence among the 8 firms from the different sectors (1.290). Dependence among the set of 4 insurers and 4 reinsurers (1.739) is thus lower than the dependence among insurers. This result supports the findings from the bivariate estimates. However, we can now interpret these results with the theoretical model which we developed in the previous section.

We use Proposition 2 to interpret the estimation results and argue that the impact of market shocks is of the same magnitude as the impact of idiosyncratic shocks. An estimate of 1.905 implies that the ratio of $\bar{\beta}^{\alpha}/\bar{i}$ is close to but smaller than 1. The estimate of 1.739 implies that the ratio of $\bar{\beta}^{\alpha}/\bar{i}$ is smaller than 1. This indicates that the impact of idiosyncratic risk in the reinsurance sector is larger than in the insurance sector.

The explanation for the larger impact of idiosyncratic risk in the reinsurance sector is that the risk exposure of reinsurers is more heterogenous than the risk exposure of insurers. Dependence can arise out of the same investments or out of the same insurance risks. Possibly the insurance risks of reinsurers differ to a larger extent

Insurers	Reinsurers	Oil	Firms
1.481	1.333	1.538	1.053
$1 \leq E[\kappa \vert \kappa \geq 1] \leq 4$			
Jan. 1995 - June 2005			

Table 4.4: Dependence among 4 companies

than the insurance risks in the insurance sector. Since we do not have information on the insurance portfolio of the companies, it is difficult to validate this explanation. Another possible explanation is that the investment risks in the insurance sector are more alike than in the reinsurance sector. This may originate from the interest rate risk of life insurance policies, which is a relatively large risk for direct insurance companies. Another possibility is that the equity investments made by (life) insurance companies may be larger than the equity investments made by reinsurers. Losses on the stock market may therefore have a larger impact on insurers. If regulators deem the sector risk as high, these possible explanations offer a starting point for regulators to reduce the dependence among firms, by reducing the common risk exposures.

Dependence among firms from different sectors is lower than the dependence in the insurance sector, since the estimated dependence among eight firms is only 1.290. The idiosyncratic risk is the most important risk factor for the firms from different sectors and is a factor 3.45 times bigger ($\bar{\beta}^{\alpha} = 3.45\bar{\imath}$, since $\bar{\beta}^{\alpha}/\bar{\imath} = 0.29$). The common factors $\bar{\beta}^{\alpha}$ are clearly of importance for the risks in the insurance sector.

Dependence among four firms

We also estimate the dependence among four firms. The estimates are given in Table 4.4. The failure measure estimate for four insurers is 1.481. The estimate of the dependence among four firms from different sectors is 1.053. It is clear that dependence in the tails is much smaller for firms from different sectors than among insurance companies. An extreme negative return of one of the firms from unrelated sectors is almost unrelated to the losses of the other firms. The downside risk dependence between four reinsurance companies is 1.333. This is lower than the dependence among insurers. Dependence among the tail risk of large oil companies

(1.538) is of the same order as dependence in the insurance sector, and much higher than among the independent firms. Sector risk in the insurance sector is therefore of the same magnitude as sector risk in the oil sector.

The 1.481 estimate for the block of 4 insurers implies that idiosyncratic risk is very relevant. For large n and t, the failure measure is equal to 1 plus the ratio of the average market risk and the average idiosyncratic risk for the insurers, i.e. $E[\kappa|\kappa \geq t] = 1 + \bar{\beta}^{\alpha}/\bar{i} = 1.481$. Since the ratio is smaller than 2, idiosyncratic risk appears more important than market risk. Since the expected number of firms from different sectors realizing a loss is equal to 1.053, which is close to 1, it is evident that there are hardly any common risk factors causing joint losses.

The tail dependence among firms from different sectors is very low. Even though the firms are from different sectors, they can be exposed to similar risks. The stock market crash of September 11, 2001 had an impact on all stock prices. Such broad macro shocks could have resulted in a higher dependence in stock prices among the firms from the different sectors. The failure estimator could have returned a higher value than the estimated 1.053. But given that it does not, idiosyncratic risk appears to be the dominant risk factor.

In a way it is remarkable that the dependence among reinsurers is lower than among insurance companies. Since reinsurers provide insurance against major catastrophes, they can receive claims arising out of the same (natural) catastrophe, such as hurricanes. However, it seems that these simultaneous losses are smaller than we expected.

One can argue that the dependence within the oil sector should be relatively high, since the results of oil companies are driven by changes in oil price. The oil price has a major impact on profits and losses for companies in the oil sector. Even though it is difficult to point at a single factor causing the dependence among insurers, such as the oil price for oil companies, there should be a similar explanation for the dependence among insurers. The estimates are larger in the eight firm setting, than the estimates in the four firm setting. The expected number of insurers that crash, given the crash of one insurer, increases from 1.481 to 1.905, in the eight firm setting. However, the increase is limited, if we consider that the maximum possible value for the failure measure doubled from 4 to 8.

4.6 Conclusion

There is an increasing interest in the impact of extreme losses of insurers for the stability of the financial system. To this end the downside risk dependence between the losses of insurance companies is investigated. We provide an explanation for a similar exposure to losses, based on the idea that multiple insurers carry similar risks.

For the design of optimal regulation, it matters if regulators have to deal with sector wide risk or firm specific risk. When firms are exposed to similar risks, all insurers realize losses on either their assets or liabilities, during a crisis. We model and estimate the effect of risk diversification on downside risk for the insurance sector.

The probability that multiple insurers realize a loss is relevant for our understanding of insurance sector risk. We therefore define a conditional failure measure based on the expected number of firms that crash, conditional on a large loss of one firm and estimate this measure. Moreover, the impact of market risk and idiosyncratic risk on the expected number of firms that crash is investigated. We proof that the measure converges to the ratio of idiosyncratic and common risk factors. This ratio is therefore an indicator for the importance of sector risks.

Insurers limit and diversify their risk exposure by reinsurance contracts. We investigate the dependence among reinsurers, to discover whether risk in the reinsurance sector is similar to insurance risks. When the dependence between pairs of firms is investigated, we conclude that reinsurance sector risk differs from insurance sector risk.

The conditional failure measure is also estimated to understand dependence in the insurance sector. It is found that common risk factors are an important source of risk in the insurance sector and to a smaller extent in the reinsurance sector. Idiosyncratic risk is relatively important for the reinsurance sector.

Dependence in the insurance sector is of the same order as in the oil sector. This implies there is a similar factor driving the returns in the insurance sector as in the oil sector. Tail dependence is relatively high in the insurance sector, when compared to a portfolio of stocks from different sectors.

4.7 Appendix

4.7.1 The Failure measure with multiple factors or firms

Downside risk and the two factor model

The dependence between firms is higher if the common return component A is more important. To show this, suppose that the returns of individual firms are driven by two different kinds of common factors A_1 and A_2. These two different common risk factors can for example arise out of a similar investment risk and similar insurance liabilities. The return specification for the individual firms now reads $F_1 = A_1 + A_2 + I_1$. The univariate firm risk $\Pr(F_1 > t)$, for large t is equal to

$$\Pr(F_1 > t) = 3t^{-\alpha} + o(t^{-\alpha}), \tag{4.16}$$

which is the sum of the probability of a loss of one of the three factors in the firm specification, following the convolution theorem. We showed before how we calculate the denominator of the failure measure, $1 - P(F_1 \leq t, F_2 \leq t)$. Since we have 4 elements in the specification of the returns of the individual firms which can cause a loss (A_1, A_2, I_1, I_2), the sum of the probabilities that one of these factors causes a loss will be equal to $4t^{-\alpha} + o(t^{-\alpha})$. When we substitute this and (4.16) in (4.1), the dependence measure reads for large t

$$\lim_{t \longrightarrow \infty} E[\kappa | \kappa \geq 1] = \frac{2(3t^{-\alpha})}{4t^{-\alpha}} = \frac{6}{4}. \tag{4.17}$$

Thus the dependence increases if an extra common risk component is added.

Downside risk: three firms in a single factor model

To understand the dependence among multiple firms, we give a theoretical exposition of dependence in a setting with three firms. In a setting with more than two firms $(n > 2)$ the failure measure can range from 1 to n. When the returns of a firm follow the specification in (4.4), the firm can crash due to a market shock A or a firm specific shock I_i. The failure measure in a setting with 3 firms then reads

$$\lim_{t \longrightarrow \infty} E[\kappa | \kappa \geq 1] = \lim_{t \longrightarrow \infty} \frac{P(F_1 > t) + P(F_2 > t) + P(F_3 > t)}{1 - P(F_1 \leq t, F_2 \leq t, F_3 \leq t)}$$

$$= \frac{3(2t^{-\alpha})}{4t^{-\alpha}} = \frac{6}{4}, \tag{4.18}$$

which is in between 1 and 3. The value of the failure measure (4.18) equals the value in a setting with two firms and three risk drivers as in equation (4.17). However, since (4.18) is calculated for a setting with three firms, the measure can be higher than two. This is not possible if there are only two firms. The result of 6/4 in (4.18) is therefore relatively low, while it is relatively high in (4.17).

4.7.2 Data

The companies used for the estimation of dependence within the different sectors and between pairs of insurers and reinsurers are given in Table 4.5.

4.7.3 Bivariate estimation

In this section we elaborate on the bivariate estimation technique employed in the paper. We first rewrite the failure measure and turn it into an estimator.

From elementary probability theory we know that $P(X_1 \leq t, X_2 \leq t) = 1 - P(\max[X_1, X_2] > t)$ and $P(X_1 > t) + P(X_2 > t) = P(\max[X_1, X_2] > t) + P(\min[X_1, X_2] > t)$. One can therefore rewrite the conditional expectation as follows

$$E[\kappa|\kappa \geq 1] = \frac{P(X_1 > t) + P(X_2 > t)}{1 - P(X_1 \leq t, X_2 \leq t)} = 1 + \frac{P(\min[X_1, X_2] > t)}{P(\max[X_1, X_2] > t)}. \tag{4.19}$$

The estimation of the probability of multiple crashes can thus be reduced to the estimation of two univariate probabilities. This greatly facilitates the empirical analysis, since one can proceed on basis of the previously described univariate estimation methods for the minimum and maximum return series. We use the notation P_{min} for $P(\min[X_1, X_2] > t)$ and the corresponding notation for the maximum. If the tail index α is identical for the minimum (α_i) and maximum (α_a) series, we obtain the following non-parametric estimator

$$E[\kappa|\kappa \geq 1] = 1 + \frac{\widehat{P}_{\min}}{\widehat{P}_{\max}}. \tag{4.20}$$

In Slijkeman et al. (2005) we show that (4.20) can be calculated using a simple counting procedure for the minima and maxima. We must take t large, since we

INSURERS	REINSURERS	OIL FIRMS	INDEPENDENT FIRMS
ALLIANZ	MUNICH RE	BP	RD SHELL
ING	SWISS RE	TOTAL	SAP
GENERALI	HANNOVER RE	RD SHELL	L'OREAL
AXA	SCOR	REPSOL	TELEFONICA
AEGON			BMW
AVIVA			NOKIA
PRUDENTIAL			BASF
ZFS			PHILIPS ELECTRONICS

Table 4.5: Selected firms

are interested in the limit behavior of (4.19). We take t equal to 7.5%, since this corresponds to a value at the bound of the sample. The estimated dependence among all possible combinations are given in Table 4.6.

4.7.4 Multivariate results for different quantiles

For the estimation of the dependence we have to determine a threshold $Q_{1,var}$. For the estimation of the dependence among 4 and 8 firms, the threshold corresponding to the $10th$ largest order statistic of the univariate return series X_i was selected. In this section we present the estimation results for a higher and lower threshold, $Q_{1,var}$. The returns corresponding to the 5^{th}, 20^{th} and 30^{th} order statistic are taken as a threshold. This threshold is subsequently taken for the estimation of (4.13). The results for the dependence among 4 firms are given in Table 4.7, the results for the dependence among 8 firms are given in Table 4.8. When the dependence is estimated for a higher threshold (i.e. larger losses), this dependence is a bit lower, but remains of the same order. When the dependence for a lower threshold is evaluated, this no longer corresponds to the dependence among extreme returns. The 30^{th} largest return in 10 years can hardly be considered as an extreme return. Even for this lower threshold however, the conclusions on the relative importance of sector risks for the different sectors do no change considerably. Thus our procedure appears robust against the threshold selection.

