Essays on Systemic Risk

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Mannheim, March 2009 *Marcel Prokopczuk*

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Chapter 1

Introduction

1.1 Definition of Systemic Risk

'The term "Systemic Risk" belongs to the folklore of the discussion about banks and banking supervision.' Hellwig (1998, p. 123)[1]

During the last years, systemic risk has moved to the center stage of interest of academics and practitioners, as well as politicians and regulators. This thesis aims to be part of the progress in advancing the understanding of this specific type of risk.

To date, no mutually accepted definition of systemic risk can be found in the literature. Many authors mean different things when they write about systemic risk. In this section, we give a brief overview of various possible definitions of systemic risk and clarify our understanding of systemic risk.

Generally, systemic risk can be defined in a very broad way. One can think about any threat that accrues from or that is transmitted via a system. Possible examples are the threat of epidemic plagues, where diseases are transmitted via the contact of human beings (which can be regarded as a system), or the threat of a wide-area power blackout, originating from the failure of one transformer station,

[1] Original in German, translated by the author.

with propagating capacity overloads through the power grid. Consequently, the Organization for Economic Co-operation and Development (OECD) defines systemic risk as *'a risk that affects the systems on which society depends – health, transport, environment, telecommunications, etc.'*, see OECD (2003, p. 9).

In this thesis, we are concerned with systemic risk in an economical or financial context. Different definitions of systemic risk can be found in these fields as well. Table 1.1 provides an overview of possible definitions of systemic risk. These definitions vary mostly with respect to their generality. Kaufman and Scott (2003) provide a quite general definition, not specifying exactly what is meant by a system. Others, e.g. Hellwig (1998), focus their definition on the financial system, but are general about the consequences of systemic risk. In contrast, Acharya (2001) is quite precise about these consequences, as the joint failure of multiple banks is explicitly mentioned. The list provided in Table 1.1 is by no means exhaustive and is rather displayed to disclose the heterogeneity of definitions of systemic risk in an economic or financial context across the literature.

In this thesis, we do not only consider systemic risk in the financial system but also in other sectors. Thus, our understanding of systemic risk is best captured by the definition of Kaufman and Scott (2003). This definition has the advantage of including almost all of the definitions used in the relevant literature, while still being economically driven compared with other general definitions such as the one of Das and Uppal (2004), which is more of a statistical nature.

As outlined in the overview paper of de Bandt and Hartmann (2000), which has become a standard reference paper in the systemic risk literature, it is useful to fill a definition of systemic risk with more structure. Although these authors focus on the financial sector or entire economies when discussing systemic risk, we can adopt part of their classification scheme. Depending on the nature of the primary shock, one can distinguish between systemic risk in the *broad* and systemic risk in the *narrow* sense.

Systemic risk in the broad sense comprises simultaneous failures or adverse behavior of a large number of companies due to a macroeconomic shock, e.g. a

Table 1.1: **Possible Definitions of Systemic Risk**

This table contains various possible definitions of systemic risk or systemic crises.

Source	Definition
Kaufman (1994, p. 123)	*'The risk of widespread failure contagion is referred to as systemic risk.'*
Rochet and Tirole (1996, p. 733)	*'Systemic risk refers to the propagation of a bank's economic distress to other economic agents linked to that bank through financial transactions'*
Hellwig (1998, p. 125)*	*'Systemic risk describes the problem that due to interdependencies between banking institutions of a financial system, difficulties at one bank put the functional capability of the entire system into question'*
Staub (1999, p. 3)*	*'The possibility that due to mutual dependencies between institutions of a financial system problems of single banks or institution spread over the system and challenge its functional capability.'*
Acharya (2001, p. 1)	*'A financial crisis is "systemic" in nature if many banks fail together, or if one bank's failure propagates as a contagion causing the failure of many banks'*
Ergungor and Thomson (2005, p. 2)	*'In a systemic crisis, multiple banks fail simultaneously, and the collective failure impairs enough of the banking system's capital so that large economic effects are likely to result and the government is required to intervene.'*
Kaufman and Scott (2003, p. 371)	*'Systemic risk refers to the risk or probability of breakdowns in an entire system, as opposed to breakdowns in individual parts or components, [...].'*
Das and Uppal (2004, p. 2810)	*'The risk from infrequent events that are highly correlated across a large number of assets'*
Gischer et al. (2005, p. 109)*	*'The risk that the financial system loses its functional capability due too a massive crisis.'*
Krahnen (2006, p. 58)*	*'Systemic risk is the risk of a joint default of legally independent financial institutions.'*
Nier et al. (2007, p. 2034)	*'Systemic risk arises when the failure or weakness of multiple banks imposes costs on the financial system and ultimately on the economy as a whole.'*

* Original in German, translated by the author.

sharp jump in the oil price or a strong decrease in overall consumer demand. This type of systemic risk originates primarily from similar business models and joint exposures to common risk factors.

Systemic risk in the narrow sense originates from microeconomic shocks, occurring at one company and then propagating to other companies. This process is commonly referred to as contagion in the literature.[2] For this to happen, it is necessary for the second key element of narrow systemic risk, namely a *transmission channel*, to exist.

In general, one can distinguish two different ways a shock is transferred to other companies. The first possible transmission channel is based on multilateral exposures between the companies considered, i.e. the companies have economic exposures against each other. Therefore, this effect, based on real exposures, is frequently labeled *real contagion*, and consequently the associated transmission channel is called the *real channel*. Notably, this channel is particularly relevant to the banking sector, as the financial exposures between banks can reach high levels through the interbank market.

The second way that shocks can spill over to other companies is by means of information. Bad news about one company can reveal information about the situation for related companies, and thus signal investors, creditors, and other agents to update their beliefs with respect to these companies. This type of contagion, based on the *information channel*, is commonly referred to as *information contagion*. Figure 1.1 illustrates the distinct definitions of systemic risk. Systemic risk in the narrow sense is shown in the upper part of the figure, where a micro-shock occurring at Company A propagates via either the real or the information channel to other related companies. Of course, this chain reaction does not need to stop after hitting Company B and could be further transmitted to other companies.

[2] The term contagion is used in at least as many ways as the term systemic risk in the literature. We follow the definition of Kaufman (1994, p. 123): *'Contagion is a term used to describe the spillover effects of shocks from one or more firms to others'.*

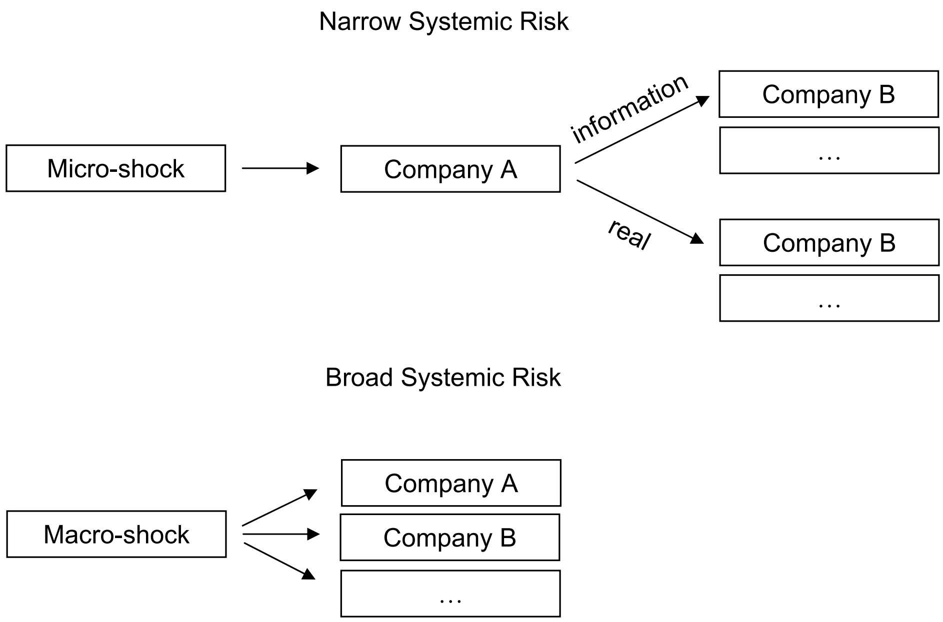

Figure 1.1: **Systemic Risk**

This figure illustrates the two different concepts of systemic risk. The upper part shows systemic risk in the narrow and the lower part systemic risk in the broad sense.

The lower part of Figure 1.1 illustrates systemic risk in the broad sense. Here, an initial shock hits multiple companies simultaneously, also leading to possible defaults. Empirically, it might be difficult to disentangle narrow and broad systemic risk as they do not necessarily need to occur independently. For example, one could imagine a situation where first, a macroeconomic shock weakens a system of companies, and then a microeconomic shock propagates through the system, causing the destabilized system to collapse.

1.2 Systemic Risk in the Banking Sector

Although we define systemic risk in a general economic context, not exclusively focusing on the banking sector, this sector is still of special interest due to several reasons. First, by providing financing services for corporate companies and for private households, as well as for governmental institutions, the banking sector plays a crucial role in every economy, and thus, deserves special attention. This central role is also a standard argument for the need for banking regulation and supervision.

Second, it is also often hypothesized that the banking sector is more vulnerable to systemic risk. This seems to be especially true for systemic risk in the narrow sense as banking institutions lend and borrow considerable amounts of money via the interbank market. These short-term loans are usually without any collateral or third-party guarantees. Banks having considerable exposures to each other can lead to real contagion as the failure of one bank could cause it to fail on its interbank liabilities, bringing other banking institutions into trouble. The induced liquidity problems could force other banks to withhold repayments themselves, propagating the shock through the interbank system, which may cause the failure of several other banks that actually do not even have a direct business relationship with the bank that experienced the shock in the first round. This process is often illustrated using a picture of dominoes, one falling after the other. The former governor of the Bank of England, Sir Edward George, illustrated real contagion in the banking sector in a very lively way as the consequence of *'... direct financial exposures, which tie firms together like mountaineers, so that if one falls off the rock face others are pulled off too'*, George (1998).

However, the view that the interbank market increases the threat of systemic crises is not undisputable. For instance, it can be argued that the interbank market acts as a risk-sharing device, and thus actually reduces the threat of systemic risk. In a recent network-based simulation study, Nier et al. (2007) show that the degree of connectivity has a non-monotonic effect on the systemic risk of a banking system. First, an increase in connectivity within the system increases the systemic risk due to contagion between banks. However, after reaching a sufficiently high degree of connectivity, the systemic risk due to contagion effects actually decreases. Similar results are obtained by Allen and Gale (2000), who build a microeconomic equilibrium model. In their model, the banking system becomes more capable of absorbing initial shocks if its members are sufficiently connected. Thinking about the illustration of George (1998) this argument translates to the fact that mountaineers secure each other by being tied together and thus prevent crashes.

A second argument for the higher systemic risk in the banking sector is based on the similar business models of banks and highly correlated asset values. This similarity could make the banking sector susceptible to information contagion. On the individual level, banks are subject to the risk of experiencing a bank run à la Diamond and Dybvig (1983), if depositors are concerned about the solvability of the banking institution. If negative information about one bank is revealed, this could also lead to bank runs at other banks, as depositors question their credit-worthiness due to similarities in their business models. One can distinguish between the cases where the withdrawing of money is based on relevant information or just rumors, where the default of the institutions becomes a self-fulfilling prophecy.

Additionally, a mixture of the risks due to interbank exposures and bank runs, namely an interbank run, might occur. Counterparty banks might question the financial standing of the bank in trouble and withdraw their interbank credit lines, creating liquidity problems at the considered bank. This effect is described theoretically in the model of Flannery (1996), where banks have only imperfect information on their counterparty banks.

One of the best and most well-known examples of such an interbank run actually occurred in 1984, when Continental Illinois, at that time one of the top 10 banking institutions in the US, experienced massive liquidity problems. Rumors regarding the solvency of the bank caused many other banks to withdraw their interbank credit from Continental Illinois, enforcing Continental's liquidity problems. Finally, the Federal Deposit Insurance Corporation (FDIC) intervened and organized a bailout to rescue the bank.[3]

The case study of Continental Illinois provides an excellent example of the two main measures commonly employed to reduce the risk of a systemic banking crisis, namely the presence of a *deposit insurance* as well as the existence of a *lender of last resort* (see e.g., Dewatripont and Tirole (1993)). The assistance of governmental authorities in crisis situations is, however, not without controversy: empirical studies on banking system stability such as Demirgüç-Kunt and Detragiache (2002) or Barth et al. (2002) actually find that an explicit deposit insurance tends to increase the likelihood of banking crises.

The need for a lender of last resort has a long history and dates back to Thornton (1802) and Bagehot (1873). Its merit for the stability of financial markets was questioned by Goodfriend and King (1988) and Kaufman (1991) among others. Supporters of the existence of a lender of last resort include Freixas et al. (2000) and Rochet and Vives (2004).

Furthermore, it is frequently questioned whether regulation of the banking sector actually reduces systemic risk. On the one hand, Aghion et al. (2000) show in a theoretical model that an unregulated banking system exhibits an increased likelihood of contagious bank failures. On the other hand, Eichberger and Summer (2005) show that capital adequacy regulation can increase systemic risk. In a more practically oriented paper, Daníelsson et al. (2001) criticize the new Basel II regulation framework, arguing that, in total, the new regulatory framework is destabilizing rather than stabilizing the global financial system.

Summarizing, compared with other industries lacking regulation, bank failure contagion is hypothesized:[4]

- as more likely to occur,

[3]Details of the Continental Illinois crisis can be found in Wall and Peterson (1990), FDIC (1997), and Hellwig (1998).

[4]See Kaufman (1994, p. 124).

- to occur faster,
- to spread more broadly within the industry,
- to result in larger losses of failures,
- to result in larger losses to creditors (as banks hold lower capital ratios than other firms),
- to spread more beyond the banking industry and cause substantial damage to the financial system as a whole and the macroeconomy.

1.3 Costs of Systemic Bank Crises

A systemic banking crisis has the potential to cause substantial losses in the welfare of the affected economy. In Figure 1.2, we present a list of historic banking crises and the associated fiscal costs, i.e. costs covered by the taxpayer, as estimated by the International Monetary Fund (IMF), (see Honohan and Klingebiel (2000) and Caprio and Klingebiel (2003)). Note that the numbers in the figure include direct costs covered by the governments only as other costs are very difficult to assess. Most importantly, the numbers do not cover any indirect costs due to negative consequences for the real economy as the slowdown of economic activity is likely to be even more severe in many instances. Moreover, costs incurred by debtors and creditors are not included. This list is led by the Indonesian, followed by the Argentinean, Chilean, Thai, and Turkish bank crises.

One might have the impression that systemic risk is a major problem for emerging countries only. In absolute terms, however, the biggest crisis is clearly the Japanese banking crisis beginning in the 1990s, the costs of which are estimated by the IMF to equal 120 trillion yen or 1 trillion US dollars.[5] Furthermore, Hoggarth

[5]See Caprio and Klingebiel (2003); a detailed discussion on the Japanese banking crisis can be found in Nakaso (2001).

et al. (2002) find in an empirical study that output losses incurred during banking crisis periods in developed economies are on average higher than in less developed countries. Hence, systemic risk is an important issue for both emerging as well as developed nations, and is clearly worth studying.

1.4 Contribution and Organization of the Thesis

In this thesis, we contribute to the existing literature by shedding light on three different aspects of systemic risk, organized in three self-contained chapters. A detailed discussion of the contribution to the literature and of the relevant literature will, therefore, be given at the beginning of each chapter. A short summary of the most important contributions is given below, together with a short overview of the topics treated.

In **Chapter 2**, we empirically investigate the degree of systemic risk in the banking sector versus other industry sectors in the United States and in Germany. We characterize the systemic risk in each sector by the lower tail dependence of stock returns. Our study differs from the existing literature in three aspects. First, we compare the degree of systemic risk in the banking sector with other sectors in the economy. Second, we analyze how the systemic risk depends on the states of the economy and of the stock market. Third, we investigate the problem of systemic risk in an international context by comparing the US and the German banking systems. Our study shows, in most cases considered, that the systemic risk of the banking sector is significantly larger than in all other sectors. Moreover, the degree of systemic risk is higher under adverse market conditions. Finally, we find that the banking sector in Germany shows a lower systemic risk than the US banking sector. This finding allows different interpretations. On the one hand, one can argue that the US and German banking systems are quite different and, thus, exhibit different degrees of systemic risk. On the other hand, one might argue that the different results are due to the fact that the regulation in Germany is more

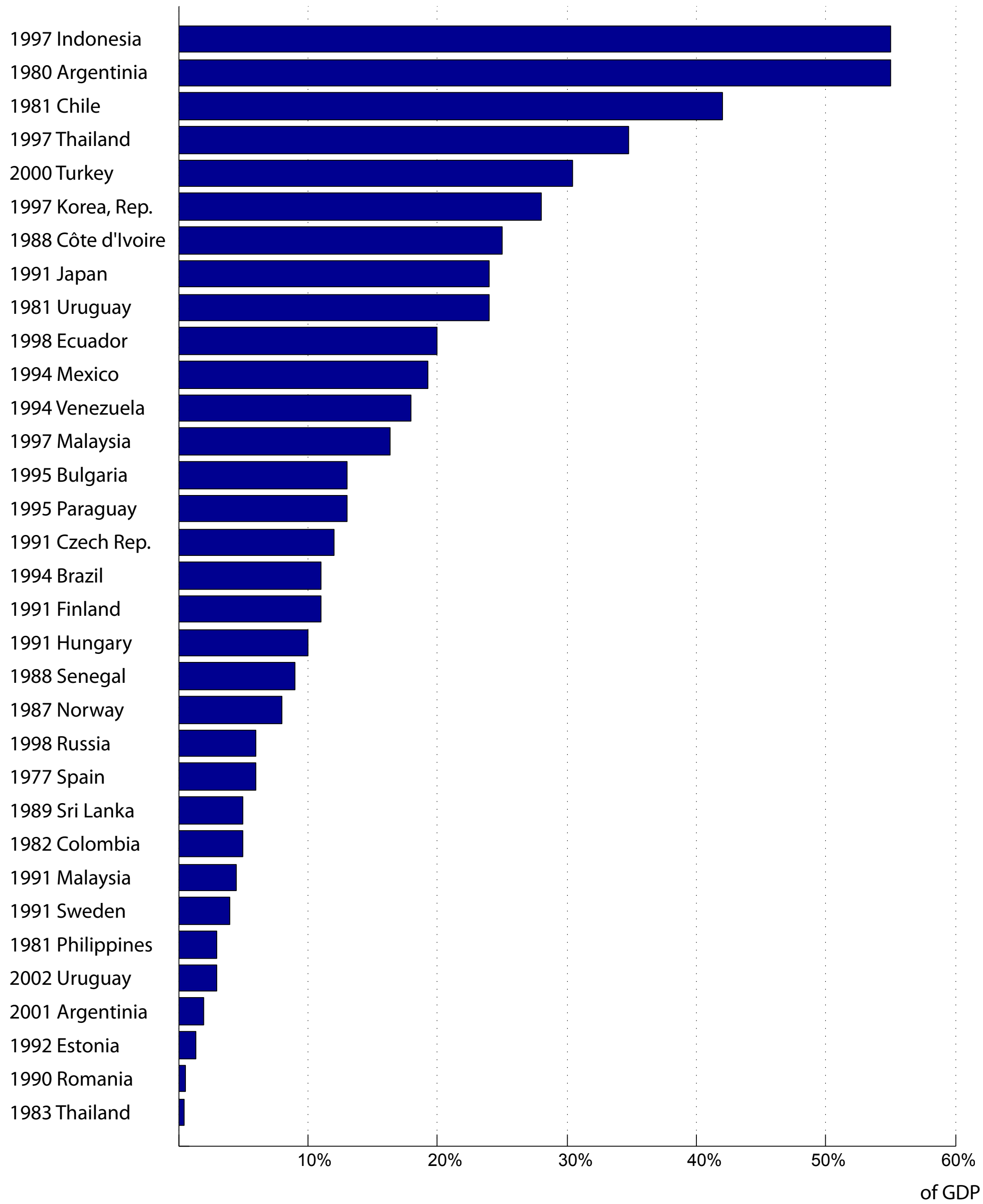

Figure 1.2: **Fiscal Cost of Systemic Crises**

This figure shows the fiscal cost of past systemic banking crises. The unit is percentage of GDP. The date is the estimated year of the origination of the crisis. Source: Honohan and Klingebiel (2000) updated using information from Caprio and Klingebiel (2003).

successful.

In **Chapter 3**, we investigate whether information contagion is present in the banking sector by analyzing how banks are affected by negative earnings surprises of their competitors. The banking sector is of crucial importance to the economy and, thus, is highly regulated on an individual bank level. However, a high degree of contagion risk should call for regulation of the financial network rather than solely regulating on an individual level. To be able to make a judgement about the significance of possible information contagion effects, we compare the results of the banking sector with the results of the non-banking industries. We find that earnings surprises cause significant contagion in the banking sector. In contrast, we do not find this effect in the non-banking sectors, including the insurance sector. Moreover, the magnitude of contagion in the banking sector is positively related to the size of the bank reporting an earnings surprise, as well as the size of the affected banks.

In **Chapter 4**, we empirically analyze the consequences of systemic risk for stock market investors. To tackle this issue, we consider two different investment strategies, one strategy being crisis conscious, i.e. taking the possibility of systemic events into account, and the other one being crisis ignorant and thus disregarding systemic risk. We compare the optimal portfolio choices and investment results of these strategies in an historical simulation study, using almost three decades of historical stock price data. Our main findings are as follows: the crisis conscious investor tends to choose less extreme portfolio weights for individual stocks than the crisis ignorant investor. The overall risky investment is, however, of a similar size for both. By ignoring the possibility of systemic events, the crisis ignorant strategy performs significantly worse from the viewpoints of expected return as well as expected utility. Thus, the threat of systemic risk should be considered during the portfolio choice process.

Chapter 5 contains concluding remarks.

Chapter 2

Systemic Risk: Is the Banking Sector Special?

2.1 Introduction[1]

It is well known that the systemic risk in the banking sector is of the utmost importance for the entire economy and, therefore, subject to extensive regulation. In addition, systemic risk in the more general sense plays an important role in portfolio management, as an increase in dependence of asset returns during downside movements may spoil diversification effects when they are needed most.[2] In this chapter, we empirically investigate the degree of systemic risk in the banking sector versus other industry sectors in the United States and in Germany. To the best of our knowledge, this is the first study that compares the specific systemic risk of different countries, different sectors in the economy, and different states of the stock market and the business cycle.[3]

The empirical literature on systemic risk in the banking sector can be roughly grouped into two main streams. The first analyzes the degree of systemic risk

[1]This chapter is based on a homonymous paper co-authored by Prof. W. Bühler.

[2]This aspect is further analyzed in Chapter 4 of this thesis.

[3]As outlined in the previous chapter, we define systemic risk in the banking sector as the risk of the failure of the financial system caused by the default of at least one banking institution. This definition is analogously used for any other sector.

in an economy arising from possible contagion effects through the interbank market. These studies need information on the banking structure, especially on the network of mutual exposures, and, therefore, are conducted on a domestic level by researchers within central banks. The majority of these studies find that the risk of contagion within the interbank system is low, but not negligible.[4]

The second stream of literature analyzes the systemic risk in the banking sector through the use of stock market data. As pointed out by De Nicolo and Kwast (2002), stock prices are very well suited to studying systemic risk as they reflect the market participants' collective evaluation of the respective companies and their future potential. This stream of literature can be further divided into two groups. The first group employs the event study methodology to examine the extent to which adverse events for one bank have contagious effects on other banks' equity. Adverse events are either actual bank failures (e.g. Aharony and Swary (1983), Wall and Peterson (1990), Saunders and Wilson (1996)) or global financial crises[5] (e.g. Musumeci and Sinkey Jr. (1990), Kho et al. (2000), Bartram et al. (2005)). The evidence of contagion in these studies is ambiguous.[6]

Our study is related to the second group. Typically, studies of this group use time series of stock returns to measure the dependence structure between banking institutions over time. For example, De Nicolo and Kwast (2002) find rising correlations of bank stock returns in the US between 1988 and 1999, indicating increasing systemic risk. Schüler (2002) finds similar results for Europe using a sample from 1980 to 2001.

It is well known that correlations differ for upside and downside movements of the stock market (see e.g. Ang and Chen (2002)). Therefore, other studies focus on

[4]See e.g. for Switzerland (Sheldon and Maurer (1998)), for Italy (Angelini et al. (1996)), for Sweden (Blåvarg and Nimander (2002)), for Denmark (Bech et al. (2002)), for the US (Furfine (2003)), for the UK (Wells (2004)), for Germany (Upper and Worms (2004) and Memmel and Stein (2008)), for Belgium (Degryse and Nguyen (2004)), for Austria (Elsinger et al. (2006)) and for the Netherlands (van Lelyveld and Liedorp (2006)).

[5]Typical crises considered are the Mexican crisis 1982, the Asian crisis 1997, the Russian crisis 1998, the LTCM crisis 1998, and 09/11 2001.

[6]In Chapter 3 of this thesis we also analyze contagion in the banking sector, employing the event study methodology. We find that the banking sector exhibits negative contagion effects.

the lower tail of the joint distribution, e.g. Gropp et al. (2006) who analyze the joint co-exceedance of bank returns over a given quantile and also find increasing dependence since the introduction of the euro. Hartmann et al. (2005) apply a tail measure of extreme downside dependence to analyze the banking system stability in Europe and the US. They find a higher degree of systemic risk in the US when compared with Europe and again an increase in both regions since 1990.

Our study differs from the existing literature, especially from Hartmann et al. (2005), in the following ways. First, we do not only analyze the banking industry, but also compare the degree of systemic risk in this sector with other sectors in the economy. This enables us to put the results into perspective and allows an analysis of whether the systemic risk in the banking sector is effectively larger than in other, regulated and non-regulated, sectors of the economy.

Second, we analyze how the systemic risk depends on the state of the economy in general and the stock market specifically. Important state variables are the growth rate of the economy, the growth rate of the stock market, and the volatility of stock market returns.

Third, we investigate the problem of systemic risk in an international context by comparing the results for the German and the US banking systems and relate the results to the degree of systemic risk in other sectors in these two economies. This approach allows us to study the consequences of different regulation systems on the degree of systemic risk.[7]

Fourth, our definition of systemic risk is different from the one employed by Hartmann et al. (2005) and is, in our opinion, more meaningful for capturing systemic risk. Considering N companies, we measure the degree of systemic risk as the conditional default probability of N companies, given that one of these N companies defaults, whereas Hartmann et al. (2005) focus on the default of the largest company (bank), given that the smaller $N-1$ companies default.

We consider the systemic risk for 12 different sectors in the US and for 10 different

[7] Hartmann et al. (2005) compare the US and European banking systems.

sectors in Germany using stock market data from 1990 to 2006. The systemic risk of a sector is measured by the tail dependence of stock returns for firms operating in the same industry. Economically, the tail dependence of stock returns characterizes the probability that N companies in a sector default in the same period given that one company defaults.

We use a two-parametric Archimedean copula that combines analytical tractability with the flexibility of modeling different degrees of dependence in the lower and the upper tails of the distribution. To detect changes in the dependence structure and the crisis probability, we analyze and compare the level of systemic risk in different economic conditions. First, we estimate the degree of risk within each sector during bear and bull markets. Next, we analyze the changes between volatile and tranquil stock market conditions, and, lastly, we estimate the joint default probability during recession and boom periods. As a robustness check with respect to the subsample selection, we specify a regime-switching copula model. The advantage of this approach is an endogenous, purely data-driven determination of adverse states. Furthermore we analyze the robustness of our results with respect to the modeling of the marginal distributions and conduct a factor analysis.

Our study yields the following main results. First, in most cases considered, the systemic risk of the banking sector is significantly larger than in all the other sectors of the two considered economies. Interestingly, this is also true for the insurance sectors, which do not exhibit significant degrees of systemic risk. Thus, one can conclude that a system-based regulation should focus more on the banking and less on the insurance sector.

Second, the degree of systemic risk differs most during adverse market conditions. This result shows that the banking sector is more vulnerable to shocks than the other sectors of the economy.

Third, under adverse market conditions, the systemic risk in the banking sector is significantly higher than under non-adverse conditions for Germany as well as for the US. This finding underpins the intuitive fact that the financial regulator should be aware of possible contagion effects during these adverse market conditions.

Fourth, the banking sector in Germany shows a lower degree of systemic risk than the US banking sector. This result allows two possible explanations. First, the different degree of systemic risk might be a result of the different banking systems of the two considered economies. Second, one might argue that the regulation in Germany is more successful in minimizing the risk of systemic crises.

The remainder of this chapter is organized as follows. Section 2.2 introduces the tail dependence coefficient as a measure of dependence and systemic risk and discusses its estimation. In Section 2.3, we describe our data set and give descriptive summary statistics. The results of our empirical study are reported and discussed in Section 2.4. Section 2.5 presents the robustness checks with respect to the sample selection and the marginal model. Further analysis with respect to a sample of US investment banks as well as the recent financial crisis are presented in Section 2.6. Section 2.7 summarizes and concludes this chapter.

2.2 Measuring and Estimating Systemic Risk

2.2.1 Measuring Systemic Risk

The degree of systemic risk is defined by the conditional probability of joint defaults of several companies, given that one company defaults. Theoretically, in the case of default, a company's stock price is zero and its log stock return relative to the last non-zero stock price is minus infinity. Under this assumption, the conditional probabilities of joint extreme downward movements of N stock returns can be characterized by the dependence in the lower tail of the joint distribution.

In the case of two companies with marginal distributions F_1 and F_2 of their stock returns r_1 and r_2, their lower tail dependence can be defined by

$$\lambda_L = \lim_{u \downarrow 0} P[r_1 < F_1^{-1}(u) | r_2 < F_2^{-1}(u)]. \tag{2.1}$$

Here, $P[\cdot|\cdot]$ denotes the conditional probability. This coefficient measures the probability that one random variable has a value in the lower tail of its distribution, given that the other variable exhibits an analogous behavior. Compared with the correlation coefficient, it has the advantage that 'normal' rates of returns have no impact, and that it does not depend on the marginal distributions of the individual stock returns. Empirical studies using stock returns find unanimously asymmetric degrees of dependencies in the lower and upper tails of stock returns (see e.g. Ané and Kharoubi (2003) or Junker and May (2005)).

Using the notion of a two-dimensional copula C_2, λ_L can also be characterized by[8]

$$\lambda_L = \lim_{u \downarrow 0} \frac{C_2(u,u)}{u}. \tag{2.2}$$

If $\lambda_L > 0$, r_1 and r_2 are defined as asymptotically dependent, otherwise they are called asymptotically independent. The best-known example of a copula with asymptotic independence is the Gaussian copula, which represents the dependence structure of the multivariate Gaussian distribution.

Since we are interested in the multivariate case, we generalize (2.1) to N random variables $r_1, ..., r_N$:

$$\lambda_L^N = \lim_{u \downarrow 0} P[r_1 < F_1^{-1}(u) \wedge ... \wedge r_{N-1} < F_{N-1}^{-1}(u) | r_N < F_N^{-1}(u)]. \tag{2.3}$$

Analogous to the bivariate case, it is easily shown that (2.3) can be represented by means of the underlying N-dimensional copula C_N as

$$\lambda_L^N = \lim_{u \downarrow 0} \frac{C_N(u,u,...,u)}{u}. \tag{2.4}$$

[8]For a rigorous definition of copulas, see e.g. Nelsen (1999); for applications in finance see e.g. Cherubini et al. (2004).

Given the assumption that log stock returns are minus infinity in the case of default, λ_L^N states the probability that N companies default, given that one of the N companies defaults.

2.2.2 Estimation of the Tail Dependence Coefficient

Various ways to estimate the tail dependence coefficient have been proposed in the literature.[9] As our empirical study will be based on relatively small samples, we follow a parametric approach and use the two-parametric Archimedean copula BB7 (see Joe (1997), p.153).[10] This copula is given by

$$\begin{aligned} C_{BB7}(u_1,...,u_N) &= 1-[1-((1-(1-u_1)^\theta)^{-\delta}+... \\ &\quad ...+(1-(1-u_N)^\theta)^{-\delta}-(N-1))^{-1/\delta}]^{1/\theta}, \end{aligned} \tag{2.5}$$

where $\theta \geq 1$ and $\delta > 0$.

Using definition (2.4), we can directly derive the lower tail dependence coefficient of the BB7 copula for various dimensions. We obtain

$$\lambda_L^N = N^{-\frac{1}{\delta}}. \tag{2.6}$$

The upper tail dependence coefficient has an analogous representation as a function of N and θ. Since we only consider the lower tail dependence coefficient, we drop the subscript L in the following to make the notation simpler.

The BB7 copula has several desirable properties for our application. First of all, it

[9] Schmidt and Stadtmüller (2006) discuss nonparametric approaches. A semiparametric approach can be found in Genest et al. (1995). Finally, Frahm et al. (2005) compare various methods in a simulation study.

[10] The class of Archimedean copulas is characterized by the following representation: $C(u_1,...,u_N) = \varphi^{-1}(\varphi(u_1)+...+\varphi(u_N))$, with $\varphi : [0,1] \to [0,\infty]$, strictly monotonic decreasing, and $\varphi(1) = 0$.

is parsimoniously parameterized and analytically tractable, allowing us to compute various derivatives in closed form, facilitating maximum likelihood estimation. Second, it allows for different degrees of tail dependence in the lower and the upper tails.[11] Moreover, it follows from (2.6) that the coefficient of lower (upper) tail dependence is a function of δ (θ) only, i.e. each parameter determines the dependence in one of the two tails. This is an important property as it allows us to identify the tail dependence in the lower tail independently from the upper tail. For $\delta \to 0$ and $\theta = 1$, the variables are asymptotically independent in the lower and upper tails, respectively. The last important advantage of the BB7 copula, which is shared with all Archimedean copulas, is the straightforward extension to higher dimensions.

To estimate the copula parameters, we utilize the semi-parametric Canonical Maximum Likelihood (CML) approach (see Joe and Xu (1996)). In the first step of the CML method, we estimate for each firm i, ($i = 1, ..., N$), the empirical distribution function $\hat{F}_i$ of stock returns. $\hat{F}_i$ is estimated in a standard way on the basis of a time series of T observed consecutive log stock returns $\boldsymbol{r} = (r_{i,1}, ..., r_{i,T})$. Next, the stock returns $r_{i,t}$ are transformed into the unit interval by

$$(\hat{u}_{1,t}, ..., \hat{u}_{N,t}) = \left(\hat{F}_1(r_{1,t}), ..., \hat{F}_N(r_{N,t})\right), \qquad t = 1, ..., T. \tag{2.7}$$

In the second step, we estimate the set of copula parameters $\Psi = (\delta, \theta)$ by maximizing the (log)-likelihood function

$$\mathcal{L}(\boldsymbol{r}; \Psi) = \sum_{t=1}^{T} \log c(\hat{F}_1(r_{1,t}), ..., \hat{F}_N(r_{N,t}); \Psi), \tag{2.8}$$

[11] This property makes it more suitable for our application than the Student-t copula, which is extensively used in other studies and also risk management applications, especially credit risk, see e.g. Hull and White (2006). The Student-t copula allows for positive tail dependence but is symmetric and thus imposes equal degrees of dependence on downside and upside movements of the considered stocks, making it impossible to disentangle these two effects.

with respect to the two tail parameters. Here $c(\cdot)$ denotes the density of the copula function.

The CML approach has two advantages. It is computationally faster than a one-step estimation approach, and we do not have to make parametric assumptions about the marginal distributions. This second fact reduces the likelihood of misspecifications, which would bias our estimation of the dependence structure.

To compute standard errors, we apply a blocks bootstrap approach as our data show significant intertemporal dependencies. An alternative approach to the problem of non-iid data due to serial correlation in the first and also the second moment of our time series would be to fit an ARMA-GARCH model for the univariate processes and analyze the dependence structure of the residuals. While being aware of the violation of the iid assumption, we decided not to filter our data, due to the fact that filtering will also change the dependence structure of the data.

Based on T observations, we use a moving blocks bootstrap with a blocklength $l = T^{1/3}$ and $T - l + 1$ overlapping blocks.[12]

In summary, our estimation consists of the following steps:

1. Determine $\hat{F}_i$ nonparametrically as the empirical distribution functions.

2. Transform the observations $r_{i,t}$ with $\hat{F}_i$ into pseudo observations $\hat{u}_{i,t} = \hat{F}_i(r_{i,t})$.

3. Estimate the copula parameters Ψ with maximum likelihood.

4. Compute $\hat{\lambda}^N$ by Equation (2.6).

5. Calculate $\hat{\sigma}(\hat{\lambda}^N)$ with the blocks bootstrap as described above.

[12]See Hall et al. (1995) on the optimal choice of the block length in a blocks bootstrap.

2.3 Data Selection

Data selection poses a major challenge for our study as the systemic crisis coefficient introduced in the previous section needs to be estimated from a multivariate time series of stock returns. Since we wish to analyze the systemic risk in the banking as well as other sectors of the economy we need to select the respective companies from each considered sector. Thus, we need to find several companies operating in a common sector that have a long enough time series of stock prices available to make our approach work. This issue is complicated by the fact that companies list and delist at the stock exchange for various reasons, such as mergers and acquisitions, spin-offs, etc.

We base our study on daily log returns for US and German stocks from January 1990 to December 2006. This period covers boom and recession subperiods, volatile and tranquil, and baisse and boom subperiods of the stock market and is thus long enough to cover many different regimes of the economies but not too long to make the cross-sectional requirement of a multivariate time series of stock prices infeasible.

To study systemic risk on a sectoral level, we classify all the companies using the Industrial Classification Benchmark (ICB)[13], which classifies all companies into one of the following 10 industries: oil & gas, basic materials, industrials, consumer goods, health care, consumer services, telecommunications, utilities, financials, and technology. If one company operates in more than one industry the ICB classification assigns it to the sector in which it generates the highest revenues.

As we are especially interested in the banking sector, we analyze the financial industry on a more detailed level and split it into the sectors banks and insurance companies. The consumer goods industry consists of the sectors automobiles & parts, food & beverage, and personal & household goods. Due to the importance of the automotive industry, especially in Germany, we also subdivide the consumer

[13]See www.icbenchmark.com.

industry into these three sectors. Therefore, we consider 13 different sectors in total.

For each of the 13 sectors, we select five major companies that can be considered to be system relevant and homogeneous in their business activities. Regarding the 'systemic relevance', we rank the firms in each sector according to their market value. All the firms with a free float below 25 % of issued stocks - due to potential illiquidity problems[14] - and a continuous time series of daily return data for less than 10 years are excluded. Note that these requirements make it necessary to exclude some major companies, such as Daimler and Chrysler, as their merger in 1997 makes their independent time series relatively short.

For the oil & gas sector, we are not able to find enough companies in both the US and the German markets. For the telecommunications and the utilities sectors there is sufficient data for the US market only. This leaves us with a final sample of 12 sectors in the US and 10 sectors in Germany. All data is obtained from Thomson Financial Datastream.

Tables 2.25 and 2.26 in the appendix report the selected companies from the United States and Germany, respectively. For each company, we give a brief description of their main activities. With one exception, the consumer services sector, we consider the homogeneity of the business activities as sufficient in each sector. By the nature of the consumer sector, it is rather inhomogeneous in the US as well as in Germany. Among others, we have picked (by our selection rule) an airline carrier and a publisher in Germany. In the US, we have selected a DIY store company and a fast-food restaurant chain. Splitting up this sector would result in fewer than five firms for possible subsectors.

Tables 2.27 and 2.28 in the Appendix present the time series characteristics of the 60 US and the 50 German firms. For all the US firms, the return series cover the

[14]We make one exception from this rule for the German banking companies and include the Hypovereinsbank in our sample. The Hypovereinsbank was acquired by the Italian Unicredit in November 2005, which today owns more than 90%. However, as we do not want to omit the second largest bank in Germany from our sample we include the stock in our analysis.

full period from from January 1990 to December 2006. In the German sample, 10 of the system-relevant firms went public later than 1990. The annualized average of daily returns are positive for all the American and for 47 of the German firms. The annualized standard deviation of daily returns varies between 20 % and 40 % except for 20 of the 110 firms. Especially utility and technological firms exhibit volatilities outside this interval.

As is typical of daily stock returns, all the samples fail to pass the Jarque-Bera test of normality. The Augmented Dickey-Fuller test of stationarity shows the stationarity for every series at the 1% level of significance. The Q-Statistic of Ljung and Box tests the null hypothesis of independence and must be rejected at the 1% level in 29 out of 50 cases for the German data and in 39 out of 60 cases for the US data. Due to this evidence of autocorrelation, we will use the blocks bootstrap procedure to estimate the standard errors of our estimates as described in the previous section, which will also control for possible autocorrelation of higher moments.

2.4 Results

2.4.1 Entire Sample Period

We first present the results for the estimates of the lower tail probabilities $\hat{\lambda}^N$ for the entire sample period. The values $\hat{\lambda}^N$ are obtained by the estimation method described in Section 2.2 of this chapter. They represent estimates for the conditional probabilities that up to $N = 5$ firms default if one of these five firms default. Obviously, for larger N, more firms default simultaneously and, therefore, the $\hat{\lambda}^N$ values are better estimates of the probability of a systemic sector crisis for higher values of N, i.e. $N = 4$ and $N = 5$.

The theoretical crisis probabilities λ^N decrease in N as the event that $N + 1$ companies default is a subset of the event that N firms default as long as the first

Table 2.1: **US: Systemic Risk in the Entire Period**

*This table reports the estimation results of the crisis coefficient for the entire sample period and whether it is significantly different from zero. *** shows significance at the 1 % level, ** at the 5 % level and * at the 10 % level.*

	$\hat{\lambda}^2$	$\hat{\lambda}^3$	$\hat{\lambda}^4$	$\hat{\lambda}^5$
Banks	0.3663***	0.1969***	0.0922***	0.0552***
Automobiles & Parts	0.0794***	0.0209**	0.0146***	0.0042**
Basic Materials	0.3016***	0.0815***	0.0280***	0.0042**
Consumer Services	0.3007***	0.0542***	0.0111**	0.0027**
Food & Beverage	0.2708***	0.0407**	0.0048**	0.0018*
Healthcare	0.2968***	0.1363***	0.0355***	0.0176***
Industrials	0.1789***	0.0855***	0.0273***	0.0092**
Insurance	0.0185*	0.0184*	0.0060**	0.0029**
Pers. & Household	0.0697*	0.0303**	0.0099**	0.0013*
Technology	0.2197***	0.1044***	0.0451***	0.0183***
Telecommunications	0.4133***	0.0911***	0.0233***	0.0029**
Utilities	0.3064***	0.1391***	0.0614***	0.0347***

N companies are identical in both sets. Thus, we expect that the estimates $\hat{\lambda}^N$ exhibit a monotonous decreasing behavior.

Table 2.1 reports the estimated systemic crisis probabilities for the 12 US sectors. In the banking sector, the crisis probability is 36.6 % in the bivariate case, falling to 5.5 % when dealing with five banks. The crisis coefficient λ^N is significantly different from zero in all cases.

In the other US industry sectors, the systemic crisis probabilities for the bivariate case are mostly around 30 % and significant. However, these values decrease to much lower levels than in the banking sector for $N = 5$. For most sectors, the conditional default probability of five companies is lower than 1 %; only the crisis probabilities in the healthcare, technology, and utilities sectors remain above this. Interestingly, the insurance sector shows very low degrees of systemic risk; the crisis coefficient decreases to 0.3 % when considering five insurance companies. Overall, the banking sector shows the highest degrees of systemic risk.

To see whether this finding of a higher systemic risk in the banking sector is also statistically significant, we perform a cross-sectional test with all the other sectors.

Table 2.2: **US: Cross-Sectional Differences**

*This table reports the cross sectional differences between the banking sector and the other sectors for the entire sample period. *** shows significance at the 1 % level, ** at the 5 % level and * at the 10 % level.*

	$\Delta(\hat{\lambda}^2_{cross})$	$\Delta(\hat{\lambda}^3_{cross})$	$\Delta(\hat{\lambda}^4_{cross})$	$\Delta(\hat{\lambda}^5_{cross})$
Automobiles & Parts	0.2868***	0.1760***	0.0776***	0.0510*
Basic Materials	0.0646***	0.1154***	0.0642**	0.0510**
Consumer Services	0.0656***	0.1427***	0.0811***	0.0525**
Food & Beverage	0.0955***	0.1562***	0.0875***	0.0533**
Healthcare	0.0695***	0.0606**	0.0567*	0.0375*
Industrials	0.1874***	0.1114***	0.0649**	0.0460*
Insurance	0.3483***	0.1785***	0.0862***	0.0522**
Pers. & Household	0.2966***	0.1666***	0.0823***	0.0539*
Technology	0.1466***	0.0925***	0.0472*	0.0368
Telecommunications	-0.0470	0.1058***	0.0689**	0.0523**
Utilities	0.0599***	0.0578**	0.0308	0.0204

The null hypothesis is a smaller crisis coefficient in the banking industry. Performing this cross-sectional test of differences yields conclusive evidence of higher systemic risk in the banking sector. As displayed in Table 2.2 for two companies, 10 out of 11 sectors show significantly lower crisis probabilities than the banking sector. At the five-firms level, we find significantly different values for all but the technology and the utilities sectors.

The results for Germany are reported in Table 2.3. In the German banking sector, the crisis probability is 44.4 % in the bivariate case, falling to 1.3 % when dealing with five banks. The crisis coefficient λ^N is significantly different from zero in all the cases.

In the other sectors, we can identify two different main groups. First, the automotive, the basic materials and the industrials sectors also show significant degrees of systemic risk. Compared with the banking sector, higher default probabilities in the bivariate case for the automotive and basic materials sectors are observed. However, the degree falls to values five to ten times smaller than in the banking sector for the five-companies case. Second, the sectors consumer services, food & beverage, healthcare, and personal & household goods show only weak or no signs of systemic risk. For the insurance and the technology sectors, the results are inconclusive. The insurance sector shows a high crisis probability for low dimensions but it falls to zero when increasing the number of companies involved. This indicates a high dependence between the big players of the industry, but weak connections to smaller insurance companies. The technology sector exhibits the contrary case. For two companies, the crisis probability is 35.0 %; in the five-firms case the second highest value in the sample of 1.2 % is observed, indicating a constant degree of dependence among many firms in the sector.

Table 2.4 reports the differences in the default probabilities in the banking and the other sectors and whether they are significantly different from zero. One sees that, with up to four companies, most of the differences are significantly different from zero. In the five-companies case, the null hypothesis cannot be rejected, although we have remarkably higher crisis probabilities in the banking sector.

Comparing the results for the US and Germany one can observe a systemic crisis probability that is four times higher for the banking sector in the US. This might be a result of the different banking structures in these two countries.

Comparing the other US industry sectors with their German counterparts, we observe, as in the banking sector, smaller crisis probabilities for two companies but higher ones for four or five companies for many sectors. This finding indicates higher dependencies between the market leaders in Germany but a higher degree of overall dependence in the US.

Regarding the insurance sector, we observe very low degrees of systemic risk in both economies when considering several companies. This raises an interesting policy implication. When considering the question of whether the insurance sector should be regulated on a systemic level, this result indicates that, differently from the banking sector, system-based regulation is not necessary for the insurance sector.

Table 2.3: **Germany: Systemic Risk in the Entire Period**

*This table reports the estimation results of the crisis coefficient for the entire sample period. *** shows significance at the 1 % level, ** at the 5 % level and * at the 10 % level.*

	$\hat{\lambda}^2$	$\hat{\lambda}^3$	$\hat{\lambda}^4$	$\hat{\lambda}^5$
Banks	0.4440***	0.2868***	0.0624***	0.0132**
Automobiles & Parts	0.4683***	0.1664***	0.0199**	0.0010*
Basic Materials	0.5509***	0.2023***	0.0143***	0.0028**
Consumer Services	0.0166	0.0042	0.0000	0.0001
Food & Beverage	0.0000	0.0000	0.0000	0.0000
Healthcare	0.0762**	0.0020	0.0003	0.0000
Industrials	0.3284***	0.1064***	0.0251**	0.0019*
Insurance	0.5156***	0.1655***	0.0020*	0.0000
Pers. & Household	0.0434***	0.0070**	0.0011	0.0000
Technology	0.3502**	0.0819	0.0266*	0.0123*

2.4.2 Bull vs. Bear Markets

We expect the systemic risk to increase during adverse economic conditions, as companies will be be more vulnerable to shocks during such times. Thus, we estimate the systemic crisis probability during different economic phases. To do so, we select subperiods from the whole sample period. First, we compare the risk during bearish and bullish markets in each sector. To identify these periods, we calculate the six months' index returns for each sector using a rolling window over the entire sample period. We single out the period with the lowest return as the bear market period. As the bull market period, we use the subsample that has the the highest index return.[15]

Table 2.5 presents the estimation results during bear and bull markets for the US. It reports the systemic risk in each sector for two to five companies. For each case, the third column gives the difference of the two values and whether it is significantly different from zero. For two banks, we find a systemic crisis probability of 67.0 % in bear markets, which is almost 100 % higher than in the

[15]Note that we consider the respective sector indices. Consequently, the bear and bull phases differ across sectors.