	ALLIANZ	ING	GENERALI	AXA	AEGON	AVIVA	PRUDENTIAL	ZFS	MUNICHRE	SWISSRE	HANNOVERRE	SCOR	Mean
ALLIANZ	1.00	0.29	0.11	0.24	0.17	0.19	0.22	0.15	0.22	0.12	0.07	0.08	0.17
ING	0.29	1.00	0.06	0.26	0.38	0.26	0.29	0.16	0.32	0.11	0.19	0.16	0.23
GENERALI	0.11	0.06	1.00	0.14	0.03	0.05	0.05	0.06	0.05	0.13	0.12	0.05	0.08
AXA	0.24	0.26	0.14	1.00	0.31	0.09	0.19	0.21	0.16	0.14	0.14	0.10	0.18
AEGON	0.17	0.38	0.03	0.31	1.00	0.11	0.23	0.19	0.13	0.09	0.14	0.11	0.17
AVIVA	0.19	0.26	0.05	0.09	0.11	1.00	0.19	0.15	0.19	0.13	0.07	0.09	0.14
PRUDENTIAL	0.22	0.29	0.05	0.19	0.23	0.19	1.00	0.12	0.17	0.12	0.14	0.08	0.16
ZFS	0.15	0.16	0.06	0.21	0.19	0.15	0.12	1.00	0.07	0.26	0.07	0.10	0.14
MUNICHRE	0.22	0.32	0.05	0.16	0.13	0.19	0.17	0.07	1.00	0.12	0.19	0.15	0.16
SWISSRE	0.12	0.11	0.13	0.14	0.09	0.13	0.12	0.26	0.12	1.00	0.13	0.04	0.13
HANNOVERRE	0.07	0.19	0.12	0.14	0.14	0.07	0.14	0.07	0.19	0.13	1.00	0.12	0.13
SCOR	0.08	0.16	0.05	0.10	0.11	0.09	0.08	0.10	0.15	0.04	0.12	1.00	0.10

Table 4.6: Bivariate conditional expectation t=0.075

Order statistic of Q_1	Insurers	Reinsurers	Oil	Firms
5	1.538	1.333	1.333	1.053
10	1.481	1.333	1.538	1.053
20	1.600	1.379	1.600	1.159
30	1.690	1.412	1.500	1.212
$1 \leq E[\kappa \mid \kappa \geq 1] \leq 4$				
Jan. 1995 - June 2005				

Table 4.7: Dependence among 4 companies

Order statistic of Q_1	Insurers	Insurance/Reinsurance	Firms
5	1.739	1.600	1.250
10	1.905	1.739	1.290
20	2.133	1.928	1.404
30	2.222	2.069	1.538
$1 \leq E[\kappa \mid \kappa \geq 1] \leq 8$			
Jan. 1995 - June 2005			

Table 4.8: Dependence among 8 companies

Chapter 5

Country Risk in Banking

To promote financial stability in the EU it is important to understand the mutual dependence between financial institutions. Understanding these linkages can help with the design of appropriate policies to contain shocks and to prevent the financial system from collapsing. Especially the dependence between institutions during crisis times can reveal information about the resilience of the financial system over time.

In this chapter the dependence between the daily stock price returns of banks in times of crisis is studied. The dataset consists of banks from multiple EU countries. The degree of dependence between pairs of banks within six countries is estimated and these estimates are compared to the dependence between banks from different countries. A major risk driver for banks is the macroeconomy and the interest rate in particular. It is therefore studied how the dependence relates to the macroeconomic environment and it is investigated whether the dependence between banks did change since the beginning of the EMU.

As is documented by e.g. Campbell et al. (1997) and others, the empirical distribution of stock prices features heavy tails. That is to say, extremely large losses (and gains) do occur much more frequently, than if the returns were normally distributed. Therefore, a methodology has to be used, which takes into account the fat tail property of stock prices. Research based on normally distributed returns understates the downside risk of both individual banks and the banking system as a whole.

An important concern for regulators of the financial system is systemic risk. The following definition of systemic risk is used in De Nicolo and Kwast (2002) and Group of Ten (2001): 'Systemic financial risk is the risk that an event (shock) will trigger a loss of economic value or confidence in, and attendant increases in uncertainty about, a substantial portion of the financial system that is large enough to, in all probability, have significant adverse effects on the real economy'. Containing systemic risk is important for regulators because of the adverse effects of a crisis on the real economy. This research aims to quantify the degree of systemic risk by investigating the mutual dependence among banks.

A large literature argues that systemic risk originates from the interbank exposure. Theoretic models are presented in Allen and Gale (2000) or Rochet and Tirole (1996). They model explicitly the interbank market for deposits. Banks may face a liquidity shortage due to the collapse of another bank. Gorton (1988) argues that the business cycle is an important determinant for the risks in the banking system. However, the mutual dependence among banks can originate from other sources of risk. Banks involved in securities trading, are exposed to the well functioning of the infrastructure of the stock exchange and to risks related to clearing and settlement. Other common exposures which may create systemic risks are the impact of new accounting rules and new regulation. Liquidity shortage or macro risks are therefore not the only risks to which banks are simultaneously exposed.

In this chapter it is argued that the business cycle is an important determinant of the health of the banking system. Therefore, the relation between extremely large losses in the market value of banks and the broader market index is quantified. The broader market index is taken as a proxy for the strength of the economy. It is argued that the downside risk dependence between banks may arise from an exposure to similar risks. Banks own similar assets and liabilities and the risks of their assets and liabilities may be highly related. All banks e.g. borrow money at the deposit market. Banks are therefore exposed to interest rate risk. Since banks provide loans to firms, they all carry credit risks. Credit risk is highly related to the stance of the economy. If multiple banks are indirectly exposed to the state of the economy, this creates dependence. When loans are concentrated in the same industry or country, this also creates dependence. Because of these similar exposures to credit risk and interest rate risk, it is plausible that banks have similarities in their risk profile.

The assumption that the returns of banks are normally distributed understates the downside risk of individual banks and the dependence among bank returns within the banking system. The fat tail property of the stock price returns of individual banks therefore has to be taken into account. This is important, since the effects of diversification are different under normality than under the assumption of fat tailed distributed returns. When studying the dependence between extreme losses, the correlation measure, which is so intimately related to the normal distribution, is often inappropriate. Forbes and Rigobon (2002) elaborate on the shortcomings of the correlation measure and show a caveat of applying this measure. In Slijkerman et al. (2005) we show that the normal distribution underestimates the risk of daily losses of banks' market value.

The effects of financial sector consolidation are especially interesting in case of European banks, because the introduction of the common currency now exposes banks to the same monetary environment. Boot (2003) discusses the financial sector consolidation in Europe. Before EMU, the monetary environment for banks was different from country to country. The introduction of the euro introduced the same interest rate and term structure to all participating countries. Therefore, the interest rate risk for all banks has become equal. Moreover, it created opportunities for banks to offer products across borders and to diversify the lending portfolio with loans to foreign companies. Due to this, one would expect the dependence between banks in the eurozone to increase. However, the dependence between banks from the same country might decrease due to the possibility to diversify the lending portfolio across the euro area. Kremers et al. (2003) discuss the supervisory approach to financial conglomerates and the risks posed by them.

In the theory section the downside risk dependence between banks in the EU is analyzed, to understand the effects of risk diversification on downside risk. The returns of individual banks are modelled by a multifactor model and it is studied whether the dependence between banks in the same country is higher than the dependence between banks from different countries. It can be show that the dependence between banks from neighboring countries is lower than the dependence among banks within a country. As a result of mergers, individual banks become more diversified, but the banking system in general may become more vulnerable to a systemic shock.

Subsequently, the aggregate risk of banks is estimated. The value of banks is approximated by their total market value, on a daily basis. It is shown empirically that the dependence structure within the banking industry changes if we leave out macroeconomic risk factors. The dependence originates from common shocks to the banking sector, affecting multiple banks in a specific country. Moreover, it is found that the dependence increased since the start of the European Monetary Union.

De Nicolo and Kwast (2002) estimate the dependence among banks in the US. They find that the degree of interdependency among large and complex banking organizations did increase over time. According to De Nicolo and Kwast, interdepencies arise because banks are exposed to similar risks. A similar exposure of banks to risks may for example originate from a similar exposure to the inter-bank loan market or from a similar exposure to counterparty risk. The increase in the degree of interdependencies implies that also the potential for a systemic crisis did increase. Their research is highly related to this research, except for the fat tail aspect. Gorton (1988) investigates the relation between banking crises and the macroeconomy, and finds that the macroeconomy is an important explanatory variable for banking crises. This finding is relevant for our research since it implies that crises are not random events. Crises are caused by a slowdown in the economy which results in a lower discounted value of firms and therefore of the assets held by banks. This supports the view that the dependence among banks originates from an exposure to similar risk factors, such as the growth of the macroeconomy.

Most of the literature applies an event study for the relation between bank performance and loan quality. For example Musumeci and Sinkey (1990) study the stock price reaction of banks to the Brazilian default. They do not find investor contagion in reaction to Brazil's debt moratorium. Smirlock and Kaufold (1987) study the effect on banks of the Mexican default and find that financial markets could asses the degree of exposure of banks to Mexican loans. Some authors have studied the dependence between banks in the EU. There are indications that the dependence between banks within the different countries in the EU is higher than the dependence between banks across borders (see e.g. Moerman, 2005). De Bandt and Hartmann (2002) discuss the literature on systemic risk more extensively. The Basel Committee on Banking Supervision (1999) provides a good overview of the empirical impact of banking regulation, specifically the 1988 Accord.

The difference with earlier work is that in this research a model is provided to analyze the probability of extreme events. We focus on the tails of the distribution and specifically investigate the effects of macroeconomic shocks. The results indicate that the dependence did change since the beginning of the EMU. This result differs from findings by Hartmann et al. (forthcoming), who also apply extreme value theory. However, they test whether a parameter of the model does change over time, while in this research, a change over time of the conditional failure probabilities is investigated.

In the following, a theoretical model is presented, which provides the rational for the estimations. Next, the dependence measure is described, followed by the estimation of the dependence between banks. Subsequently, the relation between dependence and macroeconomic risk is analyzed and the effects of the EMU are investigated.

5.1 Downside risk of individual banks

As an introduction to the analysis of multivariate dependence among banks, the characteristics of heavy tailed variables are presented in the context of univariate bank risk. Extreme value theory studies the limit distribution of the (joint) maxima or minima of (return) series, as the sample size increases without bound. To study the minimum, we change the sign of the returns and focus on the loss returns in the positive domain. Suppose that X_i is an independent and identically distributed random variable with cumulative distribution function $F(x)$. This variable exhibits heavy tails if $F(x)$ far into the tails has a first order term identical to the Pareto distribution, i.e.

$$F(x) = 1 - x^{-\alpha}L(x) \text{ as } x \to \infty, \tag{5.1}$$

where $L(x)$ is a slowly varying function such that

$$\underset{t\longrightarrow\infty}{Lim}\frac{L(tx)}{L(t)} = 1, x > 0. \tag{5.2}$$

It can be shown that the two previous conditions are equivalent to

$$\underset{t\longrightarrow\infty}{Lim}\frac{1-F(tx)}{1-F(t)} = x^{-\alpha},\ \alpha > 0,\ t > 0. \tag{5.3}$$

The coefficient α is known as the tail index and indicates the number of bounded moments of the distribution. When a distribution has finite endpoints or exponentially decaying tails (like the normal and lognormal distributions) it fails (5.3) and all moments are bounded. A high realization of a variable should be interpreted as a large loss, so we can focus on positive random variables for the study of our downside risk.

In the following, the downside risk for twenty European banks is quantified. The dataset comprises the three largest banks in Germany, Spain, The Netherlands, Italy and the UK, as well as two large French banks. The dataset contains the banks for which daily data are available since January 1992[1].

The probability is estimated that the daily stock return of a bank is lower than a prespecified probability level, x_{var}. To estimate this probability, we use the inverse quantile estimator from De Haan et al. (1994)

$$\widehat{p} = \frac{m}{n}\left(\frac{X_{M+1}}{x_{var}}\right)^{\widehat{\alpha_{(m)}}}, \ \widehat{\alpha}_{(m)} = \frac{1}{m}\sum_{j=0}^{m}\ln\left(\frac{X_j}{X_{m+1}}\right). \tag{5.4}$$

This probability estimate depends on the tail index estimator α (based on the m highest order statistics), the random number of excess m, the sample size n and the threshold level x_{var}.

If a bank loses a quarter of its market value on a given day, this raises serious concern about its viability. In our case x_{var} is somewhat arbitrarily chosen at 25%. Estimation details are given in the Appendix. In line with Slijkerman et al. (2005), we choose $m = 50$. The univariate risk for the banks can be found in Table 5.1. The results give an indication of the probability of a loss larger than 25% for an individual bank. The average probability is 0.0108, or about one day per 100 years. The probabilities range from 0.0018 (twice every 1000 years) for BPE to 0.0321 (three times in 100 years) for ING. The risk of Fortis and ING is larger than the risk for other banks. This may be the result of the relatively high risk of the insurance division. In this section we described the fat tail property of individual banks. Our main research question however concerns the importance of macro factors for the degree of dependence between banks. In the following section, the importance of country risk for the downside risk of different combinations of banks is analyzed.

5.2 Dependency Measure

For the stability of the financial system it is desirable that extreme losses of a single bank are well contained and do not cause losses at other banks. Financial sector regulation aims at preventing the collapse of individual institutions, but is also designed to contain the impact of financial crisis to a limited number of institutions.