Table 2.4: **Germany: Cross-Sectional Differences**

*This table reports the cross sectional differences between the banking sector and the other sectors for the entire sample period. *** shows significance at the 1 % level, ** at the 5 % level and * at the 10 % level.*

	$\Delta(\hat{\lambda}^2_{cross})$	$\Delta(\hat{\lambda}^3_{cross})$	$\Delta(\hat{\lambda}^4_{cross})$	$\Delta(\hat{\lambda}^5_{cross})$
Automobiles & Parts	-0.0243	0.1203***	0.0425**	0.0122
Basic Materials	-0.1069	0.0845***	0.0481	0.0104
Consumer Services	0.4275***	0.2825***	0.0623***	0.0131
Food & Beverage	0.4440***	0.2868***	0.0624***	0.0132
Healthcare	0.3678***	0.2847***	0.0620***	0.0132
Industrials	0.1156***	0.1804***	0.0372*	0.0113
Insurance	-0.0715	0.1213***	0.0604***	0.0132
Pers. & Household	0.4006***	0.2797***	0.0612***	0.0132
Technology	0.0938***	0.2048***	0.0358*	0.0009

entire sample period. For the bull market, the probability is less than half that of the entire period and less than a quarter of the bear market value. This pattern sustains while increasing the number of banks considered. For five banks, a crisis probability of 22.3 % is estimated in bear markets (four times higher than in the entire sample), whereas the probability for the bull market is only 0.7 % (seven times lower than in the entire sample). All the differences are significantly different from zero.

The automobile and industrial sectors show similar patterns, although at a lower level. For the other sectors, we observe rising crisis probabilities during bear markets compared with the entire sample period. For many cases, we find higher crisis probabilities in bull markets. This may indicate that periods of fast rising stock prices are also vulnerable for shocks (burst of a bubble), although the evidence is not conclusive.

Testing whether the differences between the banking sector and the other industries are significant gives conclusive evidence once again. Table 2.6 reports the results. For seven out of eleven cases, the difference is significant at the 1 % level, and for the other four cases at the 5 % or 10 % level.

Table 2.7 displays the results for Germany. Analyzing the banking sector first,

Table 2.5: **US: Systemic Risk in Bear and Bull Markets**

*This table reports the estimated crisis coefficients for the different sectors during bearish and bullish market conditions. The column Δ gives the difference and its significance. *** shows significance at the 1 % level, ** at the 5 % level and * at the 10 % level.*

	$N=2$			$N=3$		
	$\hat{\lambda}_{bear}$	$\hat{\lambda}_{bull}$	Δ	$\hat{\lambda}_{bear}$	$\hat{\lambda}_{bull}$	Δ
Banks	0.6701***	0.1565	0.5137***	0.4755***	0.0928*	0.3827***
Automobiles & Parts	0.2598**	0.0762	0.1836***	0.1475*	0.0218	0.1258**
Basic Materials	0.6008***	0.4189***	0.1819***	0.3078***	0.0902***	0.2176***
Consumer Services	0.3045**	0.5326***	-0.2280	0.0592	0.1024*	-0.0432
Food & Beverage	0.1255*	0.3474***	-0.2220	0.0512*	0.2150***	-0.1638
Healthcare	0.5330***	0.3284***	0.2046***	0.3044***	0.2688***	0.0356
Industrials	0.4465***	0.1428**	0.3037***	0.3898***	0.0904*	0.2994***
Insurance	0.0025	0.0000	0.0025	0.0012	0.0179	-0.0167
Pers. & Household	0.0000	0.1204	-0.1204	0.0055	0.1066*	-0.1011
Technology	0.2922*	0.4992***	-0.2070	0.1642**	0.3089***	-0.1447
Telecommunications	0.6757***	0.4933***	0.1825***	0.1818*	0.1307**	0.0511
Utilities	0.5182***	0.6375***	-0.1193	0.3213**	0.4621***	-0.1408
	$N=4$			$N=5$		
	$\hat{\lambda}_{bear}$	$\hat{\lambda}_{bull}$	Δ	$\hat{\lambda}_{bear}$	$\hat{\lambda}_{bull}$	Δ
Banks	0.2829***	0.0477***	0.2353***	0.2230***	0.0074	0.2156***
Automobiles & Parts	0.1186**	0.0329	0.0857*	0.0885**	0.0025	0.0860*
Basic Materials	0.2315***	0.0271*	0.2044***	0.0244**	0.0027	0.0217
Consumer Services	0.0340	0.0339**	0.0001	0.0089	0.0110	-0.0021
Food & Beverage	0.0135	0.0565**	-0.0430	0.0049	0.0301*	-0.0252
Healthcare	0.1998***	0.1006**	0.0992**	0.1090***	0.0536**	0.0553
Industrials	0.1880***	0.0219*	0.1661***	0.1243***	0.0048	0.1196**
Insurance	0.0027	0.0196	-0.0169	0.0013	0.0243*	-0.0230
Pers. & Household	0.0054	0.0312*	-0.0258	0.0006	0.0039	-0.0033
Technology	0.0824**	0.1600***	-0.0777	0.0257	0.0844***	-0.0587
Telecommunications	0.1281*	0.0863**	0.0418	0.0570*	0.0160	0.0410**
Utilities	0.2034**	0.3174***	-0.1140	0.1191 **	0.2212***	-0.1021

Table 2.6: **US: Cross-Sectional Differences in Bearish Markets**
*This table reports the cross sectional differences between the banking sector and the other sectors during bearish market conditions. *** shows significance at the 1 % level, ** at the 5 % level and * at the 10 % level.*

	$\Delta(\hat{\lambda}^2_{cross})$	$\Delta(\hat{\lambda}^3_{cross})$	$\Delta(\hat{\lambda}^4_{cross})$	$\Delta(\hat{\lambda}^5_{cross})$
Automobiles & Parts	0.4103***	0.3279***	0.1644**	0.1345**
Basic Materials	0.0693**	0.1676***	0.0514	0.1986***
Consumer Services	0.3656***	0.4163***	0.2489***	0.2142***
Food & Beverage	0.5446***	0.4243***	0.2695***	0.2182***
Healthcare	0.1371***	0.1710***	0.0831	0.1141**
Industrials	0.2236***	0.0857	0.0949	0.0987*
Insurance	0.6676***	0.4743***	0.2802***	0.2218***
Pers. & Household	0.6701***	0.4699***	0.2775***	0.2224***
Technology	0.3779***	0.3113***	0.2006***	0.1973***
Telecommunications	-0.0056	0.2937***	0.1548**	0.1660***
Utilities	0.1519***	0.1542***	0.0795	0.1040*

we find a high conditional default probability of 72.9 % for two banks during bear markets, but it is not significantly higher than in the bull market, where it stays at 65.2 %. Three banks exhibit slightly higher values for the bull market. However, when increasing the number of banks involved, we find evidence of a higher systemic risk during bear markets, which is 11.7 % for five banks compared with 1.1 % in bull markets.

In the other sectors, the results are less conclusive. Except for the basic materials sector, there is no evidence supporting a higher degree of systemic risk during bear markets.

In Table 2.8, the cross-sectional differences between the banking industry and the other sectors during bear markets are reported. All the values are significant at the 1 % level, yielding clear evidence of higher systemic risk in the banking sector compared with other sectors, given that the respective sector is in a bearish condition.

Table 2.7: **Germany: Systemic Risk in Bear and Bull Markets**

*This table reports the estimated crisis coefficients for the different sectors during bearish and bullish market conditions. The column Δ gives the difference and its significance. *** shows significance at the 1 % level, ** at the 5 % level and * at the 10 % level.*

	$N=2$			$N=3$		
	$\hat{\lambda}_{bear}$	$\hat{\lambda}_{bull}$	Δ	$\hat{\lambda}_{bear}$	$\hat{\lambda}_{bull}$	Δ
Banks	0.7292***	0.6518***	0.0774	0.5234***	0.5243***	-0.0009
Automobiles & Parts	0.4454***	0.5084***	-0.0630	0.1818***	0.1613***	0.0205
Basic Materials	0.5185***	0.4700***	0.0484	0.1897**	0.1490*	0.0408
Consumer Services	0.1430	0.0754	0.0676***	0.0531	0.0013	0.0518**
Food & Beverage	0.0000	0.1973*	-0.1972	0.0000	0.0000	0.0000
Healthcare	0.3329***	0.0480	0.2849***	0.0187	0.0000	0.0187
Industrials	0.2840**	0.6390***	-0.3551	0.2549***	0.2501***	0.0048
Insurance	0.5558***	0.5604***	-0.0046	0.2712***	0.1681**	0.1031*
Pers. & Household	0.0855	0.0000	0.0855**	0.0343	0.0091	0.0251
Technology	0.0558	0.3707***	-0.3149	0.0376	0.1128***	-0.0752
	$N=4$			$N=5$		
	$\hat{\lambda}_{bear}$	$\hat{\lambda}_{bull}$	Δ	$\hat{\lambda}_{bear}$	$\hat{\lambda}_{bull}$	Δ
Banks	0.2018***	0.0603***	0.1414***	0.1174***	0.0107**	0.1067***
Automobiles & Parts	0.0492*	0.0179*	0.0312*	0.0048	0.0001	0.0047
Basic Materials	0.0854*	0.0225	0.0628*	0.0383*	0.0017	0.0366*
Consumer Services	0.0037	0.0000	0.0037	0.0040	0.0008	0.0032
Food & Beverage	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Industrials	0.0865**	0.0438*	0.0427	0.0126*	0.0009	0.0117
Healthcare	0.0117	0.0000	0.0117	0.0041*	0.0000	0.0041
Insurance	0.0199	0.0117	0.0082	0.0001	0.0003	-0.0002
Pers. & Household	0.0067	0.0000	0.0067	0.0005	0.0000	0.0005
Technology	0.0058	0.0116	-0.0058	0.0014	0.0014	-0.0001

Table 2.8: **Germany: Cross-Sectional Differences in Bearish Markets**

*This table reports the cross sectional differences between the banking sector and the other sectors during bearish market conditions. *** shows significance at the 1 % level, ** at the 5 % level and * at the 10 % level.*

	$\Delta(\hat{\lambda}^2_{cross})$	$\Delta(\hat{\lambda}^3_{cross})$	$\Delta(\hat{\lambda}^4_{cross})$	$\Delta(\hat{\lambda}^5_{cross})$
Automobiles & Parts	0.2259***	0.3981***	0.1525***	0.0978***
Basic Materials	0.1726***	0.3403***	0.0488***	0.0747***
Consumer Services	0.7339***	0.5799***	0.1852***	0.1003***
Food & Beverage	0.7416***	0.5942***	0.1894***	0.1013***
Industrials	0.3000***	0.3141***	0.1092***	0.0978***
Healthcare	0.4408***	0.5887***	0.1861***	0.0996***
Insurance	0.2160***	0.3959***	0.1792***	0.1013***
Personal & Household	0.6504***	0.5483***	0.1846***	0.1012***
Technology	0.2649***	0.5014***	0.1210***	0.0767***

2.4.3 Volatile vs. Tranquil Markets

In this subsection, we compare the systemic risk during volatile and tranquil stock market conditions. These periods are chosen in a similar way to the bear and bull markets, using the volatility of sector index stock returns as an indicator.

Table 2.9 reports the estimation results for the US during volatile and tranquil times. An increased systemic crisis probability of the banking sector during volatile market conditions is observed. For the two-companies case, the probability is 59.5 %, compared with 41.5 % in tranquil times. For five companies, it stays at a high level of 19.8 %, which is four times higher than for the whole period. In the tranquil market, it lies at 4 %. All the differences in the banking sector are significant.

The results for the other industries show increasing crisis probabilities during volatile times compared with the overall results in Table 2.1. In tranquil periods, they are lower than observed for the entire period, but at the five-companies level, they are significantly higher during volatile times in four cases only.

The cross-sectional comparison during volatile market conditions is reported in Table 2.10. Except for the industrial sector, all the differences are significant (at the five-firms level). In six cases, this is true at the 1 % significance level,

Table 2.9: **US: Crisis Probability in Volatile and Tranquil Markets**

*This table reports the estimated crisis coefficients for the different sectors during volatile and tranquil market conditions. The column Δ gives the difference and its significance. *** shows significance at the 1 % level, ** at the 5 % level and * at the 10 % level.*

	$N=2$			$N=3$		
	$\hat{\lambda}_{vol}$	$\hat{\lambda}_{tra}$	Δ	$\hat{\lambda}_{vol}$	$\hat{\lambda}_{tra}$	Δ
Banks	0.5952***	0.4147***	0.1805***	0.4113***	0.1570**	0.2543***
Automobiles & Parts	0.1959	0.0000	0.1959***	0.1459**	0.0000	0.1459***
Basic Materials	0.5528***	0.1959***	0.3570***	0.2898***	0.0141	0.2757***
Consumer Services	0.2827	0.0173	0.2654***	0.0294	0.0001	0.0293
Food & Beverage	0.1133	0.3753***	-0.2620	0.0018	0.1357***	-0.1339
Healthcare	0.1159	0.4585***	-0.3426	0.0816	0.1681**	-0.0865
Industrials	0.5041***	0.0000	0.5041***	0.4349***	0.0017	0.4332***
Insurance	0.0044	0.0000	0.0044	0.0047	0.0000	0.0047
Pers. & Household	0.0224	0.0025	0.0198	0.0223	0.0004	0.0220
Technology	0.3701***	0.4984***	-0.1283**	0.2188***	0.0363	0.1825***
Telecommunications	0.7132***	0.3185***	0.3947***	0.1362	0.0786***	0.0576
Utilities	0.5296***	0.0625	0.4671***	0.2778***	0.0192*	0.2585***
	$N=4$			$N=5$		
	$\hat{\lambda}_{vol}$	$\hat{\lambda}_{tra}$	Δ	$\hat{\lambda}_{vol}$	$\hat{\lambda}_{tra}$	Δ
Banks	0.2514***	0.0594**	0.1921***	0.1976***	0.0395**	0.1581**
Automobiles & Parts	0.1119***	0.0000	0.1119***	0.0865***	0.0000	0.0865**
Basic Materials	0.1551**	0.0037	0.1514***	0.0198**	0.0003	0.0196
Consumer Services	0.0308	0.0000	0.0308	0.0063	0.0000	0.0063
Food & Beverage	0.0070	0.0421**	-0.0351	0.0044	0.0229**	-0.0186
Healthcare	0.0124	0.0045	0.0079	0.0092	0.0061	0.0031
Industrials	0.2420***	0.0000	0.2420***	0.1750***	0.0000	0.1750***
Insurance	0.0097	0.0000	0.0097	0.0051	0.0000	0.0051
Pers. & Household	0.0257	0.0000	0.0257	0.0058	0.0000	0.0058
Technology	0.1149***	0.0101	0.1047***	0.0413*	0.0009	0.0404
Telecommunications	0.1037	0.0210	0.0827*	0.0397	0.0016	0.0381
Utilities	0.1596*	0.0004	0.1592*	0.0712*	0.0004	0.0708*

Table 2.10: **US: Cross-Sectional Differences in Volatile Markets**
*This table reports the cross sectional differences between the banking sector and the other sectors during volatile market conditions. *** shows significance at the 1 % level, ** at the 5 % level and * at the 10 % level.*

	$\Delta(\hat{\lambda}^2_{cross})$	$\Delta(\hat{\lambda}^3_{cross})$	$\Delta(\hat{\lambda}^4_{cross})$	$\Delta(\hat{\lambda}^5_{cross})$
Automobiles & Parts	0.3993***	0.2654***	0.1396**	0.1111*
Basic Materials	0.0424	0.1215*	0.0963*	0.1778***
Consumer Services	0.3125***	0.3819***	0.2206***	0.1913***
Food & Beverage	0.4819***	0.4095***	0.2445***	0.1932***
Healthcare	0.4793***	0.3296***	0.2390***	0.1884***
Industrials	0.0911*	-0.0236	0.0094	0.0226
Insurance	0.5908***	0.4065***	0.2417***	0.1925***
Pers. & Household	0.5728***	0.3890***	0.2257***	0.1918***
Technology	0.2251***	0.1925***	0.1366**	0.1563**
Telecommunications	-0.1180	0.2751***	0.1478*	0.1579**
Utilities	0.0656	0.1335**	0.0918	0.1264*

supporting the hypothesis of higher systemic risk in the banking sector during volatile times.

Table 2.11 displays the estimation results in volatile and tranquil stock market periods for Germany. In the banking sector, the crisis probability is 74.2 %, considering two banks in volatile times, compared with 42.2 % in tranquil times, which is significantly lower. At the five-companies level, a systemic risk probability of 10.1 % is estimated during volatile conditions, ten times higher than the result using the entire sample. In tranquil times, it drops to 0.6 %, which is 50 % lower than in the whole sample period and not significant anymore. Thus, the systemic risk of the banking sector is truly increased during volatile times.

In the other sectors, there is no evidence for this conclusion. Although the majority of estimated values are higher for the volatile periods, and smaller for the tranquil periods than the probabilities estimated using the entire sample, they are not significantly different, except for the basic materials sector.

In Table 2.12, the cross-sectional differences in volatile markets and their significance levels are presented. As for the first case considered, there is clear

Table 2.11: **Germany: Systemic Risk in Volatile and Tranquil Markets**

*This table reports the estimated crisis coefficients for the different sectors during volatile and tranquil market conditions. The column Δ gives the difference and its significance. *** shows significance at the 1 % level, ** at the 5 % level and * at the 10 % level.*

	$N=2$			$N=3$		
	$\hat{\lambda}_{vol}$	$\hat{\lambda}_{tra}$	Δ	$\hat{\lambda}_{vol}$	$\hat{\lambda}_{tra}$	Δ
Banks	0.7416***	0.4219***	0.3197***	0.5942***	0.2609***	0.3333***
Automobiles & Parts	0.5157***	0.3949***	0.1208	0.1961***	0.1290***	0.0671**
Basic Materials	0.5689***	0.5916***	-0.0227	0.2539***	0.1958***	0.0581
Consumer Services	0.0076	0.0382	-0.0306	0.0143	0.0000	0.0143*
Food & Beverage	0.0000	0.1101**	-0.1101	0.0000	0.0013	-0.0013
Healthcare	0.3008***	0.0859	0.2149***	0.0055	0.0004	0.0051
Industrials	0.4416***	0.4643***	-0.0227	0.2800***	0.1660**	0.1140***
Insurance	0.5256***	0.1278	0.3978***	0.1983**	0.0156	0.1827
Pers. & Household	0.0912	0.0232	0.0680	0.0459**	0.0057	0.0401**
Technology	0.4766***	0.5579***	-0.0812	0.0928*	0.0917***	0.0011
	$N=4$			$N=5$		
	$\hat{\lambda}_{vol}$	$\hat{\lambda}_{tra}$	Δ	$\hat{\lambda}_{vol}$	$\hat{\lambda}_{tra}$	Δ
Banks	0.1894***	0.0738**	0.1156***	0.1013***	0.0057	0.0957***
Automobiles & Parts	0.0369**	0.0045	0.0323**	0.0036	0.0000	0.0036
Basic Materials	0.1406***	0.0707	0.0698***	0.0266**	0.0008	0.0259**
Consumer Services	0.0041	0.0000	0.0041	0.0011	0.0000	0.0011
Food & Beverage	0.0000	0.0002	-0.0002	0.0000	0.0000	0.0000
Healthcare	0.0033	0.0000	0.0033	0.0018*	0.0000	0.0018
Industrials	0.0802	0.0422**	0.0380	0.0036	0.0043	-0.0007
Insurance	0.0102	0.0001	0.0101	0.0000	0.0000	0.0000
Pers. & Household	0.0047	0.0054	-0.0007	0.0002	0.0000	0.0002
Technology	0.0684**	0.0414*	0.0270	0.0246	0.0094	0.0152

Table 2.12: **Germany: Cross-Sectional Differences in Volatile Markets**

*This table reports the cross sectional differences between the banking sector and the other sectors during volatile market conditions. *** shows significance at the 1 % level, ** at the 5 % level and * at the 10 % level.*

	$\Delta(\hat{\lambda}^2_{cross})$	$\Delta(\hat{\lambda}^3_{cross})$	$\Delta(\hat{\lambda}^4_{cross})$	$\Delta(\hat{\lambda}^5_{cross})$
Automobiles & Parts	0.2838**	0.3417***	0.1526***	0.1125***
Basic Materials	0.2107***	0.3337***	0.1164***	0.0791**
Consumer Services	0.5862***	0.4703***	0.1981***	0.1134***
Food & Beverage	0.7292***	0.5234***	0.2018***	0.1174***
Industrials	0.4452***	0.2686***	0.1152*	0.1047***
Insurance	0.1734***	0.2522***	0.1819***	0.1173***
Healthcare	0.3963***	0.5047***	0.1900***	0.1133***
Personal & Household	0.6436***	0.4892***	0.1951***	0.1169***
Technology	0.6734***	0.4858***	0.1959**	0.1160***

evidence of higher probabilities of joint conditional defaults in the banking sector during volatile times. For the five-companies case, eight out of nine sectors show significance at the 1 % level, and one at the 5 % level.

Comparing the results for the US and Germany, one observes that, similar to the results of the entire sample period, the risk in the US banking sector is lower when compared with the German one for the two-companies case and distinctively higher when considering five banks.

2.4.4 Recession vs. Boom Periods

The growth rate of the GDP serves as the third indicator of adverse conditions, i.e. we subsample recession and boom periods. Note that, compared with the previous two cases, the periods selected in this subsection are identical for all the sectors. In the US, we identify two recession periods.[16] In Germany, we identify four

[16]The identification of recession periods in the US is delicate as we hardly observe negative GDP growth rates during the observation period. We identify two short recessions 09/1990 – 03/1991 and 01/2001 – 09/2001. The second one does not completely fulfil our criterion of two consecutive quarters with negative GDP growth, as we have a positive growth rate in the second quarter of 2001. The selected boom periods are 10/1993 – 06/1994, 04/1997 – 09/1997, 07/1998 – 12/1998, and 07/1999 – 12/1999.

recession periods, indicated by at least two consecutive quarters of significant negative growth.[17] The GDP data was obtained from Thomson Financial Datastream as well.

Table 2.13 reports the results for the US. Surprisingly, the crisis probability of the banking sector in booming periods is higher when compared with recession periods. In the other sectors, this effect is not observable. Mostly increased probabilities during recessions and decreased ones during boom periods are reported. For up to four companies, these differences are also significant for seven sectors.

To discover the reason for the unexpected finding in the banking sector during recessions, this case is examined more closely. The sample is split into the recession of 1990/1991 and the recession of 2001. For these two periods, the systemic crisis probabilities are estimated separately. We find that, for the first period, the systemic risk in the banking sector was extremely low, with 10.9 % for two banks, 6.6 % for three banks, and 4.1 % and 1.0 % for four and five banks, respectively. In the recession of 2001, the results are completely different, namely 53.5 %, 36.5 %, 20.8 % and 16.1 %, indicating that the first recession period did not increase the systemic banking risk, whereas the second one did. This finding may be due to the fact that until 1999 the Glass-Steagall Act was in force, which separated investment and commercial banking activities. It is also in line with Hartmann et al. (2005), who discover increasing systemic risk in the US banking sector during the 1990s.

To analyze the cross-sectional differences between the banking sector and the other sectors, we rely on the second recession only, since we are mainly interested in the systemic risk prevailing under the current regulation regime. Table 2.14 reports the cross-sectional differences during the recession of 2001. The crisis probabilities are significantly higher in all the sectors except for the utilities sector.

Table 2.15 displays the crisis probabilities for these periods in Germany. The banking sector shows increased systemic risk during recessions. For the two-banks

[17] These are 02/1991 – 08/1991, 02/1992 – 08/1992, 08/1995 – 02/1996, and 08/2002 – 05/2003. The boom periods used in the subsequent study are 08/1991 – 02/1992, 08/1997 – 02/1998, and 05/1999 – 05/2000 as they show consecutive growth of GDP above average.

Table 2.13: **US: Systemic Risk in Recessions and Boom Periods**

*This table reports the estimated crisis coefficients for the different sectors during recessions and boom periods. The column Δ gives the differences and its significance. *** shows significance at the 1 % level, ** at the 5 % level and * at the 10 % level.*

	$N=2$			$N=3$		
	$\hat{\lambda}_{rec}$	$\hat{\lambda}_{boom}$	Δ	$\hat{\lambda}_{rec}$	$\hat{\lambda}_{boom}$	Δ
Banks	0.2690***	0.4926***	-0.2237	0.1387**	0.2811***	-0.1424
Automobiles & Parts	0.2348***	0.1154**	0.1193***	0.0968***	0.0358**	0.0611***
Basic Materials	0.3697***	0.2753***	0.0944***	0.1277***	0.0550**	0.0727***
Consumer Services	0.4046***	0.3554***	0.0492**	0.1119**	0.0881***	0.0239
Food & Beverage	0.4080***	0.2229***	0.1851***	0.1433**	0.0129	0.1303***
Healthcare	0.3979***	0.2071***	0.1908***	0.2352***	0.0764***	0.1588***
Industrials	0.3622***	0.1252***	0.2370***	0.1921***	0.0776***	0.1145***
Insurance	0.0918**	0.0713	0.0205	0.0487**	0.0340*	0.0147
Pers. & Household	0.2563**	0.0576	0.1987***	0.1226*	0.0247	0.0979***
Technology	0.3179***	0.2456***	0.0723**	0.1824***	0.0943***	0.0882***
Telecommunications	0.4795***	0.3465***	0.1330***	0.1258***	0.0845**	0.0413*
Utilities	0.3954***	0.3913***	0.0041	0.1996***	0.2028***	-0.0031
	$N=4$			$N=5$		
	$\hat{\lambda}_{rec}$	$\hat{\lambda}_{boom}$	Δ	$\hat{\lambda}_{rec}$	$\hat{\lambda}_{boom}$	Δ
Banks	0.0594**	0.1413***	-0.0819	0.0289*	0.0920***	-0.0631
Automobiles & Parts	0.0493***	0.0229**	0.0264*	0.0170**	0.0062*	0.0108
Basic Materials	0.0662***	0.0218*	0.0444***	0.0077**	0.0021	0.0056
Consumer Services	0.0232**	0.0238***	-0.0007	0.0094*	0.0052*	0.0042
Food & Beverage	0.0347	0.0011	0.0336*	0.0141	0.0005	0.0135
Healthcare	0.0845***	0.0240**	0.0604**	0.0476***	0.0137**	0.0339
Industrials	0.0878***	0.0294**	0.0585**	0.0273**	0.0115**	0.0159
Insurance	0.0168*	0.0072*	0.0095	0.0067	0.0014*	0.0053
Pers. & Household	0.0645**	0.0110*	0.0535**	0.0084	0.0017	0.0067
Technology	0.0767***	0.0407***	0.0360*	0.0285***	0.0173**	0.0112
Telecommunications	0.0417***	0.0177**	0.0239	0.0071**	0.0025*	0.0046
Utilities	0.1001***	0.1073***	-0.0072	0.0633***	0.0752***	-0.0118

Table 2.14: **US: Cross-Sectional Differences During Recessions**

*This table reports the cross sectional differences between the banking sector and the other sectors during recessions. *** shows significance at the 1 % level, ** at the 5 % level and * at the 10 % level.*

	$\Delta(\hat{\lambda}^2_{cross})$	$\Delta(\hat{\lambda}^3_{cross})$	$\Delta(\hat{\lambda}^4_{cross})$	$\Delta(\hat{\lambda}^5_{cross})$
Automobiles & Parts	0.0913***	0.1402***	0.0880***	0.1043***
Basic Materials	0.1404***	0.1781***	0.0939***	0.1407***
Consumer Services	0.0711**	0.2569***	0.1826***	0.1495***
Food & Beverage	0.1811***	0.3009***	0.1939***	0.1546***
Healthcare	0.1152***	0.1341***	0.1289***	0.1112***
Industrials	0.2132***	0.1496***	0.0957***	0.0936***
Insurance	0.4396***	0.2829***	0.1598***	0.1413***
Pers. & Household	0.4522***	0.3205***	0.1680***	0.1602***
Technology	0.1741***	0.1408***	0.1101**	0.0971**
Telecommunications	0.0263	0.1685***	0.1000***	0.1381***
Utilities	0.0437**	0.0225	-0.0533	-0.0406

case, the probability of a joint default given that one defaults is, with 63.2 %, almost twice as big as in periods of strongly growing GDP. Considering five banks, the crisis probability is 2.9 %, more than 100 % higher than estimated during the entire period and almost 200 % higher than in booming times. For up to four banks, the differences between recession and boom periods are significant. This significance vanishes for the five-banks case.

In the other industries, in seven cases, increasing probabilities for two companies during recession periods are observed. For the consumer services and food & beverage sectors, the values are close to zero, as in the other cases considered. For five companies, the crisis probabilities increase in six cases; however, in none of the non-banking sectors does the systemic crisis probability stay significantly above zero.

The cross-sectional inspection during recession periods is reported in Table 2.16. It shows a higher systemic risk of the banking sector in all the cases and between all the sectors considered. For up to four companies, these differences are significant except for the industrial sector. For five firms, the crisis probability is almost three percentage points higher for the banking sector compared with the others,

Table 2.15: **Germany: Crisis Probability During Recessions and Boom Periods**

*This table reports the estimated crisis coefficients for the different sectors during recessions and boom periods. The column Δ gives the differences and its significance. *** shows significance at the 1 % level, ** at the 5 % level and * at the 10 % level.*

	N = 2			N = 3		
	$\hat{\lambda}_{rec}$	$\hat{\lambda}_{boom}$	Δ	$\hat{\lambda}_{rec}$	$\hat{\lambda}_{boom}$	Δ
Banks	0.6317***	0.3555***	0.2762***	0.4966***	0.1725***	0.3241***
Automobiles & Parts	0.6035***	0.3791***	0.2244***	0.2602***	0.1241***	0.1361***
Basic Materials	0.5820***	0.5169***	0.0651*	0.2465**	0.1950***	0.0515
Consumer Services	0.0063	0.0054	0.0009	0.0054	0.0025	0.0030
Food & Beverage	0.0000	0.0000	0.0000	0.0000	0.0001	-0.0001
Healthcare	0.2534***	0.0415*	0.2119***	0.0318*	0.0005	0.0313**
Industrials	0.4568***	0.2430*	0.2138***	0.2471***	0.0560	0.1911***
Insurance	0.5772***	0.5523***	0.0249	0.1947***	0.1926***	0.0021
Pers. & Household	0.0775**	0.0759	0.0016	0.0209	0.0013	0.0196
Technology	0.3625***	0.4615**	-0.0990	0.0853**	0.2147	-0.1294
	N = 4			**N = 5**		
	$\hat{\lambda}_{rec}$	$\hat{\lambda}_{boom}$	Δ	$\hat{\lambda}_{rec}$	$\hat{\lambda}_{boom}$	Δ
Banks	0.1292***	0.0376*	0.0916**	0.0289***	0.0103	0.0186
Automobiles & Parts	0.0226*	0.0229**	-0.0003	0.0005	0.0005	0.0000
Basic Materials	0.0257*	0.0368**	-0.0112	0.0036	0.0034	0.0002
Consumer Services	0.0000	0.0000	0.0000	0.0002	0.0001	0.0001
Food & Beverage	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Healthcare	0.0043	0.0001	0.0042	0.0020	0.0000	0.0020
Industrials	0.0937***	0.0140	0.0797	0.0099	0.0015	0.0084
Insurance	0.0077***	0.0034***	0.0043	0.0001	0.0001	0.0000
Pers. & Household	0.0048	0.0001	0.0047	0.0002	0.0000	0.0002
Technology	0.0073**	0.1001	-0.0928	0.0010	0.0799**	-0.0789

Table 2.16: **Germany: Cross-Sectional Differences in Recessions**

*This table reports the cross sectional differences between the banking sector and the other sectors during recessions. *** shows significance at the 1 % level, ** at the 5 % level and * at the 10 % level.*

	$\Delta(\hat{\lambda}^2_{cross})$	$\Delta(\hat{\lambda}^3_{cross})$	$\Delta(\hat{\lambda}^4_{cross})$	$\Delta(\hat{\lambda}^5_{cross})$
Automobiles & Parts	0.0282	0.2364***	0.1067**	0.0284
Basic Materials	0.0497	0.2502***	0.1036*	0.0254
Consumer Services	0.6254***	0.4912***	0.1292***	0.0287
Food & Beverage	0.6317***	0.4966***	0.1292***	0.0289
Healthcare	0.3782***	0.4649***	0.1249***	0.0270
Industrials	0.1749***	0.2495***	0.0355	0.0190
Insurance	0.0545	0.3019***	0.1216*	0.0289
Pers. & Household	0.5542***	0.4757***	0.1244**	0.0288
Technology	0.2692***	0.4114***	0.1219**	0.0280

however, the significance of this difference vanishes. Thus, there is evidence of a higher systemic risk in the banking industry, although it is weaker than for the other two adverse periods considered. This may be due to the fact that we selected the first two adverse time periods based on a sector-specific indicator (the sector stock index). Regarding the recession identification, the growth rate of the GDP was used. Since different sectors may react with different time lags to recession periods, the results might be biased through this effect.

2.5 Robustness Checks

2.5.1 Sample Periods

So far, we have detected the periods of adverse conditions by stock market and economic indicators. As a robustness check for the previous results, we investigate the issue of whether different regimes in stock returns regarding the dependence structure exist. The core question is whether the dependence in the lower tail of the joint distribution increases in adverse regimes.

Regime-switching models for financial time series were introduced by Hamilton

(1989) and Hamilton (1990). A copula-based regime-switching study can be found in Rodriguez (2007); however, this paper focuses on the macroeconomic dependence during the Mexican and the Asian crises and analyses the changes in regimes in GARCH volatility processes.

The estimation of the specification we suggest is computationally demanding, thus we restrict ourselves to the bivariate case in the banking sector only. We estimate the bivariate regime-switching model for the bank stock returns considered in the previous section and the banking sector index returns. This shows how the systematic risk in the tail of the distribution changes among the different regimes.[18] Furthermore, to keep things tractable, we assume the marginal distributions of stock returns to be normal with constant mean μ but switching variances $\sigma^2_{s_t}$, $s_t = \{1, 2\}$ between the two regimes.[19] We choose this specification since the volatility of returns is the usual measure of risk at a univariate level. The joint behavior is modeled, as in the previous section, using the BB7 copula with dependence parameters δ_{s_t} and θ_{s_t}. These parameters also depend on the current regime s_t at time t. The probabilities of switching from one regime to another are assumed to follow a Markov chain with transition matrix Q:

$$Q = \begin{pmatrix} q_{11} & 1 - q_{11} \\ 1 - q_{22} & q_{22} \end{pmatrix}, \tag{2.9}$$

where $q_{ij} = P(s_t = j | s_{t-1} = i)$.

The estimation of the parameters is conducted as described in Hamilton (1994) and Kim (1994). Note that the copula approach allows us to keep the likelihood function analytically tractable since we can decompose the multivariate density function into the marginal distributions and the copula. The log-likelihood function can be written as

[18] Hartmann et al. (2005) call the tail dependence between stock and index returns '*tail-β*', analogous to the standard definition of systematic risk.

[19] As noted in previous sections, the assumption of normality in the margins may induce a misspecification bias.

$$\mathcal{L}(\boldsymbol{r};\Theta) = \tag{2.10}$$
$$\log \prod_{t=1}^{T} \mathbf{1}' \begin{pmatrix} c(u_{1,t}, u_{2,t}|s_t = 1, \theta_1, \delta_1) f_1(r_{1,t}|s_t = 1, \mu_1, \sigma_{11}) f_2(r_{2,t}|s_t = 1, \mu_2, \sigma_{12}) P(s_t = 1) \\ c(u_{1,t}, u_{2,t}|s_t = 2, \theta_2, \delta_2) f_1(r_{1,t}|s_t = 2, \mu_1, \sigma_{21}) f_2(r_{2,t}|s_t = 2, \mu_2, \sigma_{22}) P(s_t = 2) \end{pmatrix},$$

where $\mathbf{1}$ is the two-dimensional unit vector, Θ the parameter vector, and $u_{i,t} = F_i(r_{i,t})$ for $i = 1, 2$.

Table 2.17 reports the results for the US. We report the two dependence parameters during each regime as well as the standard deviations, the latter on an annualized basis. In the last two rows, the lower tail dependence coefficient during the two distinctive regimes is reported.

For each bank, we can observe two different volatility regimes: the first one with relatively low volatility and the second regime with high volatility. With changing volatility, we also observe increasing dependence parameters δ_{s_t}, and thus increasing systemic risk (see Equation (2.6)).

Considering for example the results for Citigroup, one observes a much higher crisis probability of 36.6 % during the volatile regime, compared to only 3.5 % during the tranquil regime. Only the estimated values for Bank of America are inconclusive as the crisis probability does not change significantly. Similar results are observed for the other banks considered.

Table 2.18 displays the results for Germany, which are similar to the results for the US. For example, the crisis coefficient of Deutsche Bank changes from almost zero to 72 %. Thus, we observe a pronounced increase of systemic risk during regimes of high volatility. For all the other banks, we find clear evidence of increased systemic risk during the volatile regimes, confirming the results of the previous section using a data-driven regime selection approach.

Table 2.17: **US: Estimation Results of the Bivariate Regime-Switching Copula Model**

This table reports the results of the bivariate regime switching model for each of the banks considered. The second series is in each case the banking index. Note that the reported standard deviations of daily returns are annualized. The corresponding lower tail dependence coefficients are reported in the last two rows.

	Citigroup	Bank of America	JP Morgan	Wells Fargo	Wachovia
$\hat{\delta}_1$	0.2067	0.7950	0.3521	0.0992	0.0992
$\hat{\delta}_2$	0.6897	0.8040	0.6221	0.6930	0.7048
$\hat{\theta}_1$	1.2503	1.9606	1.4300	1.2550	1.1977
$\hat{\theta}_2$	2.4770	2.4991	1.7600	2.4840	2.4774
$\hat{\sigma}_{1,Index}$	0.0174	0.2668	0.0193	0.0303	0.0032
$\hat{\sigma}_{1,Stock}$	0.0002	0.2813	0.0176	0.0017	0.0047
$\hat{\sigma}_{2,Index}$	0.1971	0.0997	0.2187	0.2019	0.1984
$\hat{\sigma}_{2,Stock}$	0.3186	0.0133	0.3587	0.2662	0.2688
$\hat{\lambda}_1$	0.0349	0.4182	0.1397	0.0009	0.0009
$\hat{\lambda}_2$	0.3660	0.4223	0.3282	0.3678	0.3740

2.5.2 Marginal Distributions

In this section, we conduct a robustness analysis of the results with respect to the modeling choice of the marginal distributions of stock returns. In the previous sections, we have argued to use the empirical distribution functions to avoid misspecification bias. As a robustness check, we repeat the estimation for the entire sample period with the alternative of a parametric form for the marginal distribution functions.

As our preliminary data analysis in Section 2.3 showed, leptokurticity is present in nearly every time series used in this study. Skewness should be a less important point, but is still present in some of our data. Since we wish to obtain a good fit to the data, we have to use a parametric form allowing for these stylized facts. To do so, we employ the skewed Student-t distribution (see Fernandez and Steel (1998) as reference), which allows for heavy tails as well as skewness. The standardized density $g_\upsilon(x)$ with υ degrees of freedom is given by

Table 2.18: **Germany: Estimation Results of the Bivariate Regimes-Switching Copula Model**

This table reports the results of the bivariate regime switching model for each of the banks considered. The second series is in each case the banking index. Note that the reported standard deviations of daily returns are annualized. The corresponding lower tail dependence coefficients are reported in the last two rows.

	Deutsche Bank	HVB	Commerzbank	Depfa Bank	IKB
$\hat{\delta}_1$	0.0847	0.0988	0.1856	0.0711	0.0692
$\hat{\delta}_2$	2.0969	0.6890	0.7801	0.3387	0.4124
$\hat{\theta}_1$	1.1583	1.1968	1.2611	1.7697	1.1164
$\hat{\theta}_2$	4.1598	2.4750	2.4801	1.6515	1.2068
$\hat{\sigma}_{1,Index}$	0.0391	0.0276	0.0039	0.0002	0.0452
$\hat{\sigma}_{1,Stock}$	0.0525	0.0094	0.0013	0.0765	0.0002
$\hat{\sigma}_{2,Index}$	0.2635	0.2062	0.2005	0.2104	0.2075
$\hat{\sigma}_{2,Stock}$	0.3473	0.3227	0.2797	0.3203	0.1837
$\hat{\lambda}_1$	0.0003	0.0009	0.0239	0.0001	0.0000
$\hat{\lambda}_2$	0.7185	0.3657	0.4113	0.1292	0.1862

$$g_v(x) = \begin{cases} \frac{2}{\gamma+\frac{1}{\gamma}} f_v(\frac{x}{\gamma}) & \text{for} \quad x \geq 0 \\ \frac{2}{\gamma+\frac{1}{\gamma}} f_v(x\gamma) & \text{for} \quad x < 0, \end{cases} \tag{2.11}$$

where $f_v(x)$ denotes the standard Student-t density with v degrees of freedom. For $\gamma = 1$, one obtains the standard Student-t distribution. As for the copula, we estimate the parameters of the marginal distributions by employing the method of maximum likelihood.

Table 2.19 reports the estimated crisis probabilities employing the parametric marginal distributions for the US, using the entire sample period 1990 to 2006 as in Section 2.4.1. Thus, the results are directly comparable to Table 2.1. We compare the estimated values for the banking sector first. The differences are very small. They range, in absolute terms, from 0.1 % for the three-banks case to 1.1 % when considering two banking institutions. All the estimated values remain highly significant. For the other sectors considered, we have some deviations regarding the significance level. This result of rather small differences with respect to the

Table 2.19: **US: Robustness Against the Choice of Marginal Distributions**

*This table reports the estimation results of the crisis coefficient using the skewed Student-t-distribution as marginal model for the entire sample period. *** shows significance at the 1 % level, ** at the 5 % level and * at the 10 % level.*

	$\hat{\lambda}^2$	$\hat{\lambda}^3$	$\hat{\lambda}^4$	$\hat{\lambda}^5$
Banks	0.3549***	0.1955***	0.0937***	0.0566***
Automobiles & Parts	0.0727***	0.0198**	0.0140**	0.0042**
Basic Materials	0.2973***	0.0807***	0.0274***	0.0043**
Consumer Services	0.2960***	0.0517***	0.0113**	0.0026*
Food & Beverage	0.2682***	0.0382**	0.0046*	0.0020
Healthcare	0.2821***	0.1237***	0.0301***	0.0143**
Industrials	0.1654***	0.0783***	0.0249**	0.0079*
Insurance	0.0175	0.0158*	0.0076**	0.0038**
Pers. & Household	0.0553	0.0252*	0.0080*	0.0010
Technology	0.2127***	0.0955***	0.0411***	0.0165**
Telecommunications	0.4133***	0.0893***	0.0236***	0.0033*
Utilities	0.2889***	0.1349***	0.0570***	0.0287***

modeling of the marginal distributions remains valid for most of the other sectors. In some cases, the significance level changes; this can mainly be attributed to the fact of discrete significance levels. Overall, we conclude that the differences between using a non-parametric versus a parametric model for the marginal distribution are immaterial.

The results for Germany, which are reported in Table 2.20, can be directly compared with Table 2.3 of Section 2.4.1. One can clearly observe that the differences are, as for the US, minimal. The crisis coefficient for two banks changes from 44.4 % using the empirical distribution function to 42.4 % using the parametric model, both highly significantly different from zero. This picture remains while increasing the number of companies considered. For the case of five banks, the difference between the two estimated values amounts to 0.0002, which can be considered to be negligibly small. As in the original estimation, the significance level is at 5 %.

Table 2.20: **Germany: Robustness Against the Choice of Marginal Distributions**

*This table reports the estimation results of the crisis coefficient using the skewed Student-t-distribution as marginal model for the entire sample period. *** shows significance at the 1 % level, ** at the 5 % level and * at the 10 % level.*

	$\hat{\lambda}^2$	$\hat{\lambda}^3$	$\hat{\lambda}^4$	$\hat{\lambda}^5$
Banks	0.4237***	0.2739***	0.0581**	0.0134**
Automobiles & Parts	0.4630***	0.1629***	0.0211**	0.0013
Basic Materials	0.5468***	0.2019***	0.0429***	0.0041**
Consumer Services	0.0156	0.0044	0.0000	0.0001
Food & Beverage	0.4630***	0.1629***	0.0211*	0.0013
Healthcare	0.0709**	0.0020	0.0004	0.0000
Industrials	0.3324***	0.1096***	0.0269**	0.0025
Insurance	0.4985***	0.1605***	0.0003	0.0000
Pers. & Household	0.0421*	0.0071	0.0013	0.0000
Technology	0.4002***	0.1056***	0.0355*	0.0176

2.5.3 Factor Analysis

As a final robustness check, we conduct a factor analysis for each set of stock return series. This analysis will provide information about the entire multivariate distribution of the considered stock returns, not only the lower tail as in the main part of this study. Thus, this analysis is not directly able to be helpful for drawing conclusions about systemic risk but will indicate whether the observed stronger dependence of the banking sector in the tail of the distribution is also present in the overall distribution, indicating stability of the results.

A factor analysis requires a decision on the number of common factors. As the number of factors should be able to capture the main explaining factors, but should also be much smaller than the number of considered variables, we use two factors for each of the five considered companies of one sector.[20]

Table 2.21 and Table 2.22 report the results of the factor analyses. We report the uniquenesses, i.e. the portion of idiosyncratic variance, and the portion of

[20]See e.g. Härdle and Simar (2007, p. 251). To infer the optimal number of factors, we employed likelihood ratio tests. The hypothesis of only one factor was rejected for every sector. Therefore, we decided to use two factors for each sector.

Table 2.21: **US: Factor Analysis**

This table reports the results of the factor analysis for the 12 considered US sectors. The five columns u_i denote the uniquenesses of the respective stock returns, the last column reports the proportion of explained variance by the two common factors.

	u_1	u_2	u_3	u_4	u_5	Cum. Var.
Banks	0.487	0.348	0.315	0.501	0.450	0.580
Automobiles & Parts	0.801	0.005	0.601	0.561	0.684	0.470
Basic Materials	0.471	0.407	0.541	0.193	0.948	0.488
Consumer Services	0.397	0.498	0.640	0.767	0.806	0.379
Food & Beverage	0.555	0.455	0.744	0.835	0.664	0.350
Healthcare	0.471	0.381	0.490	0.822	0.516	0.464
Industrials	0.554	0.543	0.520	0.632	0.647	0.421
Insurance	0.421	0.005	0.530	0.765	0.680	0.520
Pers. & Household	0.460	0.868	0.513	0.689	0.750	0.344
Technology	0.430	0.630	0.447	0.511	0.677	0.461
Telecommunications	0.063	0.511	0.744	0.652	0.927	0.421
Utilities	0.563	0.377	0.394	0.558	0.476	0.527

variance explained by the two common factors. The latter can be interpreted in the following way: the higher the fraction of variance that can be explained by the common factors, the higher the dependence among the five considered companies. For the US banking sector, this fraction is 58 %, the highest among all the sectors. The uniquenesses are of a relatively equal size, between 32 % and 50 %. For the German banks considered, the fraction of variance explained by the common factors is lower with 46 %, but is still the highest among all the German sectors. The uniquenesses of the fourth and fifth bank of the German sample are high, indicating less exposure to the common factors.

Overall, the factor analysis supports the result of a high degree of dependence in the banking sectors, indicating the robustness of the results found in the main section.

Table 2.22: **Germany: Factor Analysis**

This table reports the results of the factor analysis for the 10 considered German sectors. The five columns u_i denote the uniquenesses of the respective stock returns, the last column reports the proportion of explained variance by the two common factors.

	u_1	u_2	u_3	u_4	u_5	Cum. Var.
Banks	0.352	0.428	0.337	0.768	0.817	0.460
Automobiles & Parts	0.432	0.315	0.698	0.888	0.969	0.339
Basic Material	0.283	0.302	0.665	0.736	0.964	0.410
Consumer Services	0.596	0.935	0.761	0.774	0.545	0.278
Food & Beverage	0.746	0.992	0.940	0.961	0.005	0.251
Industrials	0.570	0.515	0.609	0.822	0.751	0.347
Insurance	0.239	0.306	0.805	0.927	0.975	0.349
Healthcare	0.005	0.826	0.844	0.869	0.919	0.308
Pers. & Household	0.943	0.128	0.785	0.748	0.981	0.283
Technology	0.505	0.500	0.620	0.754	0.764	0.371

2.6 Further Analyses

2.6.1 Commercial Banks vs. Investment Banks

Traditionally, the US banking sector has been separated into commercial and investment banks.[21] In this subsection, we analyze the systemic risk among the major US investment banks compared with their commercial counterparts.[22] Ex-ante, it is unclear whether one should expect higher or lower crisis probabilities compared with the commercial banking sector. On the one hand, the business models are more homogeneous in the investment banking sector and, thus, a higher degree of systemic risk should be observable. This argument is supported by the fact that investment banks have higher exposures to each other through derivatives transactions and also fewer, but bigger, players exist in the market. On the other hand, investment banks operate more globally than their commercial counterparts,

[21] During the recent financial crisis, several investment banks have been acquired by commercial banks (e.g. Merrill Lynch). Thus, the separation of the banking sectors is, at present, not as clear-cut as it has been in the past.