[1] There are three exceptions: HSBC, BNP Paribas and SPI. The start of the data series of these banks can be found in Table 5.8 in the Appendix. There is no third large French bank with data available from 1992 onwards.

	Probability (Xi < -0.25) * 260		Probability (Xi < -0.25) * 260
RBS	0.0064	BNP	0.0135
HSBC	0.0031	SOCIETE GENERAL	0.0080
BARCLAYS	0.0062	DEUTSCHE BANK	0.0081
BSCH	0.0075	COMMERZBANK	0.0197
BBVA	0.0116	HYPOVEREINSBANK	0.0099
BPE	0.0018	UNICREDITO ITALIANO	0.0139
ING	0.0321	BANCA INTESA	0.0075
ABN AMRO	0.0068	SAN POALO IMI	0.0054
FORTIS	0.0218		

Table 5.1: Downside risk of individual banks

To this end the probability of simultaneous losses at multiple banks is quantified. To understand the impact of losses at a specific bank on other banks, the expected probability that the stock market value of a bank crashes can be measured, given the crash of a competitor. Let F_1 and F_2 be the stochastic returns on banks' equity and t be the common high loss level. The conditional expectation of a loss at two banks, given the loss at one bank is of interest. We therefore want the probability that $F_2 > t$, given that $F_1 > t$ and the probability that $F_1 > t$ given that $F_2 > t$, where F_1 and F_2 are the stochastic loss returns and t is the common high loss level. Since we are interested in a crash of a bank given the crash of another bank and vice versa, we will condition on either event. Let κ denote the number of banks which crash. The failure measure of Xin (1992) is used as the measure of systemic risk. In two dimensions it reads

$$E[\kappa|\kappa \geq 1] = \frac{P(F_1 > t) + P(F_2 > t)}{1 - P(F_1 \leq t, F_2 \leq t)}. \tag{5.5}$$

The failure measure is the conditional expectation of the number of banks that crash, given that there is at least one crash. Hartmann et al. (2004) give a further motivation for this measure. Note that

$$E[\kappa|\kappa \geq 1] - 1 = \frac{P(F_1 > t, F_2 > t)}{1 - P(F_1 \leq t, F_2 \leq t)} \tag{5.6}$$

is the conditional probability that both firms fail, given that there is a failure of at least one of the firms. We will use either interpretation, depending on the context. A stylized model of the univariate risk of banks will be used, to derive the probabilities needed to analyze the dependence with the failure measure (5.5).

5.3 Country risk

As Gordon (1988) showed, the business cycle is an important determinant of the risks to which banks are exposed. Since the riskiness of loans made by banks is to a large extent determined by the business cycle of a specific country, the risk exposure of banks within this country might be similar. The risk diversification benefits that can be derived from mergers between banks within a given country are limited, according to this view.

However, the benefits following a merger between banks within a country can be higher, since there might be more possibilities to cut costs or to improve returns, because of monopoly rents. An interesting analysis of the benefits of internationalization strategies is given in Slager (2004). Since we take the perspective of a regulator in this research, we focus on the benefits of risk diversification that can be derived from mergers within a given country compared to mergers across borders.

Some intuition is given by presenting two graphs, which show the performance of three major banks in Spain (Figure 5.2) and Germany (Figure 5.3). From these figures it is clear that in general the performance of the Spanish banks since January 1999 (BSCH +26%, BBVA +7% en Banco Popular +80%) is much better than the performance of the German banks (Commerzbank -33%, HypoVereinsbank -62%). Over the sample period the Spanish economic performance was quite well, while the German economy slowed down. Deutsche Bank however increased in value (+42%). Deutsche Bank is a large international bank with income from the trading portfolio.

We argue that the profits of banks are related to the macroeconomy, because the quality of their credit is related to the performance of the economy. Firms can strengthen their balance sheets in an economic upturn, which implies a solid loan quality for banks. During a recession the loan quality will deteriorate. Macroeconomic developments are therefore the source of a common risk factor in the loan books of banks, based in the same country.

Another common risk factor is the level of interest rates. There is a close relation between interest rates and the macroeconomy. According to economic theory, the real interest rates are high if the growth rate of the gross domestic product in a country is high. Moreover, the level of the interest rate and the difference between short term and long term interest rates is an important determinant of the income for banks. If interest rates increase, the public is willing to save more (ceteris paribus), since they receive a higher return on their savings. A declining interest rate encourages firms to borrow more (c.p.). The difference between the short term and long term interest rates affects the profitability of banks, because banks borrow against the short term rate and provide loans to firms against the longer term rate. The short term interest rate is set by central bankers. There is therefore a direct relation between interest rate risk and monetary policy. One would therefore expect that there exists a relation between monetary policy and the riskiness of banks, because banks are affected by changes in interest rates. The beginning of the EMU provides an interesting natural experiment. The hypothesis that the dependence between banks increases if they start to operate in a similar monetary environment can be investigated, by estimating the dependence between banks before and after the introduction of the single currency. This test provides an important insight into the relation between economic integration and downside risk dependence between banks.

De Nicolo and Kwast (2002) show for the US that the correlation between the stock returns of banks did change over time, due to financial sector consolidation. We would therefore expect that also the dependence among European banks did increase.

5.4 Modelling dependence

In this section the degree of dependence among banks is modelled. The degree of risk diversification between banks from the same country or from neighboring countries will be analyzed. This improves our understanding of the effect of mergers on systemic risk.

In the following, stylized, model, the dependence between financial institutions is analyzed by explicitly taking into account the common risk exposure of banks. The approach is similar to the Arbitrage Pricing Theorem (APT) of Ross (1976). According to the APT, the rate of return on a particular security is affected by several risk factors. Assume that two banks, indexed by $i = 1, 2$, are exposed to three different sources of risk. Suppose that the returns of a bank (B_i) are driven by three independent random variables: a broad measure for financial sector risk (F), country risk (C_j, where $j = 1, 2$, denotes the country) and firm specific risk (I_i). For the downside risk of the returns of the banks, losses larger than t in the tail of the distribution are of interest. Suppose that the three sources of risk (F, C_j and I_i) follow a unit scale Pareto distribution on $[1, \infty)$, i.e.

$$P(F > t) = P(C_i > t) = P(I_j > t) = t^{-\alpha}. \tag{5.7}$$

We study the dependence between large losses in the tails of distributions. The tail of a broad class of heavy tailed random variables, such as the Student-t distribution, can be approximated by the Pareto distribution. The result obtained for the Pareto distribution therefore carry over to all random variables which exhibit regular varying tails. Since the returns of the banks follow the sum of the three sources of risk

$$B_i = F + C_j + I_i, \tag{5.8}$$

it turns out that the tails of the return distribution of the banks are to a first order also Pareto distributed. The probability of a loss for a sum of random variables with Pareto tails is given by Feller's convolution theorem (1971, VIII.8). The convolution theorem states that the probability of a large loss for a combination of variables which follow a power like distribution, satisfies

$$\lim_{t \longrightarrow \infty} P(B_1 > s)/3t^{-\alpha} = 1. \tag{5.9}$$

For large losses (t large), the theorem thus holds that the convolution of F, C_j and I_i can be approximated by the sum of the univariate distributions of F, C_j and I_i. All that counts for the probability of the sum is the (univariate) probability mass which is located along the three axes from the points onward where the plane $F + C_j + I_i = t$ cuts the axes. The probability that the convolution of F, C_j and I_i is larger than t, given 5.7, is therefore

$$P(B_1 > s) = 3t^{-\alpha} + o(t^{-\alpha}), \tag{5.10}$$

for large t. It is assumed that the size of the univariate risk is equal for all banks. However, the dependence between the banks is not always equal, since the banks may be exposed to a different country risk, C_j.

5.4.1 Dependence within a country

In this section, we investigate the dependence between extreme losses for banks within the same country. We compare the probability that two banks realize a large loss with the probability that a merger of the two banks realizes a large loss. By comparing the likelihood of a loss of the merged bank with a simultaneous loss at two autonomous banks, we can quantify the effect of mergers on systemic risk. Systemic risk is defined as the failure of all banks in the banking system, being one or two banks in this stylized example. If the risk of failure of the merged bank is lower than the risk of a simultaneous failure of two autonomous banks, regulators may induce banks to merge, to lower the system's risk. However, if mergers do not reduce the risk, regulators may favour a setting with two autonomous banks.

First, consider the probability of a simultaneous large loss for two banks. The probability that both bank B_1 and B_2 realize a loss larger than t equals

$$P(F + C_1 + I_1 > t, F + C_1 + I_2 > t) = 2t^{-\alpha} + o(t^{-\alpha}), \tag{5.11}$$

for t large. This result follows from Feller's convolution theorem. When the two portfolio inequalities $F + C_1 + I_1 > t$ and $F + C_1 + I_2 > t$ hold simultaneously, only the probability mass above t along the $F + C_1$ axis in the portfolio is in common, but no mass along the I_1 or the I_2 axes. Note that the sum of F and C_1 can be treated as one variable. The probability that $F + C_1$ is larger than t, for large t, is equal to $2t^{-\alpha} + o(t^{-\alpha})$.

We will now investigate the risk that a merged bank realizes a large loss. We can compare this probability with the probability of a simultaneous loss of two banks. If the probability that a merged bank realizes a large loss is higher than the probability of a simultaneous loss at the two autonomous banks, this implies that the risk of a breakdown of the financial system is higher following a bank merger. We have to take into account that the loss that can be incurred by a merger bank can be twice as large, since it has a capital buffer which is the sum of the two banks. We therefore calculate the probability $P(B_1 + B_2 > 2t)$. Consider the sum of returns of two banks within the same country. The returns of the merged bank $B = B_1 + B_2$ are driven by the factors F, C_1, I_1, I_2. Following the convolution theorem, the probability of a large loss for this merged bank can be approximated by the sum of the probabilities of a large loss of the individual risk factors. The likelihood of a large loss for the merged bank therefore reads, for t large

$$P(2F + 2C_1 + I_1 + I_2 > 2t) = 2(1 + 2^{-\alpha})t^{-\alpha} + o(t^{-\alpha}), \tag{5.12}$$

where

$$P(2F + 2C_1 > 2t) = P(F + C_1 > t) = 2t^{-\alpha}$$

and

$$P(I_1 + I_2 > 2t) = 2(2^{-\alpha}t^{-\alpha}),$$

since

$$P(I_1 > 2t) = P(I_2 > 2t) = (2t)^{-\alpha} = 2^{-\alpha}t^{-\alpha}.$$

We can now formulate our first proposition.

Proposition 5.1 *If the two banks B_1 and B_2, from the same country, merge, the probability that this merged bank realizes a large loss is larger than the probability of a simultaneous large loss at the two autonomous banks, i.e. $P(B_1 + B_2 > 2t) > P(B_1 > t, B_2 > t)$, where $B_1 = F + C_1 + I_1$ and $B_2 = F + C_1 + I_2$ with $P(F > t) = P(C_i > t) = P(I_j > t) = t^{-\alpha}$.*

Proof. Evaluate whether $P(B_1 + B_2 > 2t) > P(B_1 > t, B_2 > t)$. It follows from (5.11) and (5.12) that the probability of a simultaneous loss at the two banks is lower than the probability of a loss at the merged bank. ■

An explanation for this result is that larger banks do increase systemic risk since losses are no longer isolated to a single small bank. In a merged bank losses affect the profitability of the entire holding company, including the profit making divisions. Losses reduce profitability at the holding level of the merged bank and are not contained to smaller divisions or banks. If there are two separate banks and one of the banks realizes an extreme loss, this has on average a much more limited effect on the other bank. Due to a common exposure, modelled with F and C_1, there can be simultaneous losses at the two separate banks. However, the idiosyncratic loss I_i now only affects a single bank. On the contrary, if the two banks merge the idiosyncratic losses I_1 and I_2 do have an impact on the total value of the merged entity.

5.4.2 Dependence across borders

Next, consider the probability of a simultaneous large loss for two banks when the banks are based in a different country. We analyze the probability of an extreme loss of two banks, $Pr(B_1 > t, B_2 > t)$ when the country risk for the two banks, C_1 and C_2, differs. If the country risks in the portfolios are independent, the probability that both banks realize a loss larger than t is smaller than in the previous setting.

The only source of risk which can generate a simultaneous loss for the two banks is the broad measure of financial risk F. Following the convolution theorem, only the mass above t along the F axis contributes to the probability of a simultaneous loss. Thus for large t

$$P(F + C_1 + I_1 > t, F + C_2 + I_2 > t) = t^{-\alpha} + o(t^{-\alpha}). \tag{5.13}$$

We also analyze the probability of a loss for a cross-border merger, consisting of two banks from a different country. The probability of a loss for this merged bank may be lower since the new bank may benefit from country risk diversification. The risk of the merged bank B is determined by the independent risk factors F, C_1, C_2, I_1, I_2. Following Feller, the probability of a large loss for B equals

$$P(2F + C_1 + C_2 + I_1 + I_2 > 2t) = (1 + 4/2^{\alpha})t^{-\alpha} + o(t^{-\alpha}), \tag{5.14}$$

for t large. However, regulators are not only concerned with the risk of a single institution, but also with the stability of the financial system. We argue that the financial system is relatively stable if the probability that multiple institutions fail at the same time is relatively low. In the following proposition we describe the impact on systemic risk of a merger between a domestic bank and a foreign bank.