[22] As no significant (pure) investment bank exists in Germany, we restrict the analysis to the US.

Table 2.23: **Commercial vs. Investment Banks**

*This table reports the estimation results of the crisis coefficient for the sample of commercial and investment banks. *** shows significance at the 1 % level, ** at the 5 % level and * at the 10 % level.*

	$\hat{\lambda}^2$	$\hat{\lambda}^3$	$\hat{\lambda}^4$	$\hat{\lambda}^5$
Commercial Banks	0.5242***	0.3245***	0.1701***	0.1176***
Investment Banks	0.6010***	0.4260***	0.3161***	0.2365***

increasing the potential diversification benefits. The commercial banks are much more exposed to regional crises, as for example experienced during the savings and loans crisis in the US during the 1980s and 1990s.

We consider the five major investment banks operating during our sample period, namely Goldman Sachs, Morgan Stanley, Merril Lynch, Lehman Brothers, and Bear Stearns. The time series of available stock prices is shorter than for the industry sectors considered in the main section. We are able to obtain the multivariate time series for all five banks from May 1999, when Goldman Sachs went public, until 2006. To be able to conduct a meaningful comparison, we re-estimate the systemic crisis probabilities in the commercial banking sector during the same time period.

Table 2.23 reports the results. We can observe an increased crisis probability of between 52.4 % and 11.8 % for the commercial banks during the 1999 - 2006 period, compared with the entire period, when the crisis probabilities were between 36.6 % for two banks and 5.5 % for five banks, respectively.

The crisis coefficient for the investment banks is estimated between 60.1 % for two banks and 23.7 % for five banks and, thus, shows a higher degree of systemic risk, compared with the commercial banks. The difference for the higher dimensional case ($N = 5$) is especially noteworthy, as the crisis probability is twice as big as in the commercial banking sector. Thus, we can conclude that the dependence introduced by the similarity of business models seems to increase the downside dependence in the investment banking sector compared with the commercial banking sector.

2.6.2 Financial Crisis

It is natural to ask how the 2007/2008 financial crisis changed the systemic risk in the different sectors. We thus repeat the estimation for the time period June 1st, 2007 to October 10th, 2008, which marks the most recent observations as we conduct the analysis. Unfortunately, we have to restrict ourselves to the US data, as we are not able to collect a data set for the German banking sector comparable to the data used before. The Hypovereinsbank is not listed anymore as it has been taken over by the Italian Unicredit. Similarly, Depfa Bank merged on October 1st, 2007 with Hypo Real Estate. Moreover, the IKB Deutsche Industriebank was one of the first victims of the crisis and was finally sold to Lone Star.
For the US, all the banks considered in the main section are still exchange listed. In two sectors we have to make minor changes as companies were acquired by investors or competitors. The telecommunication company Alltel was acquired in May 2007 and thus replaced by Embarq; the utilities company TXU was acquired in October 2007 and thus replaced by the FPL Group. All the other sectors' representatives remain unchanged.
Table 2.24 reports the results of the estimation. Comparing the results with the systemic risk during the entire preceding study period (Table 2.1), a substantial increase in the systemic crisis probabilities in the banking sector is observable. For the two largest banks, the conditional joint default probability rose to 69.8 %, around 33 percentage points higher than before. Considering a larger number of banks, it remains at a high level; for five banks, the crisis probability is at 29.9 %, 24 percentage points higher than before.
The other sectors considered also show increased joint default probabilities, although mostly on a lower level. Only basic materials and utilities show crisis probabilities of an equal size. The size of the crisis probabilities in these two sectors is somehow surprising and it is difficult to come up with a convincing explanation.

Table 2.24: **US: Systemic Risk during the 2007/2008 Financial Crisis**

*This table reports the estimation results of the crisis coefficient for the financial crisis from 07/01/07 to 10/10/08. *** shows significance at the 1% level, ** at the 5% level and * at the 10% level.*

	$\hat{\lambda}^2$	$\hat{\lambda}^3$	$\hat{\lambda}^4$	$\hat{\lambda}^5$
Banks	0.6980***	0.5489***	0.4188***	0.2992***
Automobiles & Parts	0.3266***	0.2032***	0.1407***	0.0925***
Basic Materials	0.6980***	0.5489***	0.4188***	0.2992***
Consumer Services	0.5068***	0.2463***	0.1410***	0.0719**
Food & Beverage	0.5825***	0.2504***	0.0963***	0.0507**
Healthcare	0.3771***	0.2125***	0.1027***	0.0763***
Industrials	0.3966***	0.3213***	0.2049***	0.1611***
Insurance	0.1192	0.1018**	0.0925***	0.0707***
Pers. & Household	0.3881***	0.2611***	0.1560***	0.0858***
Technology	0.4942***	0.3167***	0.2000***	0.1421***
Telecommunications	0.6871***	0.3412***	0.1816***	0.1120***
Utilities	0.6744***	0.4777***	0.3703***	0.3061***

Comparing the systemic risk in the banking sector with the previous 'crisis' periods, it can be seen that the financial crisis period carried a larger degree of systemic risk. For five banks, it is 8 percentage points higher than in the bear market period, 10 percentage points higher than in the volatile market period, and 27 percentage points higher than during recessions.

Therefore, one can conclude that the proposed crisis coefficient has reacted to the financial crisis in the expected fashion, confirming the validity of its definition.

2.7 Conclusion

In this chapter, we address the question of the existence and strength of systemic risk in the banking sector and other industry sectors of the United States and Germany using security market information. To do so, we apply a copula-based measure of dependencies in the tail of the multivariate distributions of stock returns. We estimate this crisis coefficient for the entire sample period as well as for selected subperiods of adverse market conditions. As a robustness check, we specify a two-state regime-switching copula model that allows for switching dependencies and volatilities between two different regimes. Furthermore, we analyze the robustness with respect to the modeling of the marginal distributions, conduct a factor analysis of the stock returns, and analyze the investment banking sector, as well as the recent financial crisis.

Our main results are as follows: we find significantly higher systemic risk in the banking sectors of the US and Germany compared with the other sectors of the respective economies. Due to the importance of the banking sector, this clearly justifies the need for a supervising authority whose task is to prevent a systemic crisis affecting the entire economy. Presuming that banking regulation lowers systemic risk, the need for stricter regulation is supported. However, as discussed in the first chapter, theoretical studies, such as Eichberger and Summer (2005), show that systemic risk might increase as a consequence of extensive regulation. Thus, it is difficult to draw unambiguous policy implications. Considering the insurance sector, we find evidence for very low degrees of systemic risk. This suggests the policy implication that a system-wide regulation of the insurance sector is not necessary and one should focus on the banking sector.

Second, the degree of systemic risk in a sector strongly depends on the state of the economy, characterized by the sector's stock market index or the business cycle. In adverse states, the systemic risk is considerably higher than in positive environments. This finding indicates a high sensitivity of the banking sector to the economic conditions, demanding the full attention of the regulator during adverse periods of time. The result of higher systemic risk during volatile times in the banking sector is confirmed by the results of the estimated regime-switching copula model.

Third, our cross border comparison of the banking sectors in Germany and the United States supports the results of Hartmann et al. (2005), who find higher extreme dependencies in the US banking system when compared with the European one. On the one hand, the different degrees of systemic risk in the two banking sectors might be a result of the different structures of the two banking systems. On the other hand, one might argue that this result implies a more successful banking regulation in Germany compared with the US.

2.8 Appendix A

Table 2.25: **US: Company Description**

Company	Principal Activities
General Motors	Automotive and Other Operations and Financing and Insurance Operations
Ford Motor Co.	Production and selling of cars and trucks.
Johnson Controls	Automotive systems and building controls
Harley-Davidson	Motorcycles and Related Products
Genuine Parts Co.	Distribution of automotive replacement parts, industrial replacement parts, office products and electrical and electronic materials
Citigroup	Provision of financial services
Bank of America	Provision of banking and certain non-banking financial services
JPMorgan Chase	Provision of global financial services
Wells Fargo & Co.	Provision of banking, insurance, investment, mortgage banking and consumer financing services
Wachovia	Provision of commercial and retail banking and trust services
Du Pont De Nemours & Co	Manufacturing and selling of materials, synthetic fibers, agriculture and biotechnology products.
Dow Chemical	Manufacturing and selling of chemicals, plastic materials, agricultural and other specialized products and services.
Alcoa	Production of aluminum products
Phelps Dodge	Production of copper, carbon black, magnet wire and continuous-cast copper rod
Newmont Mining	Acquisition, development, exploration and production of gold properties worldwide
Wal-Marts Stores	Operation of retail stores in various formats
Home Depot	Selling of assortment of building materials, home improvement and lawn and garden products
Disney Company	Provision of entertainment and information
Comcast	Development, management and operation of broadband communications network
McDonald's	Operation and franchise restaurant businesses under the McDonald's brand.
Coca-Cola	Manufacturing, distribution and marketing of nonalcoholic beverage concentrates and syrups
Pepsico	Manufacturing, marketing and selling of salty, sweet and grain-based snacks, carbonated and non-carbonated beverages and foods
Anheuser-Busch	Beer manufacturing and wholesale
Archer-Daniels-Midland	Production, transportation, storage, processing and merchandising of agricultural commodities and products
Kellogg	Manufacturing and marketing of ready-to-eat cereal and convenience food products

Continued on next page

Table 2.25 – continued from previous page

Company	Principal Activities
Johnson & Johnson	Manufacturing and marketing of a range of products in the health care field
Pfizer	Discovering, development, manufacturing and selling of prescription medicines for humans and animals and also healthcare products
Merck & Co.	Development, manufacturing and marketing of a broad range of innovative products to improve human and animal health
Amgen	Discovering, development, manufacturing and marketing of human therapeutics based on advances in cellular and molecular biology
Abbott Laboratories	Discovering, development, manufacturing and selling of a broad and diversified line of health care products.
General Electric	Development, manufacturing and marketing of a wide variety of products for the generation, transmission, distribution, control and utilization of electricity
Boeing	Offering of products and services in aerospace industry
United Technologies	Provision of high technology products and services to the building systems and aerospace industries worldwide
3M	Research, manufacturing and marketing of various products
Caterpillar	Design, manufacturing and marketing of construction machinery and engines.
American International	Provision of general and life insurance operations, financial services, retirement savings and asset management
Berkshire Hathaway	Provision of insurance and reinsurance of property also casualty risks and reinsure life, accident and health risks world-wide
St. Pauls Travellers	Provision of commercial property-liability and non life reinsurance products and services worldwide
AFLAC	Provision of supplemental health and life insurance services
Loews	Provision of property and casualty insurance, production and selling of cigarettes and operate offshore oil and gas drilling rigs and natural gas pipeline systems
Procter & Gamble	Manufacturing and marketing consumer products
Altria Group	Manufacturing and marketing various consumer products, including cigarettes, grocery products, snacks, beverages, cheese and convenient meals
Colgate-Palmolive	Manufacturing and marketing a wide variety of consumer products
Kimberly-Clark	Manufacturing and marketing of various health and hygiene products
Nike	Design, production, development and market ing of high quality sports and fitness footwear, apparel, equipment and accessory products
Microsoft	Development, manufacturing, licensing and supporting a wide range of software products for a multitude of computing devices
IBM	Provision of business and information technology services
Intel	Design, development, manufacturing and marketing computers, networking and communication products
Hewlett-Packard	Provision of products, technologies, solutions and services to individual consumers and businesses.

Continued on next page

Table 2.25 – continued from previous page

Company	Principal Activities
Oracle	Development, manufacturing, marketing and distributionof computer software.
AT&T	Provision of communication services and products
Verizon	Provision of wireline and wireless communication services
Sprint Nextel	Provision of communication products and solutions
ALLTEL	Provision of wireline and wireless communication
Leucadia	Telecommunication, healthcare services, banking and lending, manufacturing, winery operations, real estate activities and development of copper mine
Exelon	Energy generation and delivery
Dominion Resources	Generation, transmission, distribution and selling of gas and electric energy
Southern Company	Acquisition, development, building, operation of power production and delivery facilities
TXU	Generation of electricity, wholesale energy trading, retail energy marketing, energy delivery, and other energy-related services
Duke Energy	Provision integrated energy services, offer physical delivery and manage electricity and natural gas

Table 2.26: **Germany: Company Description**

Company	Principal Activities
BMW	Development, Manufacturing and selling of a range of cars and motorcycles
VW	Design, manufacturing and distribution of cars and other vehicles worldwide
Continental	Manufacturing tires, plastic products and other industrial rubber products
Rheinmetall	Supply of automotive components and defence equipments
Elringklinger	Manufacturing of cylinder-head gaskets and other sealing and plastic components mainly for the automotive industry
Deutsche Bank	Provision of a range of banking and financial services
HVB	Provision of universal banking and financial services
Commerzbank	Provision of banking services
Depfa Bank	Provision of a range of banking, financial and related services to public sector clients worldwide
IKB	Provision of banking services, predominantly by granting medium and long term loans to small and medium sized companies
BASF	Chemicals, Plastics, Performance Products, Agricultural Products & Nutrition and Oil & Gas
Bayer	Health care, nutrition and high-tech materials sectors
Linde	Industrial gas, Engineering and Material handling
K+S	Supply of agricultural and industrial products and related services
Fuchs Petrolub	Manufacturing and marketing of lubricants, speciality chemicals, oil products, polishing products, base oil, heating oil and fuel
Deutsche Lufthansa	Provision of passenger and freight airline services and related businesses, both domestically and internationally
Celesio	Pharmaceutical wholesale, Pharmacies and Solutions
Karstadt Quelle	Management of department stores, mail order services, information and finance services and real estate services
Axel Springer	Printing, publishing and sale of newspapers, magazines, books and periodicals
TUI	Tourism, Shipping and other operating units
Suedzucker	Production of sugar
Gabriel Sedlmayr	Brewing an distribution of beer and other beverages
Baywa	Sale of agricultural and horticultural products
KWS Saat	Cultivation of a variety of crops and other food produce including sugar beet, maize, seeds, grain and cereals
Stuttg. Hofbraeu	Brewing of beer and sale of soft drinks and other non-alcoholic beverages
Siemens	Information and Communications, Automation and Control, Power, Transportation, Medical, Lighting
Thyssen Krupp	Steel, Services, Automotive, Technology, Elevators, Engineering
MAN	Supply of capital goods and systems in the fields of commercial vehicle construction, mechanical and plant engineering

Continued on next page

Table 2.26 – continued from previous page

Company	Principal Activities
GEA Group	Customized Systems, Process Equipment, Process Engineering and Plant Engineering
Pfleiderer	Marketing of engineered wood, surface-finished panels and rail sleeper technology, provison of infrastructure for the energy and communication sectors
Allianz	Life/Health, Property/Casualty, Banking, Asset Management
Muenchener Rueck	Provision of insurance and reinsurance services
Hannover Rueck	Provision of all major types of reinsurance services
Gerling	Provision of a comprehensive range of general insurance business, including accident, liability, motor and property insurance
Nuernberger	Provision of a wide range of insurance policies, including life, accident, disability, health, automobile, general liability and other insurance services
Bayer Schering	Development and manufacturing of pharmaceuticals and diagnostic substances
Altana	Research, manufacturing and marketing of innovative prescription drugs and chemical products
Schwarz Pharma	Research, development, manufacturing and marketing of pharmaceuticals
Merck	Development, manufacturing and distribution of pharmaceuticals and chemicals
Stada Arzneimittel	Manufacturing of generic drugs
Beiersdorf	Develop, produce and market cosmetics, health care products and adhesives.
Henkel	Cosmetics/toiletries, Detergents/household cleaners, Adhesives
Adidas	Production and marketing of sports goods
Puma	Design, manufacturing and marketing of sporting goods
Bijou Brigitte	Manufacturing, importation and retailing of custume jewellery, gold and silver jewellery, precious stones and fashion accessories
SAP	Development, marketing, and selling of a variety of software solutions for organizations including corporations, government agencies, and educational institutions
Infineon Technologies	Design, research, development, manufacture and marketing of semiconductors and complete systems solutions used in a variety of micro electrical applications
United Internet	Marketing, sales and other services in the fields of telecommunications, information tech nology, data processing and related areas
Software AG	Development and license of enterprise system software products, enterprise application integration and electronic business
freenet.de	Provision of internet connectivity services

Table 2.27: **US: Summary Statistics**

This table reports descriptive statistics of the daily log returns. The fourth and fifth column give the start and end date of the time series. The mean and the standard deviation are reported on an annual basis. The next two columns give the skewness and the excess kurtosis. The Min and Max columns report the smallest and highest return observed in the sample period. The column ADF reports the Augmented Dickey-Fuller Test of a unit root. The next column reports the value of the Q-Statistic with m lags. We follow Tsay (2005) and use $m = \log(T)$. *The last column gives the Jarque-Bera-Test of Normality. *** shows significance at the 1 % level, ** at the 5 % level and * at the 10 % level.*

Sector	Name	ISIN	Start Date	End Date	μ	σ	S	K	Min	Max	ADF	Q(m)	JB
Automobiles & Parts	Harley-Davidson	US4128221086	01-Jan-90	29-Dec-06	0.2329	0.3439	-0.2892	8.76	-0.2486	0.1300	-16.09***	13.32***	14240.6***
	General Motors	US3704421052	01-Jan-90	29-Dec-06	0.0318	0.3251	0.0761	3.80	-0.1504	0.1665	-14.95***	6.59	2676.8***
	Johnson Controls	US4783661071	01-Jan-90	29-Dec-06	0.1560	0.2627	0.1236	4.17	-0.1309	0.1097	-16.81***	18.61**	3227.9***
	Ford Motor Company	US3453708600	01-Jan-90	29-Dec-06	0.0359	0.3343	0.1390	3.97	-0.1589	0.1451	-15.96***	27.14***	2932.5***
	Genuine Parts	US3724601055	01-Jan-90	29-Dec-06	0.0847	0.2006	0.2520	3.45	-0.0951	0.0808	-16.33***	38.33***	2247.9***
Banks	Citigroup	US1729671016	01-Jan-90	29-Dec-06	0.1997	0.3271	0.0309	4.92	-0.1711	0.1684	-16.49***	22.33***	4485.7***
	Bank of America	US0605051046	01-Jan-90	29-Dec-06	0.1204	0.2929	-0.1422	3.89	-0.1443	0.0988	-16.60***	47.81***	2813.8***
	JPMorgan Chase & Co.	US46625H1005	01-Jan-90	29-Dec-06	0.1217	0.3454	0.1585	5.45	-0.1998	0.1487	-15.54***	10.81	5505.0***
	Wells Fargo	US9497461015	01-Jan-90	29-Dec-06	0.1699	0.2631	0.1152	2.67	-0.0919	0.0953	-17.69***	24.16***	1324.7***
	Wachovia	US9299031024	01-Jan-90	29-Dec-06	0.1333	0.2764	0.0497	3.62	-0.1171	0.1075	-17.11***	18.41**	2424.4***
Basic Materials	Du Pont De Nemours & Co	US2635341090	01-Jan-90	29-Dec-06	0.0789	0.2670	0.0539	3.25	-0.1170	0.0941	-17.13***	21.47***	1955.5***
	Dow Chemical Company	US2605431038	01-Jan-90	29-Dec-06	0.0671	0.2791	0.0125	4.31	-0.1118	0.1079	-17.73***	14.88*	3432.9***
	Alcoa	US0138171014	01-Jan-90	29-Dec-06	0.0865	0.3138	0.2073	3.19	-0.1166	0.1315	-17.21***	17.54**	1909.7***
	Phelps Dodge	US7172651025	01-Jan-90	29-Dec-06	0.1476	0.3323	0.4218	5.59	-0.1278	0.2373	-16.55***	15.83**	5921.2***
	Newmont Mining	US6516391066	01-Jan-90	29-Dec-06	0.0185	0.4003	0.4150	4.47	-0.1826	0.1927	-16.72***	32.94***	3827.6***
Consumer Services	Wal-Marts Stores	US9311421039	01-Jan-90	29-Dec-06	0.1254	0.2928	0.0376	3.54	-0.1560	0.0902	-16.97***	40.56***	2325.7***
	Home Depot	US4370761029	01-Jan-90	29-Dec-06	0.1799	0.3360	-0.9693	17.51	-0.3388	0.1213	-17.19***	31.48***	57396.3***
	Disney (Walt) Company	US2546871060	01-Jan-90	29-Dec-06	0.0807	0.3045	-0.1165	8.02	-0.2029	0.1420	-16.25***	11.09	11916.3***
	Comcast	US20030N1019	01-Jan-90	29-Dec-06	0.1206	0.3984	0.2849	3.73	-0.1622	0.1754	-16.74***	26.55***	2634.1***
	McDonald's	US5801351017	01-Jan-90	29-Dec-06	0.1026	0.2649	-0.0423	4.26	-0.1372	0.1031	-16.18***	10.85	3360.2***
Food & Beverage	Coca-Cola	US1912161007	01-Jan-90	29-Dec-06	0.1062	0.2417	-0.0492	4.15	-0.1107	0.0922	-17.14***	16.56**	3191.0***
	Pepsico	US7134481081	01-Jan-90	29-Dec-06	0.1192	0.2606	0.3688	6.45	-0.1183	0.1497	-16.55***	42.37***	7802.0***
	Anheuser-Busch	US0352291035	01-Jan-90	29-Dec-06	0.1138	0.2221	-0.1694	3.24	-0.0861	0.0745	-16.57***	62.77***	1962.2***
	Archer-Daniels-Midland	US0394831020	01-Jan-90	29-Dec-06	0.0845	0.2886	-0.1104	5.71	-0.1843	0.1319	-15.71***	39.12***	6043.2***
	Kellogg	US4878361082	01-Jan-90	29-Dec-06	0.0863	0.2435	0.3037	4.40	-0.0995	0.1030	-16.73***	39.22***	3655.0***
Healthcare	Johnson& Johnson	US4781601046	01-Jan-90	29-Dec-06	0.1400	0.2366	-0.2824	6.26	-0.1725	0.0789	-16.86***	57.89***	7297.4***
	Pfizer	US7170811035	01-Jan-90	29-Dec-06	0.1427	0.2886	-0.1971	2.92	-0.1182	0.0927	-17.32***	42.18***	1604.9***
	Merck & Co.	US5893311077	01-Jan-90	29-Dec-06	0.0967	0.2770	-1.3578	25.54	-0.3117	0.1225	-16.25***	29.56***	122006.1***
	Amgen	US0311621009	01-Jan-90	29-Dec-06	0.2370	0.3905	-0.0045	4.43	-0.2231	0.1406	-15.79***	50.52***	3623.3***
	Abbott Laboratories	US0028241000	01-Jan-90	29-Dec-06	0.1223	0.2715	-0.3094	5.83	-0.1760	0.1175	-18.16***	45.33***	6356.1 ***
Industrials	General Electric	US3696041033	01-Jan-90	29-Dec-06	0.1316	0.2512	0.0441	4.48	-0.1129	0.1174	-16.96***	20.73***	3723.2***
	Boeing	US0970231058	01-Jan-90	29-Dec-06	0.1012	0.3004	-0.5278	8.05	-0.1939	0.1100	-16.36***	17.30**	12202.9***
	United Technologies	US9130171096	01-Jan-90	29-Dec-06	0.1461	0.2735	-1.6024	33.04	-0.3320	0.0938	-17.04***	41.47***	203793.6***
	3M Company	US88579Y1010	01-Jan-90	29-Dec-06	0.1045	0.2267	0.0208	4.44	-0.1008	0.1050	-16.33***	22.06***	3655.5***
	Caterpillar	US1491231015	01-Jan-90	29-Dec-06	0.1407	0.3064	-0.1535	4.00	-0.1569	0.1030	-16.62***	7.11	2975.8***
Insurance	American International	US0268741073	01-Jan-90	29-Dec-06	0.1229	0.2607	0.1070	3.71	-0.1102	0.1046	-16.52***	39.38***	2557.0***
	Berkshire Hathaway	US0846701086	01-Jan-90	29-Dec-06	0.1432	0.2296	0.4446	6.03	-0.0977	0.0974	-16.75***	41.68***	6871.3***
	St. Pauls Travellers	US7928601084	01-Jan-90	29-Dec-06	0.1022	0.2590	0.2975	5.70	-0.1232	0.1299	-16.42***	24.97***	6076.6***
	AFLAC	US0010551028	01-Jan-90	29-Dec-06	0.1770	0.3011	0.3640	5.40	-0.1413	0.1491	-17.63***	21.14***	5483.2***
	Loews	US5404241086	01-Jan-90	29-Dec-06	0.0884	0.2258	-0.2395	7.17	-0.1606	0.0852	-16.10***	20.13***	9542.4***
Pers. & Household	Procter & Gamble	US7427181091	01-Jan-90	29-Dec-06	0.1315	0.2497	-3.2106	76.19	-0.3766	0.0910	-16.78***	29.45***	1081169.9***
	Altria Group	US02209S1033	01-Jan-90	29-Dec-06	0.1472	0.2943	-0.8415	16.00	-0.2614	0.1507	-15.15***	12.51	47871.1***
	Colgate-Palmolive	US1941621039	01-Jan-90	29-Dec-06	0.1376	0.2518	-0.0811	10.67	-0.1732	0.1850	-17.05***	41.75***	21057.2***
	Kimberly-Clark	US4943681035	01-Jan-90	29-Dec-06	0.1013	0.2426	-0.1859	6.06	-0.1196	0.1007	-16.23***	35.05***	6818.5***
	Nike	US6541061031	01-Jan-90	29-Dec-06	0.1630	0.3450	-0.2589	7.38	-0.2165	0.1335	-15.54***	13.61*	10116.0***
Technology	Microsoft	US5949181045	01-Jan-90	29-Dec-06	0.2281	0.3397	-0.0460	4.70	-0.1696	0.1787	-15.71***	12.41	4093.5***
	IBM	US4592001014	01-Jan-90	29-Dec-06	0.0966	0.3009	0.0269	7.56	-0.1689	0.1237	-14.99***	11.12	10566.6***
	Intel	US4581401001	01-Jan-90	29-Dec-06	0.1693	0.4215	-0.4220	5.84	-0.2489	0.1833	-14.52***	26.43***	6435.2***
	Hewlett-Packard	US4282361033	01-Jan-90	29-Dec-06	0.1345	0.4011	-0.0798	6.30	-0.2070	0.1899	-16.01***	13.19	7346.3***
	Oracle	US68389X1054	01-Jan-90	29-Dec-06	0.1912	0.5541	-0.1569	11.57	-0.3716	0.3637	-15.34***	23.31***	24786.0***
Telecommunications	AT&T	US00206R1023	01-Jan-90	29-Dec-06	0.0820	0.2717	-0.0754	3.70	-0.1354	0.0883	-17.81***	20.02***	2540.1***
	Verizon	US92343V1044	01-Jan-90	29-Dec-06	0.0592	0.2621	0.1261	4.60	-0.1261	0.1157	-17.31***	28.89***	3930.8***
	Sprint Nextel	US8520611000	01-Jan-90	29-Dec-06	0.0467	0.3588	-0.7597	12.43	-0.2598	0.1882	-16.95***	6.38	28988.2***
	ALLTEL	US0200391037	01-Jan-90	29-Dec-06	0.1036	0.2449	-0.0410	4.36	-0.1254	0.1178	-16.60***	18.08**	3517.1***
	Leucadia National	US5272881047	01-Jan-90	29-Dec-06	0.1908	0.2400	1.0724	11.79	-0.0681	0.2076	-15.88***	7.01	26549.9***
Utilities	Exelon	US30161N1019	01-Jan-90	29-Dec-06	0.1387	0.2289	-0.3294	6.38	-0.1255	0.1054	-16.15***	11.87	7608.4***
	Dominion Resources	US25746U1097	01-Jan-90	29-Dec-06	0.1083	0.1850	-1.0008	13.76	-0.1368	0.0838	-16.60***	26.36***	35750.7***
	Southern Company	US8425871071	01-Jan-90	29-Dec-06	0.1339	0.1945	0.0690	3.76	-0.0885	0.0878	-17.89***	21.15***	2626.6***
	TXU	US8731681081	01-Jan-90	29-Dec-06	0.1180	0.2775	-3.1942	76.52	-0.3709	0.1806	-15.82***	154.90***	1090332.0***
	Duke Energy	US26441C1053	01-Jan-90	29-Dec-06	0.0925	0.2339	-0.2969	12.06	-0.1614	0.1498	-16.31***	11.78***	26976.3***