Proposition 5.2 *If the two banks B_1 and B_2, from different countries, merge, the probability that this merged bank realizes a large loss is larger than the probability of a simultaneous large loss at the two autonomous banks, i.e. $P(B_1 + B_2 > 2t) > P(B_1 > t, B_2 > t)$, where $B_1 = F + C_1 + I_1$ and $B_2 = F + C_2 + I_2$ with $P(F > t) = P(C_i > t) = P(I_j > t) = t^{-\alpha}$.*

Proof. Evaluate whether $P(B_1 + B_2 > 2t) > P(B_1 > t, B_2 > t)$. It follows from (5.14) and (5.13) that the probability of a simultaneous loss at the two banks is lower than the probability of a loss at the merged bank. ■

Since the probability of a large loss for the merged bank is larger than the probability of a simultaneous loss at the two banks, this implies that also cross-border bank mergers do increase systemic risk. The explanation for this result is again that larger banks do increase systemic risk since losses are no longer isolated to a single bank. A merged bank can absorb losses which are larger than the losses at a single bank. However, it is more likely that the merged bank realizes a loss larger than $2t$, than that two single banks realize a loss larger than t, at the same time. The stability of the financial system does therefore not necessarily benefit from bank mergers. However, when the risk of the merged bank is compared to the probability of a loss of an individual bank, the merged bank is less risky.

Corollary 5.3 *The probability that a merged bank realizes a large loss is lower than the probability that a single bank realizes a large loss, for mergers within a country and across borders, i.e.* $P(B_1 + B_2 > 2t) < P(B_i > t)$*, where* $B_i = F + C_j + I_i$ *with* $P(F > t) = P(C_i > t) = P(I_j > t) = t^{-\alpha}$ *and* $\alpha > 1$.

Proof. Verify that (5.14) is smaller than (5.10) and that (5.12) is smaller than (5.10). ∎

Note that this holds as long as diversification pays, i.e. as $\alpha > 1$. The benefit of a merger is therefore that it reduces the risk of an individual firm. The downside of bank mergers is that they may increase systemic risk.

Are these useful propositions in real life? The following example may clarify this. Consider a country with small independent banks, which provide loans to farmers and other local businesses. When some large clients go bankrupt, this has severe consequences for the small bank. From the perspective of the bank, risk will be reduced by a merger with another small bank. This is what is stated in the corollary above. However, from the perspective of systemic risk, these mergers are not beneficial and a supervisor may prefer many small banks. The bankruptcy of a small bank does not pose a threat to the system. Moreover, the probability of a simultaneous loss at two banks is low, when this risk is compared to the probability of a large loss for the merged bank. The idea is that shocks can be sufficiently large to drag down a very large banking institution. In a setting with many small banks, only one bank will be affected. If banks do merge and create larger institutions, a rough trader e.g. can ruin this combined entity. If an institution is smaller, trading losses are contained to the smaller entity.

It can also be shown that the probability of a large loss for a merged bank is lower if the merging entities are based in different countries.

Proposition 5.4 *The probability that a merged bank realizes a large loss is lower if the two merging banks are based in different countries than if the two merging banks are based in the same country, i.e.* $P(B_1 + B_2 > 2t) < P(B_1 + B_3 > 2t)$*, where*

	Single Bank	Merged Bank	Simultaneous loss
$B_i = F + C_1 + I_i$ $B_j = F + C_1 + I_j$	$P(B_i > t)$ $3t^{-\alpha}$	$P(B_i + B_j > 2t)$ $2(1 + 2^{-\alpha})t^{-\alpha}$	$P(B_i > t, B_j > t)$ $2t^{-\alpha}$
$B_i = F + C_1 + I_i$ $B_j = F + C_2 + I_j$	$P(B_i > t)$ $3t^{-\alpha}$	$P(B_i + B_j > 2t)$ $(1 + 4/2^{\alpha})t^{-\alpha}$	$P(B_i > t, B_j > t)$ $t^{-\alpha}$
C_1, C_2, I_i, I_j and F are Pareto distributed, the smaller order terms are omitted			

Table 5.2: Summary of theoretical results

$B_1 = F + C_1 + I_1$, $B_2 = F + C_2 + I_2$ and $B_3 = F + C_1 + I_3$with $P(F > t) = P(C_i > t) = P(I_j > t) = t^{-\alpha}$ and $\alpha > 1$.

Proof. Verify that 5.14 is smaller than 5.12, i.e. verify that $P(2F+C_1+C_2+I_1+I_2 > 2t) < P(2F + 2C_1 + I_1 + I_3 > 2t)$. This is the case since $1 + 4/2^{\alpha} < 2(1 + 2^{-\alpha})$, because $1 < 2/2^{\alpha}$ with $\alpha > 1$. ∎

In this subsection we have shown that the different types of mergers have a different probability of failure. A summary of the theoretical results is given in Table 5.2. It is clear that mergers reduce the probability of failure, since the risk of a merged bank is lower than the risk of a single bank. However, the probability of a simultaneous loss at two single banks is lower than the probability of a large loss at the merged bank. This indicates that a regulator may prefer two small banks instead of a larger, merged bank. In the following we show how the modeling approach can be used to understand how joint losses effect the failure measure (5.5). The results of this theoretical approach can subsequently be used to interpret the empirical estimates of this measure.

5.4.3 Conditional crash

We can now characterize the systemic stability with the measure (5.5) by using the probabilities from the previous two sections. For the numerator of the failure measure, we need the probability that an individual bank realizes a large loss. We already have this probability in (5.10). The denominator can be decomposed in the sum of the probabilities that one of the variables which determines the return of a bank is larger than t, following Fellers convolution theorem. If we examine $1 - P(B_1 \leq t, B_2 \leq t)$, we have the probability that both banks do not have a return smaller than t. This is the case if either a common shock or an idiosyncratic shock occurs, i.e. if $F > t$, if $C_1 > t$, if $I_1 > t$ or if $I_2 > t$. For two firms from the same country, with the stochastic returns following the specification in (5.8), $1 - P(B_1 \leq t, B_2 \leq t)$ is therefore equal to $4t^{-\alpha} + o(t^{-\alpha})$, the sum of the probabilities that one of these four factors generates a loss.

We can substitute the probabilities in the failure measure and approximate the value for this measure for large t, by

$$\lim_{t \longrightarrow \infty} E[\kappa|\kappa \geq 1] = \frac{P(B_1 > t) + P(B_2 > t)}{1 - P(B_1 \leq t, B_2 \leq t)} = \frac{2(3t^{-\alpha})}{4t^{-\alpha}} = \frac{6}{4}.$$

To obtain the limit value for the failure measure if the two banks are based in different countries, we only have to recalculate the denominator. The numerator is identical to the setting with two banks from the same country. Examine $1-P(B_1 \leq t, B_2 \leq t)$, the probability that two banks do not have a return smaller than t. This is the case if either a common shock or an idiosyncratic shock occurs, i.e. if $F > t$, if $C_1 > t$, if $C_2 > t$, if $I_1 > t$ or if $I_2 > t$. The denominator of the failure measure is therefore equal to $5t^{-\alpha} + o(t^{-\alpha})$ and the measure reads

$$\lim_{t \longrightarrow \infty} E[\kappa|\kappa \geq 1] = \frac{P(B_1 > t) + P(B_2 > t)}{1 - P(B_1 \leq t, B_2 \leq t)} = \frac{2(3t^{-\alpha})}{5t^{-\alpha}} = \frac{6}{5}.$$

This measure gives the conditional expectations of a crash of two banks, given the crash of one bank, when the banks are based in different countries. The conditional expectation that a second bank will crash is smaller if the two banks are from different countries, than if the two banks are based in the same country ($6/5 < 6/4$). Therefore, systemic risk in the EU should be lower than in the individual member states, since the country risk between the EU countries differs. However, if the country component C_j becomes similar in the EU, this diversification benefit decreases. The explanation for a convergence of country risks can be the introduction of the euro, which introduced a common monetary policy to the eurozone. As a result, the interest rate risk for the banks in the participating countries became similar, reducing the difference in the country risk factor, C_j.

5.4.4 Exchange of portfolio's

An interesting issue from the perspective of systemic risk are the implications of risk sharing arrangements between banks on downside risk. Banks can e.g. reduce part of the risk on their loans to firms by buying credit default swaps. As a result, the seller of the swaps is exposed to the default of similar firms. Risk sharing can also be the result of the provision of syndicated loans by banks. Banks may reduce the risk related to the provision of large loans to firms by providing the loans in a syndicate. A common risk exposure is the result from the participation of the banks in the syndicate. In this section we provide a stylized model of risk sharing arrangements. Risk sharing works, since it reduces risk at an individual firm level.

Consider the case that the banks B_{12} and B_{21} exchange half of their portfolios. Now we have two banks, B_{12} and B_{21}, the returns of which are specified in the following way

$$B_{12} = B_{21} = 1/2(F + C_1 + I_1) + 1/2(F + C_1 + I_2).$$

The probability of a large loss for one of the two single banks is equal to

$$P(2F + 2C_1 + I_1 + I_2) > 2t) = 2(1 + 2^{-\alpha})t^{-\alpha} + o(t^{-\alpha}), \tag{5.15}$$

for t large[2]. Interestingly, this does reduce the probability of the failure of an individual institution, since (5.15) is smaller than (5.10), if $\alpha > 1$. However, risk diversification does not reduce the probability of a systemic breakdown, i.e. $P(B_1 > t, B_2 > t)$ is not reduced.

Proposition 5.5 *Risk sharing by banks does increase the probability of a simultaneous loss at two banks, i.e.* $P(B_{12} > t, B_{12} > t) > P(B_1 > t, B_2 > t)$*, where* $B_{12} = B_{21} = 1/2(F+C_1+I_1)+1/2(F+C_1+I_2)$, $B_1 = F+C_1+I_1$ *and* $B_2 = F+C_1+I_2$ *with* $P(F > t) = P(C_1 > t) = P(I_j > t) = t^{-\alpha}$.

Proof. Verify that (5.15) is larger than (5.11). ■

Since the portfolios of the two banks are equal, both banks realize a large loss if one of the two banks realizes a large loss. The probability of such a loss is given in (5.15). The probability of a systemic breakdown in (5.15) can be compared with the probability of a systemic breakdown if the banks did not share their portfolios.

[2]Note that $P(B_1 > t, B_2 > t) = P(B_1 > t) = P(B_2 > t)$ if $B_1 = B_2$.

This probability is presented in (5.11). The latter probability of a systemic crisis is smaller than the probability of a systemic crisis if the banks do swap their portfolios. It follows that the probability of a systemic breakdown is therefore increased by risk diversification by banks. This is in line with results from De Vries (2005).

5.5 Data and estimation

The dataset consists of 17 banks from 6 EU countries, using daily data from 1992 to 2004. All are supervised according to the Basle Capital Accord and EU banking directives.

If the returns of banks would follow a bivariate normal distribution, the estimation of (5.5) is straightforward, since then only the first two moments have to be estimated. However, the empirical returns of asset prices often do not follow a normal distribution. Multivariate extreme value theory deals with estimators for (5.5) in case the univariate returns are fat tailed. Regulators are interested in the actual probability of multiple, simultaneous crashes. We argue that to this end, a non-parametric approach is well suited.

Of interest to us is the dependency among large losses, i.e. high levels of t. Therefore the probability is measured that two losses are larger than the specified level t. We apply a non-parametric estimator for the failure measure

$$E[\kappa|\kappa \geq 1] = \frac{P(X > t) + P(Y > t)}{1 - P(X \leq t, Y \leq t)} = 1 + \frac{P(\min[X, Y > t])}{P(\max[X, Y > t])}, \tag{5.16}$$

where $P(\min[X_1, X_2] > t)$ is the probability that the minimum of X_1 and X_2 is above the threshold t, and $P(\max[X_1, X_2] > t)$ is the probability that the maximum of both random variables exceeds t. Both probabilities can be easily estimated using (5.4). In the Appendix we show that this can be done in one swap and that this estimator captures the limiting dependence between two heavy tailed random variables. Since we evaluate the limit behavior of (5.16), we take t close to the boundary of the sample and use $t = 0.05$. A simultaneous daily loss, larger than this threshold of 5%, reflects a substantial loss for banks.

5.5.1 Dependence over time

To see whether the dependence between banks did change following the introduction of the euro, we estimate the failure measure before and after the introduction of the euro. However, if the dependence is higher after the introduction of the euro, this is not necessarily caused by the common currency. Nevertheless, it is interesting to know, whether dependence does change over time. The failure measure is estimated for the period January 1992 until June 1998 and for the period January 1999 until December 2004. In January 1999 the euro was introduced and in the months before investors already anticipated this. We therefore decided to end the sample in June 1998. As a result the sample before the introduction of the euro and after the introduction has the same size.

A characteristic of the data is that the standard deviation of the returns is different in the two periods. In line with this, the maximum loss in the two samples is of a different size. If the threshold t is taken close to the bounds of the sample in the low variance subsample, this threshold does not correspond to the bounds of the high variance subsample. We therefore choose to evaluate the failure measure for different values of t in the two samples. Since the largest losses after January 1999 are larger than the largest losses before 1999, using the same threshold t in the second period results in the estimation of dependence less far into the tails in this period. We take a value for t corresponding to the 20^{th} largest ranked observation of RBS in both samples. The threshold for the estimation of joint losses is equal to 0.03897 before 1999 and equal to 0.05854 after January 1999. If the probability of joint losses is estimated when moving t to the core of the distribution, dependence will in general be higher. Since we estimated the dependence at the same quantile of the distribution, differences in dependence between the two subsamples are therefore not related to differences in the threshold t. Transforming the observations in the two samples to the same scale does return similar results.

5.5.2 Controlling for country risk

As argued above, an important determinant of the risk of banks is the country risk. We introduced the failure measure as a risk measure to understand the dependence between large losses of banks. To control for the dependence generated by country risk, a two step procedure is followed. First, we regress the return series of banks on a measure of the macroeconomic developments within a country. This way, the country component and the firm specific component can be disentangled. Secondly, we estimate the dependence between the idiosyncratic returns of banks, which can not be explained by this country specific component. Since a large sample is a requirement for the investigation of infrequent events, a large sample of daily data is used to estimate the dependence among banks. Unfortunately, a lot of macroeconomic variables are not available on a daily basis. However, stock market indices provide a good indicator of future firm profits and the stance of the economy. If we have a measure for changes in the future profits of firms, we have a measure for the riskiness of the loans of these firms, which are provided by banks. According to Merton (1974) there is a direct link between the value of equity of firms and the riskiness of the debt of those firms. The national stock index therefore provides a good indicator of the riskiness and profitability of a bank loan portfolio.

Suppose the single factor model applies. This gives the following definition of the stock price returns of banks

$$B_{it} = b_i M_{ct} + I_{it}, \tag{5.17}$$

where the dependent variable B_{it} represents the log daily returns of bank i at time t. The explanatory variable M_{it} represents the macroeconomic stance of the economy and I_{it} represents firm specific risks of firm i at t. The variable M_{ct} can be seen as the sum of the factors F and C_j in the theoretical section. For the empirical evaluation of (5.17), we use the MSCI country indices of the different countries[3]. We estimate (5.17) by least squares. This setup provides the basis for the empirical evaluation of the common behavior of B_{it} and B_{jt}.

5.6 Dependence estimates

We first estimate (5.5) for all possible combinations of the 17 banks in our sample. This estimate provides information on the dependence between the different banks and a first indication of the relative importance of country risk. The dependence between banks from the same country, such as Deutsche Bank and Commerzbank may e.g. on average be higher than the dependence between e.g. Deutsche Bank and HSBC, where the latter banks are from Germany and the UK.

[3]Note that the MSCI indices contain financial firms. This represents the fact that financial firms have cross-share holdings.

	Domestic	EU		Domestic	EU
UK	0.15	0.14	France	0.44	0.22
Spain	0.21	0.15	Germany	0.25	0.16
Netherlands	0.35	0.18	Italy	0.15	0.14

Table 5.3: Domestic and EU dependence among firms

The results are summarized in Table 5.3. In the table the average conditional probability of a loss for combinations of banks within a country is presented (domestic dependence) and the average dependence between banks in a specific country with banks in other EU countries is given. The estimation results for all combinations of the 17 banks are given in Table 5.9 in the Appendix. The average conditional probability of a loss of two banks given the loss of one bank is 18%. It is quite revealing that the dependence for combinations of banks from the same country is higher than for combinations of banks from different countries. This result supports the findings reported by Hartmann et al. (forthcoming). Especially the dependence among banks based within the Netherlands and France is high. The probability of a large loss of ING given a large loss at Fortis and vice versa is 42%. The dependence between ABN AMRO and ING is 37%. The dependence between the French banks SG and BNP is also high, 44%. The same holds for combinations of German banks and Spanish banks. The exception is the UK, where the dependence among banks based in the UK is similar to the dependence among British banks and foreign banks. Since the dependence among banks in the UK is low, this is probably due to large differences in risk profiles among the UK banks. HSBC can e.g. be regarded as an Asian bank, though it is listed in the UK.

We conclude that the probability of simultaneous losses is in some cases quite high. If a bank realizes a loss of 5% of its market value, there is a one in five probability that a second bank also realizes a loss. Dependence is even higher for banks within the same country. We formally test the null-hypothesis that the dependence among banks within a country is higher than the dependence among banks based in different EU countries, by using the Wilcoxon/Mann-Whitney signed ranks test. The probability that the hypothesis is not rejected is 0.03, if we test whether dependence among banks within a country is similar to the dependence across borders. We therefore conclude that the risk characteristics of the two groups are different.

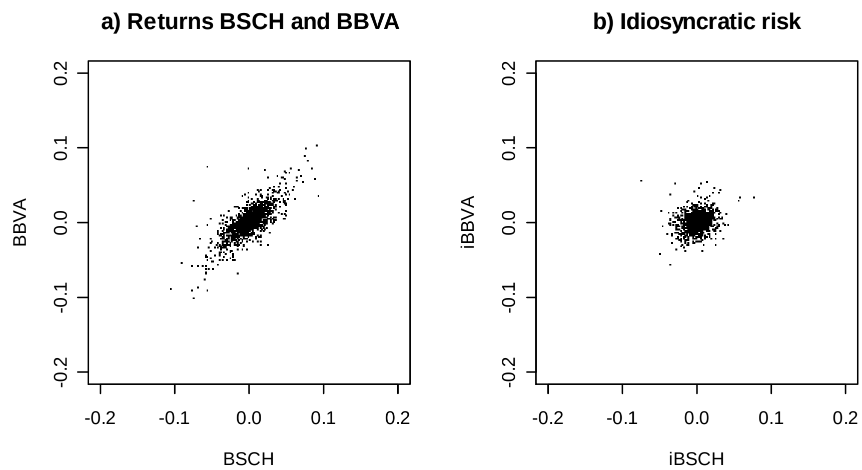


Figure 5.1: Cross-plot of returns BSCH and BBVA and idiosyncratic risk

In the following section we will see how the results hold if we leave out macroeconomic risks. Thereafter, we will investigate if the results did change due to the introduction of the euro.

5.7 Dependence and common risks

In this section the importance of macroeconomic risk factors is investigated. To obtain the idiosyncratic firm risk, we estimate (5.17) with least squares. The least squares estimates are given in Table 5.8 in the Appendix. The explanatory variable is the MSCI index of the UK, Spain, the Netherlands, France, Italy and Germany. In general the returns of banks in the EU are directly related to changes in the market index, as one would expect from the CAPM. The parameter b_i is in most cases close to or larger than 1. This implies that changes in the market index translate into similar or larger changes in the value of banks. A larger impact may be explained by the leverage of banks. Banks borrow money and invest these deposits in loans to firms. Bank equity is a buffer against losses. Large losses on the loan portfolio directly translate into lower capital ratio's because of this leveraged position.

It is, however, remarkable that the parameter b_i is smaller than 1 for the German banks. This can be the result of a large foreign exposure of the German banks in this sample. The MSCI index for Germany is probably not a good proxy for the value of

	Domestic	EU		Domestic	EU
UK	0.09	0.07	France	0.19	0.09
Spain	0.09	0.07	Germany	0.17	0.08
Netherlands	0.14	0.07	Italy	0.12	0.07

Table 5.4: Dependence and idiosyncratic risk (with low threshold)

the assets of German banks. It is a typical feature of the German banking market that the largest banks have little small local firms in their loan portfolio. If the loan portfolio of German banks consists of loans to foreign firms and multinationals, there is a limited relation between the German economy and these banks. The profitability of the largest German banks might be much more intertwined with the global economy.

We now estimate (5.5) for the dependence between the non-macro risk or idiosyncratic risks of the different banks, which we isolated via 5.17. Results are summarized in Table 5.4. In this section, equation (5.5) is estimated for a much lower threshold t than in the previous section. Since the 0.02 quantile is at the boundaries of the ordered sample, we took $t = 0.02$. If we estimate (5.5) for a threshold of 0.05, the conditional probability of a simultaneous idiosyncratic loss for two banks is close to 0, since there are hardly any simultaneous losses larger than 5%, caused by idiosyncratic risk factors.

The dependence among the idiosyncratic risks in Table (5.4) is much lower than the dependence among the bank returns in the previous section. Recall that the conditional probability of a loss of two banks given the loss of one bank is 18%. According to the results in Table (5.4), the dependence among the idiosyncratic risks is lower. If one of the two banks realizes a loss of more than 2% due to an idiosyncratic shock, the probability that the other bank is struck by a shock, larger than 2%, is equal to 13%.[4] However, the threshold of losses larger than 2% is low and most dependence between the idiosyncratic risks disappears if the threshold is raised to 5%.

We show the impact of market risk on bank returns in Figure (5.1a). In this figure a cross-plot of the daily stock price returns of BSCH and BBVA is presented. It

[4]See Table (5.10) in the Appendix for individual combinations.

	Domestic	EU		Domestic	EU
UK	0.07	0.05	France	0.27	0.09
Spain	0.19	0.05	Germany	0.20	0.06
Netherlands	0.26	0.06	Italy	0.12	0.04

Table 5.5: Dependence before EMU

is clear that there are quite some observations in the North-East and South-West quadrant of the picture. This is due to the heavy tail characteristics of the returns. In Figure (5.1b) a cross-plot of the idiosyncratic risk of the banks is given. The idiosyncratic risk corresponds to the error term in the least squares estimation of (5.17). It is revealing that there are no observations in the North-East and South-West quadrant of the figure. Since the extreme losses are not observed in the cross-plot of the idiosyncratic risks, this indicates that macro shocks cause most of the losses of banks, as one should expect from the CAPM.

Interestingly, the dependence between the bank specific idiosyncratic risks for combinations of banks within a country is again higher than the dependence among combinations of banks from different countries. Even though most dependence disappears if we use the MSCI index as a proxy for macroeconomic risk, this proxy does not explain the country risk completely. The higher dependence within countries are the result of factors which are not related to the market index. An example is the impact of regulatory changes for the financial sector. Also Gropp and Moerman (2004) report that macro shocks are an important determinant of risk in the banking system, when investigating the tail risk of multiple banks. Their results are supported by Monte Carlo simulations.

5.8 Dependence over time

To evaluate whether the dependence did change following the start of the EMU, we estimated the failure measure before the introduction of the euro and after the introduction of the euro. However, it should be noted that a possible increase in dependence since January 1999 is not necessarily caused by the common currency. In Table 5.5 we present the dependence estimates for the subsample before the intro-

	Domestic	EU		Domestic	EU
UK	0.18	0.14	France	0.39	0.22
Spain	0.12	0.10	Germany	0.24	0.16
Netherlands	0.42	0.18	Italy	0.12	0.14

Table 5.6: Dependence since EMU

duction of the euro. In Table 5.6 the dependence estimates since the introduction of the euro are given. The results clearly indicate that the dependence between banks in the EU did increase since the start of EMU.

The average probability of a loss for the two banks, given that one bank realizes a loss is 7% before the introduction of the euro. When we estimate dependence after the introduction of the euro, the probability of a second bank realizing a loss, given that one bank realizes a loss is higher. The average probability is then 16%. The estimates therefore indicate that the introduction of the common currency did have an effect on the dependence among banks, contrary to Hartmann et al. (forthcoming). A possible explanation for this opposing result is that we focus on a change over time of the probabilities of a conditional loss, while Hartmann et al. (forthcoming) test whether the tail index α is constant over time. Also Moerman (2005) investigates the dependence over time among European banks with a bivariate regime switch model. According to that approach, there are no significant differences between banks that originate from the euro area and banks from Denmark, Sweden or the UK. Further research is therefore needed to conclude that the increase in dependence is caused by the start of EMU.

To improve our understanding of the change of the dependence among banks over time, we can take a closer look at the estimation results and study the impact on a country level. In Table 5.7 we present the increase in dependence since the start of EMU for banks from different countries. We have first taken the average dependence for banks within a country and for banks from different countries before and after the introduction of the euro. Secondly, we have divided the dependence for banks in the second sample period by the dependence in the first sample period. The dependence among French banks and foreign banks before 1999 was 0.09, but after 1999 the dependence was 0.22. The increase is therefore equal to a multiple of

	EU	Domestic		EU	Domestic
UK	3.11	2.51	France	2.46	1.48
Spain	2.02	0.66	Germany	2.78	1.23
Netherlands	3.21	1.58	Italy	3.41	1.02

Table 5.7: Relative increase of dependence

2.46(0.2151/0.0874) and is more than two times higher. Similar results are obtained for the increase in dependence in other countries.