Table 2.28: **Germany: Summary Statistics**

This table reports descriptive statistics of the daily log returns. The fourth and fifth column give the start and end date of the time series. The mean and the standard deviation are reported on an annual basis. The next two columns give the skewness and the excess kurtosis. The Min and Max columns report the smallest and highest return observed in the sample period. The column ADF reports the Augmented Dickey-Fuller Test of a unit root. The next column reports the value of the Q-Statistic with m lags. We follow Tsay (2005) and use $m = \log(T)$. *The last column gives the Jarque-Bera-Test of Normality. *** shows significance at the 1 % level, ** at the 5 % level and * at the 10 % level.*

Sector	Name	ISIN	Start Date	End Date	μ	σ	S	K	Min	Max	ADF	Q(m)	JB
Automobiles & Parts	BMW	DE0005190003	01-Jan-90	29-Dec-06	0.1136	0.3021	-0.0555	5.27	-0.1599	0.1133	-17.53***	27.42***	5155.0***
	VW	DE0007664005	01-Jan-90	29-Dec-06	0.0839	0.3079	-0.2001	3.71	-0.1466	0.1250	-15.14***	42.27***	2580.4***
	Continental	DE0005439004	01-Jan-90	29-Dec-06	0.1097	0.2984	0.0272	3.48	-0.1168	0.1282	-17.04***	12.84	2247.6***
	Rheinmetall	DE0007030009	01-Jan-90	29-Dec-06	0.0905	0.3484	0.0927	6.58	-0.1478	0.2102	-16.01***	19.18**	8022.1***
	Elringklinger	DE0007856023	01-Jan-90	29-Dec-06	0.1907	0.3441	-0.1110	33.81	-0.3555	0.3295	-17.80***	44.77***	211489.9***
Banks	Deutsche Bank	DE0005140008	01-Jan-90	29-Dec-06	0.0708	0.2832	-0.1360	4.78	-0.1235	0.1277	-16.50***	30.53***	4253.4***
	HVB	DE0008022005	01-Jan-90	29-Dec-06	0.0639	0.3411	0.0647	7.02	-0.1730	0.1848	-16.21***	29.57***	9130.3***
	Commerzbank	DE0008032004	01-Jan-90	29-Dec-06	0.0635	0.3008	0.0554	7.24	-0.1349	0.1803	-16.20***	15.81**	9708.6***
	Depfa Bank	IE0072559994	13-Mar-91	29-Dec-06	0.1462	0.2947	0.0897	6.21	-0.1645	0.1435	-14.81***	17.93**	6651.2***
	IKB	DE0008063306	01-Jan-90	29-Dec-06	0.0918	0.1871	0.1096	5.53	-0.0901	0.0795	-16.27***	39.89***	5670.3***
Basic Materials	BASF	DE0005151005	01-Jan-90	29-Dec-06	0.1219	0.2510	0.0501	3.24	-0.0872	0.1074	-17.59***	16.28**	1952.7***
	Bayer	DE0005752000	01-Jan-90	29-Dec-06	0.0872	0.2895	0.8381	27.28	-0.1843	0.3230	-16.96***	13.37*	138164.7***
	Linde	DE0006483001	01-Jan-90	29-Dec-06	0.0618	0.2540	-0.0265	4.16	-0.1132	0.1048	-16.81***	8.95	3217.2***
	K + S	DE0007162000	01-Jan-90	29-Dec-06	0.1281	0.3026	-0.0568	6.19	-0.1835	0.1547	-16.21***	14.03*	7107.9***
	Fuchs Petrolub	DE0005790406	01-Jan-90	29-Dec-06	0.1121	0.2707	0.2594	5.76	-0.1267	0.1278	-16.96***	24.20***	6194.8***
Consumer Services	Deutsche Lufthansa	DE0008232125	01-Jan-90	29-Dec-06	0.0610	0.3448	-0.0688	4.22	-0.1521	0.1640	-16.20***	11.20	3309.6***
	Celesio	DE000CLS1001	01-Jan-90	29-Dec-06	0.1298	0.2780	0.0451	2.53	-0.1192	0.0944	-17.74***	24.96***	1187.8***
	Karstadt Quelle	DE0006275001	01-Jan-90	29-Dec-06	0.0093	0.3333	0.0781	5.02	-0.1772	0.1483	-16.47***	8.62	4668.5***
	Springer	DE0005501357	01-Jan-90	29-Dec-06	0.0962	0.2697	0.6612	10.30	-0.1147	0.1709	-16.36***	9.07	19958.2***
	TUI	DE000TUAG000	01-Jan-90	29-Dec-06	0.0300	0.3072	-0.0117	5.73	-0.1734	0.1254	-16.10***	25.93***	6083.5***
Food & Beverage	Suedzucker	DE0007297004	01-Jan-90	29-Dec-06	0.0569	0.2307	0.3054	7.15	-0.0919	0.1335	-15.93***	33.70***	9532.1***
	Gabriel Sedl.	DE0007224008	01-Jan-90	29-Dec-06	0.0541	0.2231	-0.0905	19.67	-0.1671	0.1256	-18.24***	72.75***	71633.0***
	Baywa	DE0005194062	01-Jan-90	29-Dec-06	0.0944	0.2698	0.8125	7.96	-0.1224	0.1466	-16.67***	28.17***	12229.6***
	KWS Saat	DE0007074007	01-Jan-90	29-Dec-06	0.0830	0.2532	-0.1681	7.91	-0.1445	0.1147	-15.49***	75.04***	11597.6***
	SHB Stuttgart	DE0007318008	01-Jan-90	29-Dec-06	0.0766	0.2531	2.9084	155.45	-0.2766	0.4257	-18.12***	21.07***	4474844.0***
Healthcare	Bayer Schering Pharma	DE0007172009	01-Jan-90	29-Dec-06	0.1288	0.2603	0.3705	12.98	-0.1545	0.2258	-16.38***	16.41**	31304.4***
	Altana	DE0007600801	01-Jan-90	29-Dec-06	0.1361	0.3073	-0.5131	14.68	-0.2648	0.1431	-16.74***	26.99***	40052.9***
	Schwarz Pharma	DE0007221905	19-Jun-95	29-Dec-06	0.1734	0.4240	3.7203	88.25	-0.2471	0.5867	-13.32***	13.13	984832.0***
	Merck	DE0006599905	20-Oct-95	29-Dec-06	0.1057	0.3379	-0.1333	4.49	-0.1530	0.1245	-14.44***	31.11***	2474.7***
	Stada	DE0007251803	16-Feb-98	29-Dec-06	0.2201	0.3098	0.6720	11.75	-0.1308	0.2280	-13.15***	18.61**	13518.4***
Industrials	Siemens	DE0007236101	01-Jan-90	29-Dec-06	0.0795	0.2977	0.0936	4.45	-0.1067	0.1565	-15.27***	35.75***	3685.4***
	ThyssenKrupp	DE0007500001	01-Jan-90	29-Dec-06	0.0843	0.3016	-0.0249	4.14	-0.1659	0.1136	-16.35***	20.67***	3178.7***
	MAN	DE0005937007	01-Jan-90	29-Dec-06	0.1091	0.3149	-0.0799	3.45	-0.1468	0.0983	-16.71***	4.37	2211.7***
	GEA Group	DE0006602006	01-Jan-90	29-Dec-06	-0.0525	0.3797	-0.5844	12.14	-0.2669	0.1595	-16.63***	27.27***	27518.1***
	Pfleiderer	DE0006764749	01-Jan-90	29-Dec-06	0.0982	0.3979	3.7998	87.49	-0.2154	0.6078	-15.84***	13.77*	1426450.0***
Insurance	Allianz	DE0008404005	01-Jan-90	29-Dec-06	0.0436	0.3098	-0.0306	6.12	-0.1568	0.1380	-15.36***	34.90***	6952.2***
	Muenchner Rueck	DE0008430026	01-Jan-90	29-Dec-06	0.0620	0.3212	-0.1317	7.36	-0.1719	0.1653	-16.52***	65.27***	10060.3***
	Hannover Rueck	DE0008402215	30-Nov-94	29-Dec-06	0.1020	0.3309	-0.5396	11.13	-0.1989	0.1538	-14.49***	32.84***	16449.8***
	Gerling	DE0008418922	01-Jan-90	29-Dec-06	0.0065	0.3701	0.9697	79.79	-0.4234	0.4795	-15.69***	57.59***	1177373.4***
	Nuernberger	DE0008435967	01-Jan-90	29-Dec-06	-0.0062	0.2370	-0.5875	21.09	-0.2289	0.1361	-16.92***	23.30***	82553.0***
Pers. & Household	Beiersdorf	DE0005200000	01-Jan-90	29-Dec-06	0.1392	0.3020	0.0302	6.17	-0.1342	0.1610	-17.15***	69.40***	7045.7***
	Henkel	DE0006048408	01-Jan-90	29-Dec-06	0.0917	0.2537	-0.0353	5.59	-0.1423	0.1081	-19.02***	7.08	5790.2***
	Adidas	DE0005003404	17-Nov-95	29-Dec-06	0.1260	0.3236	-0.0012	3.14	-0.1126	0.1024	-14.14***	30.70***	1197.7***
	Puma	DE0006969603	01-Jan-90	29-Dec-06	0.1577	0.3917	0.4442	5.79	-0.1526	0.1653	-16.58***	15.96**	6353.2***
	Bijou Brigitte	DE0005229504	01-Jan-90	29-Dec-06	0.2211	0.3171	0.4127	19.49	-0.2331	0.2831	-16.07***	12.66	70445.6***
Technology	SAP	DE0007164600	01-Jan-90	29-Dec-06	0.2111	0.4210	0.1297	9.39	-0.2554	0.2355	-15.97***	27.60***	16321.9***
	Infineon	DE0006231004	10-Mar-00	29-Dec-06	-0.1652	0.5861	3.7095	68.60	-0.1654	0.6903	-12.47***	29.02***	353024.2***
	United Internet	DE0005089031	20-Mar-98	29-Dec-06	0.2829	0.7356	5.8707	134.87	-0.2643	1.0944	-11.49***	14.17*	1751980.9***
	Software AG	DE0003304002	23-Apr-99	29-Dec-06	0.0957	0.5859	-1.0304	19.31	-0.4367	0.2271	-12.62***	25.41***	31605.8***
	Freenet	DE0005792006	02-Dec-99	29-Dec-06	0.1274	0.8693	6.4651	136.51	-0.2424	1.2278	-11.00***	5.34	1449475.4***

Chapter 3

Intra-Industry Contagion Effects of Earnings Surprises in the Banking Sector

3.1 Introduction

Systemic risk in the banking sector has been analyzed in the previous chapter by empirically investigating the degree of dependencies in the tails of competitors' return distributions. This dependence measure has the big advantage, that it can be interpreted as conditional default probability. Significantly higher crisis probabilities in the banking sector, compared with all the other sectors of the economy were found. However, inherently due to the employed approach, it is impossible to tell whether this higher degree of dependence is due to narrow or broad systemic events. Systemic events in the broad sense are due to macroeconomic shocks, e.g. a shock in the level of interest rates, effecting all companies simultaneously. Contrarily, narrow systemic events are the result of micro-shocks at one company spilling over to others. A distinction between these two types of systemic risk is important, as crisis prevention and crisis management measures should be adequate.

In this chapter, we empirically investigate whether contagion effects exist in the banking sector.[1] This question is of interest since the banking sector is of crucial importance for the entire economy. Due to the high degree of interconnection with other sectors, a crisis in the banking sector could lead to severe consequences for the economy. Thus, to prevent such crises, the banking sector is highly regulated - although, regulation takes place mainly on an individual bank level. The presence of contagion effects, which increases the risk of a systemic financial crisis, i.e. the systemic risk in the financial system, calls for a regulation which takes the multiple linkages within the system into account and minimizes the risks due to spill-over effects.

We contribute to the literature by analyzing whether negative earnings surprises have contagious effects in the banking sector, i.e. whether they cause the reporting bank's competitors to react on the new information. We furthermore compare the banking sector with all the other industry sectors, especially the insurance sector, to investigate the question whether the banking sector behaves differently.

Earnings announcements provide information about the true value of the company and claims on it. If market prices before the announcement are based on the earnings expectations and markets are efficient, a negative surprise will lead to an immediate devaluation of the firms' value.

As earnings surprises are clear cut micro events (a macro-shock would result in adjustments of analysts earnings expectations and thus, no earnings surprise would be observable), these are perfectly suited for the purpose of studying information contagion, i.e. systemic risk in the narrow sense.

Whether the competitors security prices of a firm react negatively, positively, or not at all, depends on the type of information and the structure of the sector. If the information is firm specific and if no linkages exist with the other firms, only the respective company security prices should react.

However, negative information like a decrease in sales forecasts could be related

[1] The concept contagion refers in this context to spill-over effects due to information releases or real interconnections between companies and not volatility spill-overs between markets which are also labeled contagion in the literature.

to sector specific information and thus, reveal information for the entire sector, yielding adverse reactions of competitor security prices. This type of negative reaction is commonly referred to as information contagion.[2]

A firm specific event resulting in an adverse announcement can also have direct negative consequences for the competitors. This is the case if inter-firm connections increasing the default risk of the competitors through the increased risk of the originating firm exist. The best example - which is also the motivation of our study - is the banking sector in which strong connections exist between the institutions through the interbank lending and borrowing market. Thus, a credit event at one bank could spill over to other ones, easily leading to an increase in default risk of the entire sector, i.e. an increase in systemic risk.

However, a firm specific event could also lead to the opposite effect. As discussed in Lang and Stulz (1992) and Jorion and Zhang (2007), if imperfect competition is prevailing in the sector, problems in competing firms could allow firms to increase their prices or their market share to earn (at least temporary) an additional rent.[3] This effect is not exclusive for operating problems, as financial problems can cause negative reputation which possibly causes customers to refrain from doing business with the firm as analyzed by Maksimovic and Titman (1991), and thus, switching to a competing producer or service provider.

Taking everything into account, when adverse events happen, the observable consequences will be the sum of the aforementioned effects. Theoretically, there is no reason why one or the other effect should be predominant.

To detect possible contagion effects, we employ traditional event study methodology. The event study literature on the reaction of security prices due to the release of new information is extensive. Most papers analyze the effects on the company to which the new information applies. Stock price reactions after quarterly earnings announcements were first analyzed by Ball and Brown (1968) and Jones and

[2] See also Chapter 1 for a discussion of information and real contagion.

[3] As an example for this effect Jorion and Zhang (2007) name the bankruptcy of LTV Corporation, which benefited its major competitor, Bethlehem Steel.

Litzenberger (1970). They find that earnings surprises indeed is new information which is incorporated in stock prices of the reporting company.

The literature on intra-industry contagion is no where near as extensive. Lang and Stulz (1992) and Jorion and Zhang (2007) study the intra-industry effects due to bankruptcies (announcements), where the first paper measures the effects on the stock, the latter on the credit default swap market. Both studies conclude that intra-industry contagion effects after bankruptcies exist. In addition, Jorion and Zhang (2007) find that this result holds for chapter 11 bankruptcies only. For chapter 7 bankruptcies the authors find contrary evidence, although it is statistically weak due to only 22 relevant observations.

The first paper analyzing intra-industry effects following earnings surprises is Foster (1981), where a relatively small sample of 75 events is studied. A negative impact of a firm's earnings release on the stock prices of other firms operating in the same sector is found only, if the announcing firm reacts negatively itself. Han et al. (1989) study the effect of voluntarily disclosed earnings forecasts of managers and find evidence for contagious effects. Other studies finding evidence for information transfers following earnings surprises include Han and Wild (1990) and Ramnath (2002).

Akhigbe et al. (1997) detect intra-industry effects of bond rating changes using a sample of 354 events reported in The Wall Street Journal. The effect of rating changes on earnings forecasts of rival firms, i.e. firms operating in the same industry, is studied by Caton and Goh (2003). They find significant effects, but only if the downgraded firm is non-investment grade.

None of the studies mentioned above consider the banking sector separately. The sample of Lang and Stulz (1992) does not contain any events in the banking sector. The other cited studies report their results on an aggregated level only, which may be due to the small sample sizes.[4]

[4] The sample of Jorion and Zhang (2007) includes 272, Akhigbe et al. (1997) includes 354, Caton and Goh (2003) includes 453, Foster (1981) includes 75 and Han et al. (1989) includes 195 observations in total.

A few papers analyzing adverse events in the banking sector do exist. Akhigbe and Madura (2001) study 99 publicized bank failures and find contagion effects on rival banks, which are stronger when the failed bank is large, a multibank holding, or publicly held. The contagion effects of dividends reductions at banks are analyzed by Slovin et al. (1999). Their main finding is that these reductions are negative events for both, large super-regional banks as well as regional banks themselves, but only cuts at super-regional banks have negative consequences on stock prices of other banks.

Our study is closely related to this strand of literature. We fill the gap in the literature between studies on intra-industry contagion effects of earnings surprises and studies of the banking sector. To the best of our knowledge, this is the first study analyzing contagion effects in the banking sector due to negative earnings surprises. Furthermore, we are the first to compare the results with the average of the non-banking sectors, and especially the insurance sector, which is a second highly regulated sector of the US economy.

The main results of our study are as follows. We find that negative earnings surprises cause significant contagion effects in the banking sector. In contrast, the non-banking sectors show, on average, no signs of contagious behavior. The difference between the banking sector and the non-banking sectors proves to be highly significant. When analyzing the insurance sector separately, we do not find any contagion effects which indicates a smaller degree of systemic risk in the insurance sector. Finally, we find that contagion in the banking sector is the strongest, if the originator as well as the affected institutions are important banks. These results support the need for a system-based regulation of the banking sector.

The outline of this chapter is as follows. Section 3.2 contains a description of the study design including the used data set. In Section 3.3, we present the empirical results. Concluding remarks are stated in Section 3.4.

3.2 Design of the Study

3.2.1 Goal and Overview of the Study

The goal of our study is to investigate whether information contagion is present in the banking sector and whether the banking sector behaves differently compared with the other sectors of the economy. To do so, we use negative earnings surprises, i.e. analysts' forecasts minus realized earnings, as informational event. Negative earnings surprises are perfectly suited as all macroeconomic information should already be included in the analysts' forecasts. The new negative information is thus mainly attributable to the reporting company itself. We measure the contagion effect by analyzing the reaction of the stock prices of companies operating in the same sector as the reporting company.

We first analyze whether the reporting company's stock price exhibit a significant decline to make sure that the negative earnings surprise indeed is a negative information for the reporting company. We then analyze the stock price reaction of companies operating in the same sector. To analyze whether the banking sector exhibit a different behavior we compare the results with the non-banking sectors and also the insurance sector.

3.2.2 Data

We analyze the effects of negative earnings surprises on the stock prices of the affected firms' competitors over the sample period January 1st, 1990 through March 21st, 2007 in the United States using traditional event study methodology.[5] The earnings data is obtained from the Institutional Brokers' Estimate System (I/B/E/S) retrieved via Thomson Financial Datastream.[6] We focus our study on

[5]For an overview of the event study methodology and applications in economics and finance see, e.g., Brown and Warner (1980), Brown and Warner (1985), and MacKinlay (1997). For more recent applications see also the literature discussed in section 3.1.

[6]I/B/E/S is generally viewed as the premier database and supplier of earnings forecasts for professionals and has also been used extensively in academic studies.

the US, as data availability regarding I/B/E/S is by far the best.[7] We obtain the time series of analysts' mean forecasts of earnings per share for the following quarter as well as the number of analysts covering the particular company. We then exclude all observations for which less than three analysts report earnings forecasts. Additionally, the cross-sectional standard deviations of the analysts' forecasts are obtained. For each observed earnings forecast we sample the subsequently reported earnings per share. To do this, we have to determine the precise date on which the earnings were reported. This information is obtained from the Worldscope database, and used as the event date in the following study.

We calculate Standardized Unexpected Earnings using two different approaches. First, we follow Foster et al. (1984) (model 1) and Han and Wild (1990) and compute the relative deviation of the reported earnings from the forecasted earnings, precisely,

$$SUE^1_{i,t} = \frac{EPS_{i,t} - \widehat{EPS}_{i,t}}{|EPS_{i,t}|}, \tag{3.1}$$

for company i and quarter t. $\widehat{EPS}_{i,t}$ is the mean forecast one day prior to the release of the realized earnings; $EPS_{i,t}$ is the subsequently reported earnings per share. In Equation (3.1), the deviation of the forecast from the realized earnings is standardized by the absolute value of the realized earnings, yielding a relative surprise measure. As can been seen directly from the definition of $SUE^1_{i,t}$, this way to standardize the earnings surprise could be problematic in case the company realize earnings of very small size or even zero.

Thus, to assure the robustness of the analysis with respect to the chosen surprise measure, we standardize the earnings surprise in a second way. The absolute earnings surprise is normalized by the dispersion of the analysts' forecasts,

[7] The data availability for Germany was not sufficient to conduct the study on this market.

$$SUE_{i,t}^2 = \frac{EPS_{i,t} - \widehat{EPS}_{i,t}}{\sigma[\widehat{EPS}]}, \tag{3.2}$$

with $\sigma[\widehat{EPS}]$ denoting the cross-sectional standard deviation of the analysts' forecasts. This approach, which has also been used in the literature, e.g. by Datta and Dhillon (1993) or Mendenhall (2004), incorporates the degree of surprise; a deviation from the mean forecast will be less surprising if there is a high level of discordance about the future earnings among the analysts. Analogous to our first standardization, where the Standardized Unexpected Earnings is not well defined when an earnings observation of zero occurs, this second way to normalize the earnings surprise suffers from the possibility of a zero denominator. This situation occurs if all analysts reporting to I/B/E/S exactly agree regarding their earnings forecast. Furthermore, earnings or dispersion values close to zero might distort our analysis as the standardized earnings surprises will become very large.

We tackle this stability problem in the following way. First, we delete all observations with $EPS_{i,t} = 0$ or $\sigma[\widehat{EPS}] = 0$. Second, to deal with potential outliers, we calculate the mean and standard deviation of all earnings surprises SUE^1 and SUE^2, respectively, and delete all values outside a three-sigma interval. All results reported in Section 3.3 are computed this way, using an outlier cleaned data set. To ensure robustness with respect to the outlier treatment, we have repeated the entire study once without the second step of deleting the outliers and once using a five-sigma interval instead of the three-sigma interval, both yielding very similar results, statistically undistinguishable. As an additional robustness check, we have adopted the ad-hoc approach of Mendenhall (2004) to set $\sigma[\widehat{EPS}] = 0.01$ if the reported standard deviation is zero. Again, no notable differences appeared.

Table 3.1: **Overview of the Industry Sectors**

This table reports the industry sectors considered. The classification is according to the Industry Classification Benchmark (ICB).

Oil & Gas Producers	Automobiles & Parts	Fixed Line Telecommunication
Oil Equipment, Serv. & Distr.	Beverages	Mobile Telecommunication
Chemicals	Food Producers	Electricity
Forestry & Paper	Household Goods	Gas, Water & Multiutilities
Industrial Metals	Leisure Goods	Banks
Mining	Personal Goods	Nonlife Insurance
Construction & Materials	Tobacco	Life Insurance
Aerospace & Defense	Health Care Eq.	Real Estate
General Industrials	Pharma & Biotech	General Financial
Electronic & Electrical Eq.	Food & Drug Retailers	Equity Investment Instr.
Industrial Engineering	General Retailers	Software & Computer Services
Industrial Transportation	Media	Technology Hardware
Support Services	Travel & Leisure	

3.2.3 Abnormal Returns

The subsequent analysis is based on the same period as our event data was sampled from. We group the event data by industry sector based on the Industry Classification Benchmark (ICB), resulting in 38 sectors.[8] The list of these sectors is reported in Table 3.1.[9]

To measure the reaction of competitors, i.e. firms operating mainly in the same industry sector, we sample stock market returns of all companies from the respective sectors traded at NASDAQ and covered by I/B/E/S during the examined time period. As we do not require data availability over the entire sample period, the competitor portfolio is changing as firms list/delist at NASDAQ or analysts begin/abort covering firms.

Following other studies (e.g. Akhigbe et al. (1997) or Jorion and Zhang (2007)), we form equally weighted competitor portfolios. An alternative method is to form

[8]Originally the ICB is classified into 39 sectors. However, for the sector nonequity investment instruments we have practically no observations and thus, excluded it from the analysis.

[9]As the data set used in this chapter is much larger than the data used in the other chapters of this thesis we are able to use a finer classification scheme, based on level three of the ICB.

value weighted portfolios. This would relate to the overall wealth effects in the economy; however, as we want to measure the average reaction, and not the value weighted reaction of companies to adverse news from their competitors, equally weighted returns are more appropriate in this context.

Table 3.2 reports summary statistics of the sampled competitor portfolios. Overall, the competitor portfolios include 32.13 companies per event on average. The banking sector competitor portfolio contains between 41 and 46 companies at each point in time, with an average of 45.57 banks and a standard deviation of 0.81 banks.

For each event date t, we define the abnormal return $AR_{p,t}$ of a competitor portfolio p as the difference between the realized return $R_{p,t}$ and the expected normal return conditioning on information up to time t denoted by X_t:

$$AR_{p,t} = R_{p,t} - E[R_{p,t}|X_t]. \tag{3.3}$$

The realized return is computed from end of day prices as total return, i.e. including dividends and adjusted for other price, but not wealth relevant corporate actions, such as right issues and stock splits. The expected normal return is estimated according to the market model approach,

$$E[R_{p,t}|X_t] = \hat{\alpha}_p + \hat{\beta}_p R_{m,t}, \tag{3.4}$$

where $R_{m,t}$ denotes the market index return. As the market index we employ the S&P 500 as it is the major well diversified US stock market index. The two parameters $\hat{\alpha}_p$ and $\hat{\beta}_p$ are sector specific and are estimated over the pre-event period $[t_{-T}, t_{-2}]$ for each event. We choose the estimation window to cover approximately one year, i.e. $T = 250$. Observations on other event dates are excluded from the estimation data to minimize possible correlation bias.

Table 3.2: **Size of Competitor Portfolios**

This table reports summary statistics regarding the number of stocks N being in the competitor portfolios. $\overline{N}$ denotes the sample mean whereas, σ, min, and max are the standard deviation, minimum, and maximum value, respectively.

Sector	$\overline{N}$	$\sigma[N]$	$min[N]$	$max[N]$
Banks	**45.57**	**0.81**	**41**	**46**
Nonlife Insurance	46.71	0.60	43	47
Life Insurance	12.91	0.28	12	13
Oil & Gas Producers	30.68	0.64	28	31
Oil Equipment, Serv. & Distr.	44.81	0.43	43	45
Chemicals	24.68	0.59	22	25
Forestry & Paper	1.93	0.26	1	2
Industrial Metals	11.91	0.31	10	12
Mining	3.98	0.15	3	4
Construction & Materials	17.93	0.31	16	18
Aerospace & Defense	12.92	0.31	11	13
General Industrials	22.76	0.49	21	23
Electronic & Electrical Eq.	25.93	0.28	24	26
Industrial Engineering	21.78	0.58	19	22
Industrial Transportation	14.92	0.28	14	15
Support Services	32.93	0.30	31	33
Automobiles & Parts	8.92	0.27	8	9
Beverages	9.95	0.23	9	10
Food Producers	21.97	0.17	21	22
Household Goods	18.92	0.27	18	19
Leisure Goods	7.92	0.28	7	8
Personal Goods	13.00	0.00	13	13
Tobacco	3.00	0.00	3	3
Health Care Eq.	51.89	0.31	51	52
Pharma & Biotech	33.86	0.34	33	34
Food & Drug Retailers	11.99	0.12	11	12
General Retailers	59.99	0.10	59	60
Media	38.89	0.36	37	39
Travel & Leisure	36.86	0.38	35	37
Fixed Line Telecommunication	9.98	0.13	9	10
Mobile Telecommunication	5.84	0.37	5	6
Electricity	33.59	0.72	29	34
Gas, Water & Multiutilities	20.81	0.51	17	21
Real Estate	48.81	0.51	46	49
General Financial	47.85	0.44	46	48
Equity Investment Instr.	2.00	0.00	2	2
Software & Computer Services	34.91	0.29	34	35
Technology Hardware	62.73	0.62	59	63
All	32.13	15.04	1	63

Under the null hypothesis of no abnormal reaction, the standardized average abnormal returns follow the Student-t distribution with $T-2$ degrees of freedom, which is approximately normal. The standard deviations of the abnormal returns are also estimated over the estimation windows. Following Mikkelson and Partch (1985), we adjust the estimated standard deviations by the prediction error resulting in

$$\sigma_{p,t} = s_{p,t}\sqrt{1+\frac{1}{(T-1)}+\frac{(R_{m,t}-\bar{R}_m)^2}{\sum_\tau (R_{m,\tau}-\bar{R}_m)^2}}\,, \tag{3.5}$$

where $s^2_{p,t}$ is the residual variance from the market model adjusted for autocorrelation and heteroskedasticity by the method of Newey-West.

All events with overlapping event periods $[-1, 1]$ are excluded from the analysis. We use this rather short event window to reduce problems from non-independent observations and to obtain a sufficient number of events. Compared with event studies analyzing the effects on the reporting company itself, the potential for overlapping event windows is much greater in our case, as each reporting company itself is also included in the competitor portfolio if another company from the same sector exhibits an event.

We calculate the abnormal returns for the event day [0] and the subsequent day [1]. This is done as we do not have precise information about the timing of the information release on the event day. If it were after the closing of the exchange, potential reactions would be observable on the following trading day and not on the event day.

Table 3.3: **Distribution of Events Across Time**

This table reports the distribution of negative earnings surprises over time. The displayed numbers are the sample size after deleting observations with a zero denominator in one of the definitions of standardized earnings surprises. Note that 2007 only include observations until March, 21st, which was the sampling date.

Year	1990	1991	1992	1993	1994	1995
# Earnings Surprises	1	2	298	414	366	363
Year	1996	1997	1998	1999	2000	2001
# Earnings Surprises	400	361	442	424	305	419
Year	2002	2003	2004	2005	2006	2007
# Earnings Surprises	407	475	435	444	439	24

3.3 Empirical Results

3.3.1 Description of the SUE Data

In this section, we report the results of the intra-industry contagion analysis due to negative earnings surprises. In total we sample 6,019 events of negative SUE after removing all infinite values due to zero earnings per share or volatility of earnings estimate, but before filtering using the three-sigma interval as described in the previous section.[10]

Table 3.3 reports the distribution of earnings surprises across the sample period. Except for the first two years, with almost no observations, the earnings surprise sample is well balanced across time. Table 3.4 reports the distribution of events across sectors. The smallest number of events is observed for the equity investments instruments sector. The number of events in the banking sector is among the highest.

[10]The original sample contained 6397 observations. Both values SUE^1 and SUE^2 are deleted if at least one of both is not well defined, resulting in a relative decrease of the sample size of 5.91 %.

Table 3.4: **Distribution of Events Across Sectors**

This table reports the distribution of negative earnings surprises across sectors. The displayed numbers are the sample size after deleting observations with a zero denominator in one of the definitions of standardized earnings surprises.

Sector	Earning Surprises
Banks	**308**
Nonlife Insurance	339
Life Insurance	58
Oil & Gas Producers	300
Oil Equipment, Serv. & Distr.	331
Chemicals	212
Forestry & Paper	29
Industrial Metals	138
Mining	44
Construction & Materials	139
Aerospace & Defense	122
General Industrials	245
Electronic & Electrical Eq.	219
Industrial Engineering	169
Industrial Transportation	134
Support Services	146
Automobiles & Parts	92
Beverages	73
Food Producers	97
Household Goods	118
Leisure Goods	73
Personal Goods	50
Tobacco	21
Health Care Eq.	232
Pharma & Biotech	214
Food & Drug Retailers	76
General Retailers	92
Media	259
Travel & Leisure	195
Fixed Line Telecommunication	59
Mobile Telecommunication	70
Electricity	423
Gas, Water & Multiutilities	246
Real Estate	95
General Financial	170
Equity Investment Instr.	7
Software & Computer Services	122
Technology Hardware	302
Σ	6019

Table 3.5: **Summary Statistics of Negative Earnings Surprises**

This table reports summary statistics for the negative earnings surprises SUE calculated from the sampled I/B/E/S data and after deleting outliers as describe in the text. $\overline{SUE}$ denotes the mean, whereas σ, med, min, and max are the standard deviation, median, minimum, and maximum value.

	$\overline{SUE}$	$\sigma[SUE]$	$med[SUE]$	$min[SUE]$	$max[SUE]$
SUE^1	-0.2669	0.4999	-0.1	-5.0	-0.0016
SUE^2	-2.1660	2.7015	-1.0	-21.0	-0.0170

After deleting outliers not in the three-sigma interval, the data set decreases to 5,946 observations. Summary statistics of the cleaned sample are given in Table 3.5. As we only consider negative earning surprises, the distribution is naturally skewed to the left yielding smaller mean than median values. The mean earnings surprise standardized by its absolute realization (SUE^1) is -0.27, with a minimum value of -5.0 and a maximum value of -0.0016. When standardizing using the dispersion of analyst forecasts (SUE^2) the mean is -2.17, the minimum and maximum values are -21.0 and -0.0170, respectively.

3.3.2 Results on Announcing Companies

First, we analyze the effect of negative earnings surprises on the reporting companies themselves. This analysis will show, whether on average the news indeed was a negative surprise, and we can verify the timing of the market responses to the new information, i.e. whether the reported date in the Worldscope database was actually the date of information release to the public. If the information was available to the public, or at least to the analysts making the forecasts, before the reported event date, or the date of reported earnings were not correct, we should, on average, not observe an abnormal reaction by the reporting company. In this case, we would not expect the competitor companies to react as

Table 3.6: **Share Price Reaction of Reporting Company**

This table reports the average abnormal stock reaction of the companies announcing earnings surprises. The different panels condition on certain negative SUE. The last three columns report the p-values testing the null of positive abnormal returns. Sign-test is a standard Binomial sign test, whereas ws-test stands for the Wilcoxon sign test.

NOBS	Event Date	AR (%)	p[t-test]	p[sign-test]	p[ws-test]
Panel A: $SUE^{1,2} < 0$					
5946	[0]	-0.7322	0.0000	0.0000	0.0000
5946	[1]	-0.5417	0.0000	0.0000	0.0000
Panel B: $SUE^{1} <$ -5 %					
4213	[0]	-0.7778	0.0000	0.0000	0.0000
4213	[1]	-0.5622	0.0000	0.0000	0.0000
Panel C: $SUE^{1} <$ -10 %					
2980	[0]	-0.7870	0.0000	0.0000	0.0000
2980	[1]	-0.5648	0.0000	0.0000	0.0000
Panel D: $SUE^{2} <$ -1					
3815	[0]	-0.8694	0.0000	0.0000	0.0000
3815	[1]	-0.6658	0.0000	0.0000	0.0000
Panel E: $SUE^{2} <$ -2					
1927	[0]	-1.1475	0.0000	0.0000	0.0000
1927	[1]	-0.7191	0.0000	0.0000	0.0000

well.

Table 3.6 reports the average abnormal returns of the companies announcing earnings surprises.[11] Panel A displays the results for all negative earnings surprises. Panel B and C show the results for subsamples, conditioned on SUE^1 being smaller than -5 % and -10 %; Panel D and E condition on SUE^2 being smaller than -1 and -2, respectively.

To test the significance of the results, we perform a standard t-test as well as two standard nonparametric tests. The Binomial sign test simply tests whether the median is significantly smaller than zero using information of the signs (plus or

[11] The subsequent analysis on intra-industry contagion in the following sections splits the data set further by industry (bank or non-bank) and size. We refrain from reporting the price reactions of reporting companies on this more detailed level as this is not the focus of the analysis.

minus) of the observations only, whereas the Wilcoxon sign test takes the size of deviation from zero of the observations into account. The p-values of the respective tests are reported in the last three columns.

On the event date [0] the average negative abnormal daily return is -0.73 %, which is followed by -0.54 % on the next successive day. Both values are significantly smaller than zero, with p-values very close to zero. Conditioning on more negative earnings surprises, i.e. news with a bigger negative surprise, the average abnormal returns decreases, as to expect, down to -0.78 % for $SUE^1 < -5\,\%$ and -0.79 % for $SUE^1 < -10\,\%$, and -0.87 % for $SUE^1 < -1$ and -1.15 % for $SUE^2 < -2$. All abnormal returns in the various subsamples of Table 3.6 are significantly negative. Furthermore, the first ex-event day [1] also shows significant negative average returns, which are, however, in absolute terms, about 30 % smaller than the event day abnormal returns.

The magnitude of these company specific stock price reactions after negative earnings surprises are well in line with previous studies. Rendleman Jr. et al. (1982) report stock price reactions of -1.4 %, -1.0 %, -0.7 %, -0.2 %, and 0.1 % for the first to fifth decile of earnings surprises. As they also include positive surprises, only the first five deciles are comparable. Conditioning on $SUE^2 < -1$, Datta and Dhillon (1993) find an average negative stock price reaction on the event day of -1.39 % when preceding, and -0.94 % when following dividend surprises.

We conclude that the sampled earnings surprises were indeed negative news to the market and had a significant negative price impact on the reporting companies' stocks.

3.3.3 Results on Competitor Companies

To get an first overview, Table 3.7 reports summary statistics of the abnormal returns of the competitor portfolios. The focus of this chapter lies on the banking sector, thus, we split our sample into banks and non-banks and perform the analysis

Table 3.7: **Summary Statistics of Abnormal Returns**

This table reports summary statistics of the abnormal returns in percent. q_{25} *and* q_{75} *denote the 25 % and the 75 % quantiles, respectively.*

Banks						
NOBS	Event Date	mean	std. dev.	median	q_{25}	q_{75}
291	[0]	-0.0843	0.7595	-0.0993	-0.3990	0.3164
291	[1]	0.0165	0.8130	-0.0186	-0.4057	0.3740
Non-Banks						
NOBS	Event Date	mean	std. dev.	median	q_{25}	q_{75}
5655	[0]	-0.0015	1.1004	-0.0135	-0.5321	0.5076
5655	[1]	0.0190	1.0576	0.0084	-0.4969	0.5150

separately. One can observe negative mean and median returns at date [0] for both samples, however the non-banks are much closer to zero. The standard deviations are, compared to the mean values, relatively large.

The significance levels of the abnormal returns of the competitor portfolios are reported in Table 3.8. We display the results for the sample of all negative earnings surprises as well as for the same subsamples used in Table 3.6. Again, we report p-values of the t-test, the Binomial sign test, and the Wilcoxon sign test.

The left part of the table presents the results for the banking sector, the right part of the table for the other sectors. Note that, although we report average results for all non-banks together, when computing returns for an earnings surprise in a sector, we only consider the competitors of the reporting company, i.e. firms operating in the same sector.

We consider the entire data set, i.e. Panel A, first. For the banking sector, we observe on the event date an abnormal return of -0.0843 % which is significantly negative with a p-value of 0.0143 for the t-test and 0.0275 for the Wilcoxon sign test, indicating the existence of contagion. On the subsequent day the abnormal return is slightly positive, but, not significantly different from zero.

In contrast, the non-banking sectors show, on average, no signs of contagious behavior. The average abnormal return of competitor portfolios is -0.0015 % on the event day and 0.0190 % on the subsequent day; both being not significantly different from zero, and thus, not showing any contagion effects.

Panel B and C condition on the relative deviation of the expectation from the realization. As one expects, the abnormal return decreases conditioning on stronger deviations with -0.1300 % for $SUE^1 < -5\,\%$ and -0.1781 % for $SUE^1 < -10\,\%$ on the event day, both being highly significant with p-values below 0.01 for the t-test and below 0.02 for the Wilcoxon sign test. Again, no significant abnormal returns are observed on the first post event day.

Conditioning on the degree of surprise, measured by the unexpected earnings normalized with the dispersion of forecasts (SUE^2), yields similar results. The event date return increases (in absolute terms) by the degree of surprise to -0.0913 % and -0.1332 %. Again, the post event date average abnormal return remains insignificant. In contrast, the average abnormal returns of the non-banking sectors are insignificant, even when conditioning on greater relative deviations or surprises.

To see whether the observed different behavior of the banking sector and the other sectors is also statistically significant, we test whether the difference of abnormal returns is different from zero using a standard t-test. Table 3.9 reports the results of this test. The difference on the event date is -0.0828 % for the entire set of negative earnings surprises, which is significant with a p-value of 0.0206. Conditioning on bigger surprises increases the difference and decreases the p-value down to 0.0043 for relative surprises below -10 %. Overall, the reported evidence suggests significantly higher negative reactions of competitors in the banking sector compared with the non-banking sectors.

One might ask whether the results of the conducted t-tests are biased by overlapping event windows of the banking and the non-banking sectors, and thus, correlated observations. If, for example, a negative earnings surprise in the banking

Table 3.8: **Share Price Reaction of Competitors**

This table reports the reactions of the announcing firms' competitor portfolios. The left part reports the results for the banking sector, the right part for the other sectors. The different panels condition on certain negative SUE. The last three columns of each part report the p-values testing the null of positive abnormal returns. Sign-test stands for a standard Binomial sign test, whereas ws-test stands for the Wilcoxon sign test.

Banks						**Non-Banks**					
NOBS	Event Date	AR (%)	p[t-test]	p[sign-test]	p[ws-test]	NOBS	Event Date	AR (%)	p[t-test]	p[sign-test]	p[ws-test]
Panel A: $SUE^{1,2} < 0$											
291	[0]	-0.0843	0.0143	0.0637	0.0275	5655	[0]	-0.0015	0.4539	0.1009	0.2010
291	[1]	0.0165	0.6670	0.6805	0.5857	5655	[1]	0.0190	0.9306	0.7797	0.8348
Panel B: $SUE^1 < -5\,\%$											
144	[0]	-0.1300	0.0079	0.0276	0.0104	4069	[0]	0.0007	0.5186	0.8756	0.6586
144	[1]	-0.0452	0.1994	0.0401	0.0355	4069	[1]	0.0289	0.9709	0.8833	0.9300
Panel C: $SUE^1 < -10\,\%$											
83	[0]	-0.1781	0.0062	0.0138	0.0188	2897	[0]	0.0153	0.7964	0.4556	0.2944
83	[1]	0.0151	0.5842	0.7448	0.8205	2897	[1]	0.0358	0.9736	0.7713	0.8962
Panel D: $SUE^2 < -1$											
233	[0]	-0.0913	0.0159	0.0443	0.0339	3582	[0]	-0.0013	0.4678	0.1051	0.2076
233	[1]	0.0382	0.8166	0.6529	0.5141	3582	[1]	0.0242	0.9145	0.8203	0.8116
Panel E: $SUE^2 < -2$											
109	[0]	-0.1332	0.0165	0.0175	0.0285	1818	[0]	0.0196	0.8058	0.7152	0.5164
109	[1]	0.0121	0.5774	0.7173	0.7419	1818	[1]	0.0263	0.8756	0.9237	0.8992

Table 3.9: **Results of Test of Difference**

This table reports the differences and significance levels between the average reaction of the banking sectors and the average reaction of the other sectors. ΔAR is the difference between the abnormal returns of the banking sector and the non-banking sectors reported in Table 3.8.

NOBS	Event Date	ΔAR (%)	p[t-test]
Panel A: $SUE^{1,2} < 0$			
5655 / 291	[0]	-0.0828	0.0206
5655 / 291	[1]	-0.0024	0.4759
Panel B: $SUE^{1} <$ -5 %			
4069 / 144	[0]	-0.1307	0.0098
4069 / 144	[1]	-0.0742	0.0919
Panel C: $SUE^{1} <$ -10 %			
2897 / 83	[0]	-0.1934	0.0043
2897 / 83	[1]	-0.0207	0.3885
Panel D: $SUE^{2} < -1$			
3582 / 233	[0]	-0.0900	0.0237
3582 / 233	[1]	0.0140	0.6217
Panel E: $SUE^{2} < -2$			
1818 / 109	[0]	-0.1528	0.0109
1818 / 109	[1]	-0.0141	0.4155

sector has negative consequences for a subset of sectors and not the entire market, this effect would not be completely captured by the normalizing using expected returns based on the market model. However, if this cross-sectorial dependence is present in the considered data, it will decrease the possibility of rejecting the null hypothesis successfully, as the difference in abnormal return between the related sectors would decrease. Thus, our results can be regarded as conservative and would be even stronger if controlling for overlapping event windows of banking and non-banking earnings surprises.

A second highly regulated sector of the economy is the insurance sector. Similarly to the banking sector, insurance companies are regulated on an individual level. However, when discussing regulating the financial sector on a systemic level, insurance companies are frequently mentioned as part of the system which should

Table 3.10: **Contagion in the Insurance Sector**

This table reports the reactions from the announcing firms' competitor portfolios for the insurance sector. The different panels condition on certain negative SUE. The last three columns report the p-values testing the null of positive abnormal returns. Sign-test stands for a standard Binomial sign test, whereas ws-test stands for the Wilcoxon sign test.