However, it is interesting to investigate whether the dependence among banks from different countries within the EU did increase with the same degree as the dependence among banks within a country. An increase in dependence between banks in the same country is the result of an increasingly similar risk exposure, because of risk sharing arrangements. Apart from a similar risk exposure, an increase in dependence among banks in different countries is the result of the harmonization of the monetary environment for banks.

According to the results in Table 5.7, the increase in the dependence among banks from different countries is higher than for banks which are based in the same country. The dependence among Spanish banks even declined after the introduction of the euro. A positive result of the integration process is that banks can broaden their credit risk exposure to other countries within the eurozone, without currency risk. The relative exposure to domestic risks is therefore reduced, which may explain the decreasing dependence among Spanish banks. However, the dependence between Spanish banks and other EU banks did increase, a possible result of monetary unification. Interestingly, the results for the UK show a different picture. The increase in dependence among UK based banks was lower than the increase in dependence with other banks in the EU. The UK does not participate in EMU, so the increase in dependence with domestic and foreign banks is at first sight not related to the common currency. Future research is therefore needed to fully understand the factors contributing to the increase in dependence over time.

5.9 Conclusion

In this chapter the downside risk dependence between banks in the EU is investigated. A better understanding of the downside risk of banks helps regulators to evaluate regulatory policies to improve financial stability in the EU. To this end, the downside risk of banks is modelled and the downside risk dependence between banks within a country and across borders is analyzed. It is shown that differences in country risk reduce the likelihood of simultaneous losses between domestic and foreign banks. A merger between banks from different countries returns a greater opportunity for risk diversification than a merger between two domestic banks. Finally, mergers by banks based in the same country do increase systemic risk, although the risk of the individual institutions is reduced.

In the empirical section we first estimated the dependence between banks in Europe. Empirical evidence shows that the dependence among banks based in the same country is higher than among banks from different countries. From a regulatory point of view, the cross-border mergers between banks in the EU should therefore be encouraged, since this provides better risk diversification possibilities, compared to mergers within a country.

Secondly, we have investigated empirically the relation between macroeconomic risk factors and downside risk. The results indicate that the risk of banks is to a high degree determined by macroeconomic factors. This contributes to the previous findings, which underlined that macroeconomic risks are an important source of dependence and offer most opportunities for risk diversification.

Third, the importance of macroeconomic risk factors explains why dependence among banks increased since the start of the EMU. Banks are now exposed to the same interest rate risk and other economic variables in the eurozone. The downside risk dependence may continue to increase in the following years, if the business cycle of the countries in the EU further converges.

5.10 Appendix

5.10.1 Estimation tail index

We have to estimate the tail index α and the scale coefficient C to obtain $L(x)$ in (5.4). We estimate α with the Hill (1975) estimator:

$$\widehat{\gamma} = 1/\widehat{\alpha} = \frac{1}{m}\sum_{j=0}^{m} \ln\left(\frac{X_j}{X_{m+1}}\right), \tag{5.18}$$

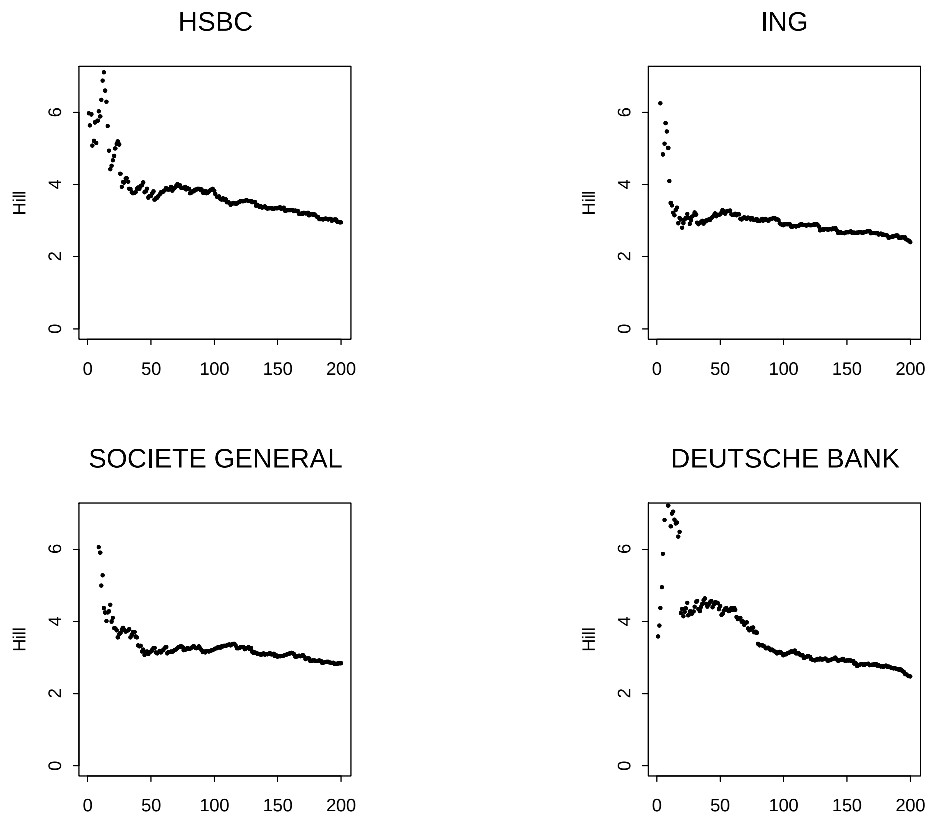
where the parameter m equals the number of highest order statistics. The number m has to be selected such that the Pareto approximation of the tail is appropriate. We select the threshold by the bootstrap method proposed in Danielsson et al. (2001). In Figure 3.3 the Hill plots for four firms are given. In a Hill plot one varies the threshold X_{m+1} or alternatively m, and plots $\widehat{\gamma}$ from (5.18) against m. In the Hill plots of Figure 3.3, where $\widehat{\gamma}$ is plotted against m, one sees considerable variation if one uses only the very top order statistics. Subsequently using more order statistics one notices some plateaus. Increasing m even further, the Hill plots all appear to be moving down. This is a result of the bias which kicks in when one uses too many central order statistics. Using too few order statistics causes the variance to dominate. Somehow one has to sail between these two vices.

The question is which threshold X_{m+1} should be selected? The plots indicate that around $m = 50$ the variance is comparatively low, while there is still a small bias in the $\widehat{\gamma}$ estimates. Since similar plots appear for all the series, we fixed m at 50 for our $\widehat{\gamma}$ estimates.

The objective of our investigation is to determine the probability that the daily stock return of a bank or insurer is lower than a prespecified probability level, X_{var}. To estimate this probability, we use the inverse quantile estimator from De Haan et al. (1994),

$$\widehat{p} = \frac{M}{n}\left(\frac{X_{m+1}}{x_{var}}\right)^{\widehat{\gamma(m)}}. \tag{5.19}$$

This estimator depends on the tail index γ, the number of higher order statistics M, the sample size n and the level x_{var}. In our case x_{var} is chosen at 25%.



Hill plots for 4 firms

5.10.2 Multivariate estimation

In this section we elaborate on the bivariate estimation technique employed in the paper. We first rewrite the failure measure, turn it into an estimator and subsequently show how the estimator performs on simulated data en real data.

From elementary probability theory we know that $P(X_1 \leq t, X_2 \leq t) = 1 - P(\max[X_1, X_2] > t)$ and $P(X_1 > t) + P(X_2 > t) = P(\max[X_1, X_2] > t) + P(\min[X_1, X_2] > t)$. One can therefore rewrite the conditional expectation as follows

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

The estimation of the probability of multiple crashes can thus be reduced to the estimation of two univariate probabilities. This greatly facilitates the empirical analysis, since one can proceed on basis of the previously described univariate estimation methods by using the minimum and maximum return series. We use the notation P_{min} for $P(\min[X_1, X_2] > t)$ and the corresponding notation for the maximum. If the tail index α is identical for the minimum (α_i) and maximum (α_a) series, we obtain the following non-parametric estimator[5]

$$E[\kappa|\kappa \geq 1] = 1 + \frac{\widehat{P}_{\min}}{\widehat{P}_{\max}}. \tag{5.20}$$

5.10.3 Identifying macroeconomic risk

In Table 5.8 the least squares estimates of equation (5.17) are given. All estimates of the coefficient b_i are significant at the 99% confidence interval. Statistics on the confidence interval are therefore omitted. In the second column the estimates for the coefficient b_i are given. The estimated constant is very small and was in many cases not significant. Because of this we do not give an economic meaning to it.

[5] Using (3.13) and $E[\kappa|\kappa \geq 1] = 1 + \frac{\frac{M_{\min}}{n}\left(\frac{X_{M+1}}{x_p}\right)^{\widehat{\alpha_{i(m)}}}}{\frac{M_{\max}}{n}\left(\frac{X_{M+1}}{x_p}\right)^{\widehat{\alpha_{a(m)}}}} = 1 + \frac{M_{\min}}{M_{\max}}$, which shows that the estimator reduces to a simple counting procedure for the minima and maxima.

Firm					R-squared	Sample
$B_{it} =$	b_i *	M_{ct}	+	I_{it} (Equation 16)		
HSBC	1.186	IUK	+	0.00056	0.444	7-10-1992
RBS	1.218	IUK	+	0.00062	0.364	
BARCLAYS	1.313	IUK	+	0.00043	0.444	
BSCH	1.257	IES	+	0.00008	0.680	
BBVA	1.217	IES	+	0.00018	0.712	
BPE	0.641	IES	+	0.00039	0.300	
ING	1.349	INL	+	0.00029	0.668	
AAB	1.154	INL	+	0.00029	0.611	
FOR	1.083	INL	+	0.00029	0.492	
BNP	1.148	IFR	+	0.00015	0.495	10-19-1993
SG	1.140	IFR	+	0.00027	0.492	
DB	0.993	IDE	+	0.00005	0.540	
COM	0.905	IDE	+	-0.00004	0.418	
HYPO	1.006	IDE	+	-0.00013	0.376	
UI	1.040	IIT	+	0.00020	0.411	
BI	1.048	IIT	+	0.00018	0.347	
SPI	1.033	IIT	+	-0.00008	0.424	4-3-1992

Table 5.8: Regression returns on index.

Figure 5.2: Spanish banking sector

Figure 5.3: German banking sector

	RBS	HSBC	BARCLAYS	BSCH	BBVA	BPE	ING	AAB	FOR	BNP	SG	DB	COM	HYPO	UI	BI	SPI
RBS	1.00	0.10	0.23	0.13	0.14	0.08	0.18	0.16	0.15	0.18	0.17	0.13	0.14	0.11	0.12	0.10	0.10
HSBC	0.10	1.00	0.10	0.12	0.13	0.04	0.10	0.14	0.07	0.13	0.12	0.14	0.13	0.07	0.11	0.06	0.07
BARCLAYS	0.23	0.10	1.00	0.13	0.15	0.19	0.24	0.20	0.19	0.22	0.23	0.19	0.16	0.10	0.17	0.14	0.15
BSCH	0.13	0.12	0.13	1.00	0.38	0.12	0.24	0.22	0.10	0.24	0.28	0.17	0.16	0.14	0.14	0.10	0.22
BBVA	0.14	0.13	0.15	0.38	1.00	0.13	0.26	0.23	0.15	0.25	0.28	0.17	0.24	0.11	0.14	0.09	0.23
BPE	0.08	0.04	0.19	0.12	0.13	1.00	0.15	0.10	0.09	0.10	0.09	0.13	0.13	0.06	0.11	0.13	0.09
ING	0.18	0.10	0.24	0.24	0.26	0.15	1.00	0.37	0.42	0.26	0.31	0.27	0.26	0.24	0.14	0.18	0.19
AAB	0.16	0.14	0.20	0.22	0.23	0.10	0.37	1.00	0.27	0.22	0.29	0.21	0.20	0.18	0.11	0.11	0.23
FOR	0.15	0.07	0.19	0.10	0.15	0.09	0.42	0.27	1.00	0.18	0.25	0.17	0.18	0.14	0.11	0.13	0.13
BNP	0.18	0.13	0.22	0.24	0.25	0.10	0.26	0.22	0.18	1.00	0.44	0.28	0.21	0.14	0.17	0.15	0.20
SG	0.17	0.12	0.23	0.28	0.28	0.09	0.31	0.29	0.25	0.44	1.00	0.27	0.23	0.16	0.17	0.12	0.18
DB	0.13	0.14	0.19	0.17	0.17	0.13	0.27	0.21	0.17	0.28	0.27	1.00	0.32	0.23	0.13	0.14	0.15
COM	0.14	0.13	0.16	0.16	0.24	0.13	0.26	0.20	0.18	0.21	0.23	0.32	1.00	0.21	0.12	0.16	0.14
HYPO	0.11	0.07	0.10	0.14	0.11	0.06	0.24	0.18	0.14	0.14	0.16	0.23	0.21	1.00	0.08	0.15	0.14
UI	0.12	0.11	0.17	0.14	0.14	0.11	0.14	0.11	0.11	0.17	0.17	0.13	0.12	0.08	1.00	0.14	0.16
BI	0.10	0.06	0.14	0.10	0.09	0.13	0.18	0.11	0.13	0.15	0.12	0.14	0.16	0.15	0.14	1.00	0.13
SPI	0.10	0.07	0.15	0.22	0.23	0.09	0.19	0.23	0.13	0.20	0.18	0.15	0.14	0.14	0.16	0.13	1.00
Mean	0.14	0.10	0.17	0.18	0.19	0.11	0.24	0.20	0.17	0.21	0.22	0.19	0.19	0.14	0.13	0.13	0.16

Table 5.9: Dependence 1992-2004 t= 0.05

	RBS	HSBC	BARCLAYS	BSCH	BBVA	BPE	ING	AAB	FOR	BNP	SG	DB	COM	HYPO	UI	BI	SPI
RBS	1.00	0.07	0.14	0.07	0.04	0.06	0.04	0.08	0.06	0.07	0.07	0.07	0.08	0.08	0.08	0.08	0.09
HSBC	0.07	1.00	0.07	0.05	0.06	0.05	0.03	0.07	0.04	0.09	0.07	0.07	0.05	0.06	0.06	0.05	0.05
BARCLAYS	0.14	0.07	1.00	0.07	0.09	0.08	0.08	0.07	0.08	0.11	0.11	0.07	0.08	0.08	0.08	0.08	0.10
BSCH	0.07	0.05	0.07	1.00	0.10	0.10	0.09	0.07	0.05	0.08	0.07	0.07	0.07	0.06	0.07	0.06	0.07
BBVA	0.04	0.06	0.09	0.10	1.00	0.07	0.06	0.06	0.04	0.07	0.07	0.07	0.09	0.06	0.05	0.04	0.05
BPE	0.06	0.05	0.08	0.10	0.07	1.00	0.07	0.06	0.08	0.08	0.08	0.06	0.07	0.06	0.07	0.05	0.06
ING	0.04	0.03	0.08	0.09	0.06	0.07	1.00	0.16	0.13	0.07	0.09	0.07	0.07	0.10	0.06	0.06	0.07
AAB	0.08	0.07	0.07	0.07	0.06	0.06	0.16	1.00	0.11	0.08	0.11	0.09	0.09	0.07	0.06	0.06	0.08
FOR	0.06	0.04	0.08	0.05	0.04	0.08	0.13	0.11	1.00	0.10	0.08	0.06	0.08	0.09	0.06	0.06	0.07
BNP	0.07	0.09	0.11	0.08	0.07	0.08	0.07	0.08	0.10	1.00	0.19	0.11	0.07	0.09	0.07	0.08	0.08
SG	0.07	0.07	0.11	0.07	0.07	0.08	0.09	0.11	0.08	0.19	1.00	0.12	0.07	0.10	0.06	0.07	0.09
DB	0.07	0.07	0.07	0.07	0.07	0.06	0.07	0.09	0.06	0.11	0.12	1.00	0.15	0.15	0.07	0.06	0.10
COM	0.08	0.05	0.08	0.07	0.09	0.07	0.07	0.09	0.08	0.07	0.07	0.15	1.00	0.20	0.08	0.07	0.11
HYPO	0.08	0.06	0.08	0.06	0.06	0.06	0.10	0.07	0.09	0.09	0.10	0.15	0.20	1.00	0.08	0.09	0.10
UI	0.08	0.06	0.08	0.07	0.05	0.07	0.06	0.06	0.06	0.07	0.06	0.07	0.08	0.08	1.00	0.12	0.12
BI	0.08	0.05	0.08	0.06	0.04	0.05	0.06	0.06	0.06	0.08	0.07	0.06	0.07	0.09	0.12	1.00	0.11
SPI	0.09	0.05	0.10	0.07	0.05	0.06	0.07	0.08	0.07	0.08	0.09	0.10	0.11	0.10	0.12	0.11	1.00
Mean	0.07	0.06	0.09	0.07	0.06	0.07	0.08	0.08	0.07	0.09	0.09	0.09	0.09	0.09	0.08	0.07	0.08

Table 5.10: Dependence 1992-2004 idiosyncratic t= 0.02

	RBS	HSBC	BARCLAYS	BSCH	BBVA	BPE	ING	AAB	FOR	BNP	SG	DB	COM	HYPO	UI	BI	SPI
RBS	1.00	0.04	0.14	0.03	0.04	0.04	0.07	0.09	0.06	0.10	0.08	0.03	0.00	0.00	0.03	0.04	0.04
HSBC	0.04	1.00	0.04	0.06	0.05	0.05	0.07	0.11	0.09	0.20	0.10	0.04	0.07	0.05	0.04	0.04	0.05
BARCLAYS	0.14	0.04	1.00	0.00	0.00	0.00	0.03	0.06	0.00	0.03	0.08	0.00	0.00	0.00	0.03	0.02	0.00
BSCH	0.03	0.06	0.00	1.00	0.25	0.17	0.07	0.00	0.03	0.13	0.08	0.13	0.10	0.07	0.03	0.04	0.04
BBVA	0.04	0.05	0.00	0.25	1.00	0.14	0.05	0.00	0.00	0.12	0.07	0.09	0.11	0.12	0.02	0.03	0.11
BPE	0.04	0.05	0.00	0.17	0.14	1.00	0.06	0.05	0.05	0.04	0.04	0.00	0.00	0.00	0.04	0.01	0.03
ING	0.07	0.07	0.03	0.07	0.05	0.06	1.00	0.35	0.19	0.11	0.11	0.18	0.16	0.05	0.03	0.03	0.08
AAB	0.09	0.11	0.06	0.00	0.00	0.05	0.35	1.00	0.25	0.15	0.03	0.07	0.08	0.00	0.03	0.03	0.04
FOR	0.06	0.09	0.00	0.03	0.00	0.05	0.19	0.25	1.00	0.09	0.00	0.07	0.09	0.00	0.02	0.03	0.02
BNP	0.10	0.20	0.03	0.13	0.12	0.04	0.11	0.15	0.09	1.00	0.27	0.09	0.10	0.06	0.04	0.08	0.09
SG	0.08	0.10	0.08	0.08	0.07	0.04	0.11	0.03	0.00	0.27	1.00	0.09	0.11	0.07	0.06	0.03	0.06
DB	0.03	0.04	0.00	0.13	0.09	0.00	0.18	0.07	0.07	0.09	0.09	1.00	0.30	0.19	0.05	0.05	0.10
COM	0.00	0.07	0.00	0.10	0.11	0.00	0.16	0.08	0.09	0.10	0.11	0.30	1.00	0.11	0.03	0.03	0.05
HYPO	0.00	0.05	0.00	0.07	0.12	0.00	0.05	0.00	0.00	0.06	0.07	0.19	0.11	1.00	0.02	0.03	0.08
UI	0.03	0.04	0.03	0.03	0.02	0.04	0.03	0.03	0.02	0.04	0.06	0.05	0.03	0.02	1.00	0.10	0.16
BI	0.04	0.04	0.02	0.04	0.03	0.01	0.03	0.03	0.03	0.08	0.03	0.05	0.03	0.03	0.10	1.00	0.11
SPI	0.04	0.05	0.00	0.04	0.11	0.03	0.08	0.04	0.02	0.09	0.06	0.10	0.05	0.08	0.16	0.11	1.00
Mean	0.05	0.07	0.03	0.08	0.08	0.04	0.10	0.08	0.06	0.11	0.08	0.09	0.08	0.05	0.05	0.04	0.07

Table 5.11: Dependence 1992-June 1998

	RBS	HSBC	BARCLAYS	BSCH	BBVA	BPE	ING	AAB	FOR	BNP	SG	DB	COM	HYPO	UI	BI	SPI
RBS	1.00	0.09	0.35	0.07	0.10	0.05	0.21	0.24	0.23	0.15	0.23	0.17	0.17	0.08	0.07	0.17	0.19
HSBC	0.09	1.00	0.11	0.06	0.06	0.17	0.07	0.07	0.06	0.10	0.10	0.13	0.13	0.02	0.14	0.08	0.16
BARCLAYS	0.35	0.11	1.00	0.08	0.16	0.06	0.21	0.24	0.22	0.22	0.30	0.20	0.19	0.09	0.13	0.19	0.23
BSCH	0.07	0.06	0.08	1.00	0.37	0.00	0.12	0.19	0.03	0.15	0.14	0.06	0.03	0.04	0.05	0.03	0.21
BBVA	0.10	0.06	0.16	0.37	1.00	0.00	0.27	0.29	0.10	0.23	0.17	0.13	0.16	0.07	0.04	0.09	0.24
BPE	0.05	0.17	0.06	0.00	0.00	1.00	0.02	0.00	0.03	0.00	0.03	0.05	0.04	0.00	0.08	0.09	0.06
ING	0.21	0.07	0.21	0.12	0.27	0.02	1.00	0.44	0.53	0.24	0.31	0.25	0.27	0.24	0.08	0.16	0.20
AAB	0.24	0.07	0.24	0.19	0.29	0.00	0.44	1.00	0.28	0.38	0.32	0.31	0.20	0.18	0.06	0.12	0.26
FOR	0.23	0.06	0.22	0.03	0.10	0.03	0.53	0.28	1.00	0.18	0.27	0.22	0.21	0.19	0.08	0.19	0.12
BNP	0.15	0.10	0.22	0.15	0.23	0.00	0.24	0.38	0.18	1.00	0.39	0.39	0.25	0.12	0.12	0.14	0.25
SG	0.23	0.10	0.30	0.14	0.17	0.03	0.31	0.32	0.27	0.39	1.00	0.32	0.28	0.17	0.08	0.11	0.25
DB	0.17	0.13	0.20	0.06	0.13	0.05	0.25	0.31	0.22	0.39	0.32	1.00	0.39	0.18	0.19	0.19	0.23
COM	0.17	0.13	0.19	0.03	0.16	0.04	0.27	0.20	0.21	0.25	0.28	0.39	1.00	0.17	0.14	0.22	0.22
HYPO	0.08	0.02	0.09	0.04	0.07	0.00	0.24	0.18	0.19	0.12	0.17	0.18	0.17	1.00	0.06	0.13	0.11
UI	0.07	0.14	0.13	0.05	0.04	0.08	0.08	0.06	0.08	0.12	0.08	0.19	0.14	0.06	1.00	0.14	0.12
BI	0.17	0.08	0.19	0.03	0.09	0.09	0.16	0.12	0.19	0.14	0.11	0.19	0.22	0.13	0.14	1.00	0.11
SPI	0.19	0.16	0.23	0.21	0.24	0.06	0.20	0.26	0.12	0.25	0.25	0.23	0.22	0.11	0.12	0.11	1.00
Mean	0.16	0.10	0.19	0.10	0.15	0.04	0.23	0.22	0.18	0.21	0.22	0.21	0.19	0.12	0.10	0.14	0.18

Table 5.12: Dependence 1999-2004

Chapter 6

Summary and Conclusions

In this research we have investigated the downside risk of financial institutions. This is the primary concern of regulators of the financial sector. Regulators are interested in the risk of large losses, threatening individual banks and insurers. The secondary focus of regulators is the soundness of the financial system. Since the risk that multiple banks or insurers realize a large loss, at the same time, is of interest, we have studied the risk diversification effects of downside risk. This helps us to understand the observed dependence between losses of multiple companies.

The intention of this research is to develop new theoretical propositions and present empirical results, which are of interest to policymakers. To keep this work concise and make it accessible to non-academics, some choices have been made. For example, the degree of dependence between the returns of two firms is represented by a probability measure and not by the parameter in a copula, which is in vogue in academics. Propositions related to extreme value theory are formulated and the dependence among firms is estimated in a similar way, based on similar assumptions. This combination of propositions and empirical results, offers an interesting approach to study the downside risk in the financial sector.

According to the traditional industrial organization view, the financial sector can be divided in the following subsectors: the banking sector, the insurance sector and the reinsurance sector. Moreover, financial conglomerates providing both banking and insurance services can be considered a subsector. The exposure to downside risk of these subsectors in investigated in the different chapters. Chapter 1 starts with an introduction to recent trends in the financial sector and to this research. In

Chapter 2 references to the broader literature are given. In the following sections a summary of the other chapters can be found.

In Chapter 3 the dependence between the downside risk of European banks and insurers is analyzed. Since the downside risk of banks and insurers differs, an interesting question from a supervisory point of view is the risk reduction that derives from diversification within large banks and financial conglomerates. The limited value of the normal distribution based correlation concept is discussed, and an alternative measure is proposed, which better captures the downside dependence given the fat tail property of the risk distribution. This measure is estimated and indicates better diversification benefits for conglomerates versus large banks. Chapter 3 is based on joint work with De Vries and Schoenmaker (Slijkerman et al., 2005).

In Chapter 4 the relation between insurers and reinsurers is studied. Simultaneous losses of the market value of insurers are modelled and measured, to understand the impact of shocks on the insurance sector. The downside risk of insurers is explicitly modelled by common and idiosyncratic risk factors. Since reinsurance is important for the capacity of insurers, the risk dependence among European insurers and reinsurers is measured. The results point to a relatively low insurance sector wide risk and indicate that the dependence among insurers is higher than among reinsurers.

In Chapter 5 the mutual relations among banks are investigated. The downside risk of multiple combinations of banks in the EU are modelled and their downside risk dependence is estimated. An explanation for the joint risks, based on macroeconomic developments, is provided. The results indicate that in general the dependence between banks based in the same country is higher and that the dependence did increase after the introduction of the euro. Evidence shows that the dependence can be explained by macroeconomic developments.

This thesis therefore offers a number of new insights on the risk diversification effect of mergers in the financial sector, from both a theoretical and an empirical perspective. The propositions in the different chapters are innovative, as is the use of the non-parametric estimator in this context. The use of this estimator and choice of European data provide us with new results. Moreover, different aspects of the methodology are explored in the chapters. The robustness of the results is shown by sampling in Chapter 3. In Chapter 4, the dependence among more than two firms is investigated. In Chapter 5, it is shown how explanatory variables can be used in this context and it is investigated whether the dependence has changed over time. Moreover, in the chapters, a different policy question is addressed. The results are useful for the design of new regulatory policies and can be the input for future research on the diversification effects of downside risk. The framework to disentangle the common and idiosyncratic shocks, incurred by multiple firms, which is presented in Chapter 4, is well suited for future theoretical research. The non-parametric estimator, which is used to estimate the probability that two firms realize a simultaneous loss, can be used for future applied research.

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Summary in Dutch
Nederlandse samenvatting

Voor de meeste mensen in Europa is de stabiliteit van het financiële stelsel en de stabiliteit van banken en verzekeraars vanzelfsprekend. Ze zijn gerust, doordat de risicomanagementsystemen van deze instellingen geavanceerd zijn en doordat goed opgeleide toezichthouders de instellingen in de gaten houden. Een gevolg van deze aanpak is, dat faillissementen in Europa zeldzaam zijn. Toch is de uitdaging voor toezichthouders om risico in de financiële sector te begrijpen aan het toenemen.

Twee trends in de financiële sector, die in het oog springen, zijn een toename van grensoverschrijdende activiteiten van instellingen en een toename van de verhandelbaarheid van de diverse risico's tussen de instellingen. De meeste financiële instellingen bieden hun producten over de grens aan en investeren hun activa in meerde landen. Verbeterde mogelijkheden om risico te beprijzen in samenhang met een geavanceerde technologische infrastructuur ondersteunen de verhandelbaarheid en overdracht van risico's tussen instellingen. Bedrijven doen dit om de risico's waaraan zij blootgesteld staan te verminderen. Deze ontwikkeling heeft echter de complexiteit doen toenemen van de risico's die financiële instellingen nemen.

Het faillissement van een financiële instelling leidt tot verliezen voor consumenten en andere belanghebbenden. Aangezien een groot verlies bij een financiële instelling gevolgen kan hebben voor de stabiliteit van het financiële systeem, is de wederzijdse afhankelijkheid van instellingen het aangrijpingspunt voor het toezicht, dat tot doel heeft de financiële stabiliteit te bevorderen. Dit is specifiek van belang in de bancaire sector, waar het betalingsverkeer verzorgd wordt door een netwerk van banken. Daarnaast staan financiële instellingen onder toezicht om de tegoeden van consumenten te beschermen.

Het eerste oogmerk van toezichthouders is om het faillissement van een bank of verzekeraar te voorkomen. Toezichthouders zijn geïnteresseerd in de kans op een sterke waardevermindering van de activa en in de kans op ongewoon grote verplichtingen, die de soliditeit van de instellingen aantasten. Statistisch gesproken zijn zij geïnteresseerd in de linker staart van de rendementsverdeling. Een techniek, die gebruikt wordt om deze verdeling te beschrijven, is de zogenoemde extreme waarden theorie. Extreme waarden theorie kan gebruikt worden om de kans op grote verliezen van de marktwaarde van banken en verzekeraars in kaart te brengen en uitspraken doen over de kans op nog niet eerder waargenomen verliezen.

Het tweede oogmerk van toezichthouders is de soliditeit van het financiële systeem. De verbanden tussen financiële instellingen kunnen er toe leiden dat grote verliezen bij een instelling gevolgen hebben voor de concurrent. Vanwege een gelijksoortige blootstelling aan risico kunnen meerdere instellingen geraakt worden door een catastrofe. Dit draagt er toe bij, dat de verliezen tussen instellingen met elkaar samenhangen. Een gevolg kan zijn, dat het aanbod van financiële diensten afneemt tijdens crises, aangezien de instellingen gelijktijdig verliezen maken, waardoor hun bereidheid om risico te nemen afneemt. Het modelleren van gelijktijdige verliezen bij meerdere instellingen draagt bij aan het inzicht in de risico's in de financiële sector. Er wordt in dit onderzoek daarom gekeken naar de kans op grote verliezen bij twee of meer banken of verzekeraars vanuit zowel een theoretische als een empirische invalshoek. Zodoende brengen we in kaart, wat de kans op grote verliezen is en welke gevolgen deze hebben voor het financiële systeem.

Het theoretisch modelleren van het neerwaartse risico verschaft nieuwe inzichten in de gevolgen van fusies voor de robuustheid van het financiële systeem. Het is echter interessant deze theoretische modellen te combineren met een empirische evaluatie van de kansverdeling van verliezen in de financiële sector. Het schatten van de kans op grote verliezen verschaft informatie over de beste manier, waarop het neerwaartse risico gediversifieerd kan worden. Zo wordt het belang van landenrisico of sectorrisico onderzocht. De sectorrisico's voor verzekeraars verschillen bijvoorbeeld van de sectorrisico's in het bankwezen.

De financiële relaties tussen verzekeraars zijn relatief beperkt vergeleken met de relaties, die banken met elkaar hebben op de financiële markten. Aangezien de meeste verzekeraars echter vaak dezelfde soort activa en passiva hebben, kan dit tot eenzelfde risicoprofiel leiden. Verzekeraars kunnen bijvoorbeeld dezelfde verplichtingen hebben vanwege overeenkomstige klanten of vanwege dezelfde regio's waarin ze actief zijn. Als verzekeraars in dezelfde activa investeren, kan dit ook de bron zijn van een overeenkomstig risicoprofiel. De herverzekeringssector staat bekend om de mogelijkheden, die het heeft om grote catastrofes te verzekeren en om de mogelijkheden, die het heeft om verzekeraars dekking te verschaffen tegen extreme verliezen. Wanneer echter de dekking van meerdere verzekeraars tegen extreme verliezen door dezelfde herverzekeraar verschaft wordt, zijn deze verzekeraars blootgesteld aan het risico van faillissement van de herverzekeraar.

Het probleem van een crisis in de bancaire sector is bekend in de literatuur. Banken zijn de hoeksteen van de financiële sector. Zij onderhouden het betalingsverkeer en verschaffen liquiditeit aan huishoudens en bedrijven evenals leningen met een langere looptijd. Banken zijn belangrijk voor de economische groei, aangezien ze de handel en investeringen helpen financieren. Daarnaast verschaffen banken aan huishoudens de mogelijkheid om te sparen. In de geschiedenis is de bancaire sector een aantal malen door ernstige crises geraakt, zoals tijdens de “ savings and loans crisis” in de Verenigde Staten. Vanwege de gevolgen voor de reële economie van een crisis is de sector streng gereguleerd, zelfs op internationaal niveau door het “Basel Committee on Banking Supervision”.

Vanuit het traditionele perspectief kan de financiële sector opgedeeld worden in de volgende subsectoren: de verzekeringssector, de herverzekeringssector en de bancaire sector. Daarnaast kunnen financiële conglomeraten, die zowel bancaire als verzekeringsproducten aanbieden, beschouwd worden als subsector. De opkomst van financiële conglomeraten maakt het relevant, in hoeverre risico's in de bancaire sector en in de verzekeringssector met elkaar verband houden. Deze problematiek is beschreven in hoofdstuk 3. Over de onderlinge afhankelijk van de verliezen van verzekeraars tijdens crises is minder bekend. Dit onderwerp wordt besproken in hoofdstuk 4, waarbij er aandacht zal zijn voor de wederzijdse afhankelijkheid tussen herverzekeraars. Door de fusies tussen banken in de EU in de afgelopen jaren zijn beleidsmakers zich meer bewust geworden van de gevolgen van risicospreiding in de bancaire sector en de gevolgen voor de kans op grote verliezen van deze fusies. De onderlinge afhankelijkheid tussen banken wordt daarom onderzocht in hoofdstuk 5.

In hoofdstuk 3 wordt de onderlinge afhankelijkheid bestudeerd tussen Europese banken en verzekeraars. Aangezien het neerwaartse risico tussen Europese banken en verzekeraars verschilt, is het voor toezichthouders een interessante vraag, of het voor financiële conglomeraten mogelijk is het risico te verlagen. De beperkingen van de correlatie coëfficiënt, een coëfficiënt die nauw samenhangt met de normale verdeling, worden besproken en een andere maatstaf wordt geïntroduceerd, welke beter geschikt is om de afhankelijkheid tussen extreme verliezen weer te geven. Dit is nuttig, aangezien toezichthouders juist geïnteresseerd zijn in extreme verliezen en de daarmee samenhangende dikstaartige verdelingsfunctie. De maatstaf wordt vervolgens geschat. De conclusie luidt, dat de neerwaartse risico's van banken en verzekeraars verschillen en dat financiële conglomeraten misschien beter in staat zijn risico's te diversifiëren dan grote banken.

In hoofdstuk 4 wordt de afhankelijkheid tussen verzekeraars en herverzekeraars besproken. De kans op een gelijktijdig groot verlies van de marktwaarde wordt gemodelleerd en vervolgens gemeten. Dit verschaft inzicht in de impact van catastrofes op de verzekeringssector. Het neerwaarts risico wordt gemodelleerd, waarbij het gemeenschappelijke risico en het idiosyncratisch risico expliciet uitgesplitst wordt. Dit verschaft inzicht in de mate, waarin de afhankelijkheid tussen bedrijven toeneemt ten gevolge van een toename van gemeenschappelijk en idiosyncratisch risico. Aangezien herverzekeraars belangrijk zijn voor de capaciteit van de Europese verzekeringssector, wordt ook de afhankelijkheid tussen herverzekeraars en verzekeraars geschat. De resultaten wijzen op een relatief laag sectorrisico voor verzekeraars. De afhankelijkheid tussen herverzekeraars is echter nog lager.

In hoofdstuk 5 wordt bekeken, in hoeverre het risicoprofiel van diverse Europese banken overeen komt. Het neerwaarts risico van meerdere Europese banken wordt gemodelleerd, evenals de kans op meerdere verliezen bij banken op hetzelfde tijdstip. Het neerwaarts risico en de samenhang wordt vervolgens geschat. Een verklaring voor een overeenkomstig risicoprofiel wordt gevonden in macro-economische ontwikkelingen. De resultaten geven aan, dat over het algemeen de afhankelijkheid tussen banken in hetzelfde land hoger is dan tussen banken uit verschillende landen. Daarnaast geven de empirische resultaten aan dat het risicoprofiel van Europese banken meer op elkaar is gaan lijken na de introductie van de euro. De euro hoeft echter niet de oorzaak te zijn van de observatie, dat het neerwaartse risico van banken meer op elkaar is gaan lijken.

Kort samengevat verschaft dit proefschrift een aantal nieuwe inzichten in de mate, waarin het neerwaartse risico diversifieerbaar is, zowel vanuit een theoretisch als een empirisch perspectief. Niet alleen de stellingen in de verschillende hoofdstukken zijn vernieuwend, maar ook het gebruik van een niet-parametrische schatter in deze context. Het gebruik van de niet-parametrische schatter en de keuze voor Europese data zorgen ervoor, dat de resultaten nieuw zijn. Daarnaast worden in de diverse hoofdstukken verschillende zaken verder uitgewerkt. De gevoeligheid van de schatter wordt zichtbaar gemaakt door een simulatie oefening in hoofdstuk 3. In hoofdstuk 4 komt de onderlinge afhankelijkheid tussen meer dan twee bedrijven aan bod. In hoofdstuk 5 wordt aangegeven hoe verklarende variabelen in het empirische raamwerk opgenomen kunnen worden. Daarnaast wordt bekeken, hoe de onderlinge afhankelijkheid tussen instellingen verandert door de tijd heen. De resultaten zijn relevant gegeven de consolidatie in de Europese financiële sector. Het onderzoek verschaft toezichthouders handvatten voor het beleid ten aanzien van fusies in de financiële sector. Daarnaast bevat het onderzoek verschillende elementen, die in toekomstig onderzoek naar de diversifieerbaarheid van neerwaarts risico verder uitgewerkt kunnen worden.

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