NOBS	Event Date	AR (%)	p[t-test]	p[sign-test]	p[ws-test]
Panel A: $SUE^{1,2} < 0$					
394	[0]	-0.0049	0.4409	0.3622	0.4789
394	[1]	-0.0083	0.4015	0.5000	0.4853
Panel B: $SUE^{1} <$ *-5 %*					
275	[0]	0.0113	0.6153	0.8362	0.6435
275	[1]	-0.0482	0.1064	0.0923	0.1443
Panel C: $SUE^{1} <$ *-10 %*					
194	[0]	-0.0581	0.1077	0.4147	0.1889
194	[1]	-0.0379	0.2095	0.4147	0.3736
Panel D: $SUE^{2} < -1$					
266	[0]	-0.0381	0.1727	0.4756	0.2984
266	[1]	-0.0041	0.4596	0.4756	0.4868
Panel E: $SUE^{2} < -2$					
161	[0]	-0.0578	0.1362	0.5000	0.1611
161	[1]	0.0015	0.5116	0.5673	0.5460

be included. To investigate the validity of this argument, we analyze the insurance sector separately, in order to see whether contagion effects exist within this sector. As can be seen from Table 3.1, insurance companies are classified as life or non-life insurers in our study. Due to the small number of events in the life insurance sector (58 observations, see Table 3.4), we report the pooled results. We consider both sectors together, however, as before, when forming competitor portfolios, only companies of the specific sector are considered. Table 3.10 reports the average abnormal stock returns for the insurance sector. Although the abnormal return of the reporting insurers' competitor portfolios are negative in most instances, the size is much smaller compared with the banking sector and only insignificantly smaller than the average of all sectors. For example, the observed abnormal return on the event day for the entire data set is -0.0049 %, -0.0843 % for the banking sector and -0.0015 % for the non-banking sectors. In all subsamples all significance tests fail to reject the hypothesis of an abnormal return greater than zero.[12] Therefore, in contrast to the banking sector, no contagion effects are observable in the sample of negative earnings surprises at the insurance companies considered.

3.3.4 Effect of Size of Announcing and Competitor Banks

Finally, we analyze whether the strength of the contagion effects differ in characteristics of the announcing banks. More precisely, we suspect that adverse events at more important banks cause stronger negative contagion effects at their competitors than adverse announcements from less important banks. The 'importance' of a bank is proxied by its size, i.e. its market capitalization, which is also obtained from Thomson Financial Datastream. We use the average market capitalization of the year in which the earnings surprise was reported. Based on this criterion, we split the banking sample by the average market capitalization of the sector, which is the annual average of the year in which the event takes place.[13] Table 3.11 displays the results of this analysis. Panel A in the upper part reports the average abnormal returns of the smaller banks in the sample, Panel B the average abnormal returns of the larger banks. The latter is, with -0.1324 %, almost twice as large as the former with -0.0715 %. The significance level is, however, less conclusive, with a p-value of 0.0683 (t-test) and 0.0749 (Wilcoxon sign test) for the subsample of big banks, and 0.0461 (t-test) and 0.0752 (Wilcoxon sign test) for the subsample of small banks. This might be a consequence of the reduced sample size for subsample B and thus, increased standard errors. Furthermore,

[12] A formal test of difference between the banking and insurance sector was also conducted. However, it was not possible to reject the hypothesis of a difference of zero at reasonable significance levels.

[13] An alternative would be to split the sample by the median market capitalization. As the sample is not equally balanced with respect to size, the average value is, however, more appropriate in this context.

Table 3.11: **Effect of Announcers' Size**

This table reports the abnormal reactions from competitor portfolios divided by the average size of the company reporting negative unexpected earnings. $\overline{MV}$ *stands for the average market capitalization ,* MV_i *for the market capitalization of the reporting bank. Sign-test stands for a standard Binomial sign test, whereas ws-test stands for the Wilcoxon sign test.*

		Banks			
NOBS	Event Date	AR (%)	p[t-test]	p[sign-test]	p[ws-test]
Panel A: Reporting Bank: $MV_i < \overline{MV}$					
230	[0]	-0.0715	0.0461	0.1312	0.0752
230	[1]	0.0161	0.8618	0.5784	0.5557
Panel B: Reporting Bank: $MV_i > \overline{MV}$					
61	[0]	-0.1324	0.0683	0.1528	0.0749
61	[1]	-0.0951	0.1422	0.3045	0.2532

one can observe a strong negative reaction on the post event day if a large bank is reporting a negative surprise, which is, however, not significant.[14]

In the next analysis, we also subdivide the competitor portfolio with respect to the size of the competitor banks. Two disjoint portfolios are formed, one containing smaller than average banks, the second bigger than average banks. We repeat the analysis for these two subsamples first, considering all events, i.e. not differentiating whether the reporting bank is a small or big one. Afterwards, we further subdivide the sample by size of the reporting bank as in the analysis at the beginning of this subsection. The results of this analysis are reported in Table 3.12.

The left part of the table displays the average abnormal earning surprises for the portfolio of all big competitors, whereas the right part contains the results for the small competitor portfolios. Panel A considers earning surprises at all banks. Panel B and C subdivide this sample into events at big and small banking institutions. When considering all earnings surprises, the average abnormal return of big

[14]We do not report the results for subsamples conditioning on the degree of earnings surprise as in the previous section, as the number of events decreases fast, especially in the large bank subsamples, yielding non informative results.

Table 3.12: **Influence of Size of Competitor Banks**

This table reports the results when splitting the competitor bank portfolio into big (above average) and small (below average) banks, measured by the market value. The left part reports the result for the big banks, the right part for the small banks. Panel A contains all events, whereas Panel B and Panel C are subset containing only the earnings announcements of big and small banks, respectively. The last three columns of each part report the p-values testing the null of positive abnormal returns. Sign-test stands for a standard binomial sign test, whereas ws-test stands for the Wilcoxon sign test.

Competitors: Big Banks						**Competitors: Small Banks**					
NOBS	Event Date	AR (%)	p[t-test]	p[sign-test]	p[ws-test]	NOBS	Event Date	AR (%)	p[t-test]	p[sign-test]	p[ws-test]
Panel A: All events											
291	[0]	-0.1086	0.0161	0.0393	0.0475	291	[0]	-0.0720	0.0322	0.0504	0.0632
291	[1]	-0.0410	0.2088	0.1205	0.1003	291	[1]	0.0374	0.8322	0.6375	0.6662
Panel B: Reporting Bank: $MV_i > \overline{MV}$											
61	[0]	-0.1842	0.0611	0.1528	0.0454	61	[0]	-0.1110	0.1054	0.1000	0.1367
61	[1]	-0.1717	0.0748	0.2213	0.1187	61	[1]	-0.0724	0.2071	0.3991	0.3856
Panel C: Reporting Bank: $MV_i < \overline{MV}$											
230	[0]	-0.0886	0.0558	0.0831	0.1546	230	[0]	-0.0616	0.0767	0.1312	0.1268
230	[1]	-0.0063	0.4550	0.1957	0.2121	230	[1]	0.0265	0.6383	0.5784	0.7424

competitor banks is with -0.1086 % smaller than the return of small competitor banks of -0.0720 %, although this difference is not significant. The same is true when analyzing the effects of negative surprises occurring at small banks. The big competitor's abnormal reaction is -0.0886 %, compared with -0.0616 % for small banks. Both values are slightly smaller than the effects reported in Panel A, considering all events. The biggest average abnormal return observed is displayed in the left part of Panel B, i.e. effects of earnings surprises at big banks on big competitor banks. On the event date, a value of -0.1842 % is observed, followed by -0.1717 % on the subsequent day. Although these values indicate the strongest spill-over potential between big banks, the significance levels are only moderate, as the sample is small.

Overall, the results reported in this section indicate that the size of the banks considered is an important factor regarding the strength of contagion effects. The highest level of contagion is observed for big competitor banks when another big bank experiences a negative earnings surprise.

3.4 Conclusion

In this chapter, we address the question of whether contagion is present in the US banking sector, measured by stock price reaction following negative earnings surprises. To put the results into perspective we compare the banking sector with the non-banking sectors.

Applying traditional event study methodology we find that negative earnings surprises are contagious in the banking sector. The degree of contagion is increased by the degree of surprise. The abnormal return of the banks' competitors portfolios is on average -0.08 % for all negative surprises and increases up to -0.18 % for greater earnings surprises. These results are significantly larger (in absolute terms) than the average abnormal returns for the non-banking sectors. Earnings surprises at important (big) banks cause more pronounced reactions at competitor banks than surprises at small banks. The highest degree of contagion is found for big banks, reacting on negative news at another big bank.

Given the importance of a stable banking system for the real economy, the existence of contagion effects makes it necessary to draw the attention of the regulator to the entire system, rather than regulating on an individual bank level. Potential contagion effects could translate through the banking system, leading to a systemic crisis.

Analyzing the second highly regulated sector - the insurance sector - separately, we do not find any signs of contagion in this sector. This finding supports the notion that a systemic regulation of the insurance sector is less important compared to the banking sector. The financial supervision should therefore focus on the banking sector when aiming to implement a system-based regulation.

Chapter 4

Portfolio Management in the Presence of Systemic Risk

4.1 Introduction

In this chapter, we empirically investigate the consequences of the presence of systemic risk on optimal asset allocation. In doing so, we consider systemic risk on a domestic level, i.e. the risk of nation wide shocks, affecting all companies of the domestic market heavily and, thus, causing the prices to jump simultaneously. This problem is of high relevance for any investor as systemic risk could spoil diversification benefits when the investor counts on it most. We therefore investigate two main questions: first, how does the optimal stock portfolio allocation change when taking systemic risk into account? - and second, what does an investor lose by neglecting the presence of systemic risk in their portfolio allocation decisions?

There exist few empirical studies on the asset allocation problem when taking systemic risk explicitly into account. Furthermore, the findings of these studies are not unambiguous. Ang and Bekaert (2002) propose a regime-switching model in discrete time to account for the possibility of changing economic environments. Using international stock index data they find that the costs of ignoring systemic crises are small when no risk-free asset is available. However, if a risk-free asset is investable, ignoring systemic effects becomes much more costly. Kole et al. (2006) follow the idea of using a regime-switching model, but formulate the asset allocation problem in continuous time. Using a data set of international stock indices, including emerging markets, they conclude that the costs of ignoring the possibility of systemic crises can be substantial. Alternatively to employing a regime-switching model, Das and Uppal (2004) propose to incorporate the presence of systemic risk by the occurrence of perfectly correlated price jumps. They study the effects of global systemic risk for index portfolios of six developed and six emerging markets, respectively. In an one-point in time analysis, they conclude that the loss from neglecting systemic risk is small. Our paper is most closely related to this work. We adopt their approach of modeling systemic risk using a Poisson jump-diffusion model in continuous time.

We contribute to the literature on systemic risk and optimal portfolio choice by extending the analysis of Das and Uppal (2004) in several directions. First, we argue that risk arising from jumps should be more important in the case of direct domestic equity investments into individual stocks, compared to the case of national indices analyzed by these authors, as domestic wide crises occur more frequently than global crises. Therefore, we conduct a study on a domestic basis, assuming an investor who invests their entire wealth in the stocks composing a major domestic stock index. In doing so, they can follow two different strategies: a crisis conscious strategy, taking the existence of systemic risk explicitly into account - or a crisis ignorant strategy, which disregards this type of risk.[1] We then analyze the differences of these two strategies with respect to portfolio composition, return, and expected utility. To the best of our knowledge, we are the first to study the effects of systemic risk on a direct stock market investment.

Second, we broaden the basis of the empirical findings by conducting an historical simulation study and repeating the estimation and portfolio choice decisions. Our results are thus less likely to be biased by current market conditions compared to

[1]The notion of crisis conscious and crisis ignorant is adopted from Kole et al. (2006).

analyzing the portfolio decision at only one point in time.

Third, as we deal with up to 30 investable securities, we have to tackle the high dimensionality of the optimization problem. To reduce the complexity of the problem we make use of the decomposition technique developed by Aït-Sahalia et al. (2009) and show, how this methodology can be applied to a real world data set in a factor model framework.

Fourth, we approach the estimation problem differently than Das and Uppal (2004) and, furthermore, disentangle the effects arising from ignoring the existence of systemic risk during the estimation of the processes' parameters and the effect emerging from the actual asset allocation decisions.

Our main results are as follows. We find that the crisis conscious investor tends to take less extreme positions in the individual stocks compared with the crisis ignorant investor. However, individual stock's exposure can also increase, if the stock is less exposed to systemic risk and thus provide diversification benefits. Interestingly, the overall fraction of wealth invested in the risky stocks remains relatively stable across the crisis conscious and the crisis ignorant strategy. When analyzing the consequences of adhering to the crisis ignorant strategy, we find that both, the loss in expected return, and the loss in expected utility, are significant from a statistical as well as from an economical perspective.

The literature on optimal portfolio choice has been pioneered by Samuelson (1969) in discrete time, companioned with the seminal work of Merton (1969) in continuous time. Merton's model has been extended along several directions. Merton (1971) extends the original framework for more general utility functions and the inclusion of jump processes, whereas Merton (1973) makes the asset processes' parameters stochastic themselves, yielding a stochastic opportunity set. These ideas have been further developed. Kim and Omberg (1996) and Liu (2007) study the portfolio choice problem for the case of stochastic opportunity sets and generalizations of the original model with respect to the utility function as well as the parameters' processes.

Optimal portfolio choice for more than one risky asset, when generalizing the return process to jump-diffusion models, is further investigated by Aase (1984). Liu et al. (2003) derive semi-analytical solutions for the allocation problem in the case of one risky and one riskless asset with jumps occurring in the price as well as in the volatility process, whereas Liu and Pan (2003) consider the case with diffusive volatility only, but add derivatives to the market setting to allow for a hedging of volatility risk.[2]

The remainder of this chapter is organized as follows. Section 4.2 describes the stochastic framework and the solution to the optimal portfolio choice problem. Section 4.3 develops the factor structure which estimation is set out in Section 4.4. Section 4.5 describes the data used, Section 4.6 provides the estimation results. In Section 4.7, we report and discuss the results of the portfolio choice decisions. Section 4.8 concludes this chapter.

4.2 Stock Price Dynamics and Optimal Portfolio Choice

4.2.1 Stock Price Dynamics

The study of diffusive stock price models incorporating jumps goes back to Press (1967). Merton (1971) discusses first the implications of jumps present in stock price processes on optimal portfolio choice in the context of stochastic jump frequency but deterministic jump amplitude. The pricing of options when stock prices follow a jump-diffusion process with stochastic jump amplitude was considered first by Merton (1976). We will briefly review this framework. Merton (1976) argues that the total variation of a stock price can be assumed to have two components. First, as in the standard diffusive Black-Scholes model, a stock

[2]Further work on this field was done by Branger et al. (2008) who merge the former two approaches into one paper. Other papers considering optimal portfolio choice with jump diffusion processes are Wu (2003) and Cvitanić et al. (2008).

price changes due to the 'usual' fluctuations of the market. As examples for these 'usual' fluctuations Merton mentions temporary imbalances in supply and demand, changes in economic outlook, or, other new information having only a marginal impact on the stock price. The second component of stock price changes are 'unusual' or 'abnormal' fluctuations in the market. These happen upon the arrival of significant information related to the company and, thus, affect the stock price strongly.

In the model proposed by Merton, the first component is modeled by a standard geometric Brownian motion, the latter by a Poisson jump process. Let S_t be a stock price at time t. Then the dynamics of S_t is assumed to follow the stochastic differential equation

$$dS_t = S_t[(r + \alpha)dt + \sigma dZ_t + P_t dN_t(\lambda)], \tag{4.1}$$

where r denotes the risk-free rate; α the excess drift (excess return), given that no jump event occurs; σ the volatility conditioning on no jump occurrence; Z_t is a standard Brownian motion; and $N_t(\lambda)$ a standard Poisson process with arrival rate λ. The random percentage change in the stock price if a jump occurs is given by the stochastic jump amplitude P_t, distributed on $(-1, \infty)$. All processes are assumed to be mutually independent. Thus, $E[P_t dN_t(\lambda))] = E[P_t]\lambda dt$ and $Var[P_t dN_t(\lambda)] = E[P_t^2]\lambda dt$. The quantity $\ln(1 + P_t)$ equals the continuously compounded return of the jump component and is assumed to follow a normal distribution with mean η and variance ν^2. Consequently, the quantity $(1 + P_t)$ follows a lognormal distribution. As long as no jump occurs, S_t is continuous and follows the standard Black-Scholes dynamics $dS_t = S_t[(r+\alpha)dt+\sigma dZ_t]$. However, if a jump occurs, $dS_t = S_t[(r + \alpha)dt + \sigma dZ_t + P_t]$. All the parameters r, α, σ, η, ν, and λ are assumed to be constant over time.

The solution to this SDE is provided by Merton (1976, p. 129):

$$S_t = S_0 e^{(r+\alpha-\frac{1}{2}\sigma^2)t+\sigma Z_t}\tilde{P}(N_t), \tag{4.2}$$

with $\tilde{P}(N_t) = 1$ if $N_t = 0$, i.e. no jump occurred between 0 and t, and $\tilde{P}(N_t) = \prod_{i=1}^{N_t}(1+P_i)$ if $N_t > 0$, where N_t is the number of jumps between 0 and t, distributed Poisson with parameter λt. As all the terms $(1+P_i), i = 1, ..., N_t$, are lognormal, S_t will be lognormal as well (for a known number of jumps). The probability of j jumps is given by

$$P(N_t = j) = \frac{(\lambda t)^j}{j!}e^{-\lambda t}. \tag{4.3}$$

As derived by Press (1967), the mean and variance of the log-return per unit time can be computed as

$$r + \alpha - \frac{1}{2}\sigma^2 + \lambda\eta, \tag{4.4}$$

and

$$\sigma^2 + \lambda(\eta^2 + \nu^2). \tag{4.5}$$

Following Das and Uppal (2004), the framework of Merton (1976) is adjusted to explicitly model the possibility of a systemic crisis. This is achieved by considering a model for n stocks, each of which follow the jump diffusion specification (4.1). In order to have a true systemic component in the model, we assume that the jump process is identical for each stock, i.e. if a jump occurs (corresponding to a systemic event), each stock will react to this event, however with a different sensitivity. Precisely, the price dynamics of stock i, $i = 1, ..., n$, is assumed to be

$$\frac{dS_{i,t}}{S_{i,t}} = (r + \alpha_i)dt + \boldsymbol{\sigma}_i'\boldsymbol{dZ}_t + \xi_i P_t dN_t(\lambda), \tag{4.6}$$

where most variables are defined as in (4.1), with the subscribed i distinguishing among the stocks, and $\boldsymbol{\sigma}_i$ denoting the ith column of the matrix $\boldsymbol{\sigma}$ defined by $\boldsymbol{\sigma}\boldsymbol{\sigma}' = \boldsymbol{\Sigma}$; $\boldsymbol{\Sigma}$ being the covariance matrix of the n stock returns arising from the pure diffusion part. $\boldsymbol{dZ}_t = [dZ_{1,t}, ..., dZ_{n,t}]'$ denotes the vector of increments of n orthogonal standard Brownian motions. Note that there does not exist a jump process for each individual stock price, but each stock price is exposed to the same jump process. Possible differences of the sensitivities of a stock with respect to the systemic jump factor are captured in the non-stochastic vector $\boldsymbol{\xi} = [\xi_1, ..., \xi_n]'$. On the arrival of a systemic event, the stock price $S_{i,t-}$ will change to $S_{i,t-}\xi_i P_{t+}$.

4.2.2 Optimal Portfolio Choice

In this section, we present the solution of the portfolio problem in the spirit of Merton (1969). We consider a constant opportunity set, i.e. the parameters of the stochastic processes are constants. As described by Kim and Omberg (1996), in the case of one risky asset, any of the two assumptions - an opportunity set which is uncorrelated with the asset returns, or a logarithmic utility function - will produce a myopic strategy with respect to the portfolio weights. As a constant opportunity set is a special case of the first assumption, we expect to arrive at a myopic solution.

Markets are assumed to be arbitrage-free and frictionless. Agents are pricetakers with full information and without short sales restrictions. They do not receive any income and optimize their expected utility with respect to their terminal wealth. We assume the standard power utility function given by $U(x) = \frac{x^{1-\gamma}}{1-\gamma}$ for the investor. They can trade continuously in the n risky assets and one risk-free asset with price S_0, which can be characterized by the differential equation

$$\frac{dS_{0,t}}{S_{0,t}} = rdt, \tag{4.7}$$

where r denotes the instantaneous risk-free rate, which is assumed to be constant. Borrowing and short selling of the risk-free asset are allowed without any restrictions.

The investor, initially endowed with wealth W_0, invests a fraction ω_i of their wealth into asset i, $i = 0, 1, ..., n$. Consequently, the budget equation $\sum_{i=0}^{n} \omega_i = 1$ must be satisfied at each point in time. The dynamics of the wealth is then given by

$$dW_t = W_t[(\boldsymbol{\omega}_t'\boldsymbol{\alpha} + r)dt + \boldsymbol{\omega}_t'\boldsymbol{\sigma}\boldsymbol{dZ}_t + \boldsymbol{\omega}_t'\boldsymbol{\xi}P_t dN_t(\lambda)], \tag{4.8}$$

where W_t denotes the wealth process; $\boldsymbol{\omega}_t = [\omega_{1,t}, ..., \omega_{n,t}]'$ is the vector of portfolio weights (of the risky assets); and $\boldsymbol{\alpha} = [\alpha_1, ..., \alpha_n]'$ is the vector of excess returns. The other variables are defined as in the previous section.

Solutions to the optimal portfolio problem for the cases with and without Poisson jump process were derived in the seminal work of Merton (1969) and Merton (1971), respectively, although in contrast to the presented framework, with deterministic jump size.

The problem of choosing optimal portfolio weights $\boldsymbol{\omega}^*$ in order to maximize expected utility over terminal wealth is given by

$$\max_{\{\boldsymbol{\omega}_t\}} \; E_0 \left[U(W_T)\right], \tag{4.9}$$

subject to the budget constraint. The resulting maximization problem including the jump process is given by:[3]

[3]See also Das and Uppal (2004, p. 2816). For a brief derivation see Appendix A.

$$
\begin{aligned}
0 &= \max_{\{\boldsymbol{\omega}_t\}} \left\{ \frac{b'(t)}{b(t)} + (1-\gamma)(r + \boldsymbol{\omega}_t'\boldsymbol{\alpha}) - \frac{1}{2}\gamma(1-\gamma)\boldsymbol{\omega}_t'\boldsymbol{\Sigma}\boldsymbol{\omega}_t \right. \\
&\quad \left. + \lambda E\big[(1 + \boldsymbol{\omega}_t'\boldsymbol{\xi} P_t)^{1-\gamma} - 1\big] \right\}, \qquad (4.10)
\end{aligned}
$$

where $b(t)$ is a function of time only. The resulting first order condition for the optimal portfolio weights is given by

$$
\mathbf{0} = \boldsymbol{\alpha} - \gamma\boldsymbol{\Sigma}\boldsymbol{\omega} + \lambda E[\boldsymbol{\xi}_t P_t (1 + \boldsymbol{\omega}'\boldsymbol{\xi}_t P_t)^{-\gamma}]. \qquad (4.11)
$$

As can be seen from (4.11), the solution coincides with the well known pure diffusion case if $\lambda = 0$.

4.3 Factor Model

The first order condition (4.11) derived in the previous section is a system of n non-linear equations. Das and Uppal (2004) solve these equations numerically to compute the optimal portfolio weights for six national stock indices at one point in time. As we wish to study in a real world example, the optimal portfolio composition of a stock portfolio with more than six components and over time, a straight numerical solving becomes infeasible in reasonable time. We thus apply the decomposition technique proposed by Aït-Sahalia et al. (2009). To do this, we have to make further structural assumptions regarding the stock price dynamics, which is assumed to be generated by a linear factor structure including jumps. In the subsequent analysis, we consider the case of two market risk factors. There exists one market wide jump risk factor and one continuous market wide risk factor. Additionally there exist k sector specific risk factors. Each company of the same sector has the same sensitivity towards the respective risk factors, including the jump risk factor; the sensitivities of firms belonging to different sectors are, however, different.

We define the indicator function $\mathbf{1}_{\{i\in K_j\}}$ as

$$\mathbf{1}_{\{i\in K_j\}} = \begin{cases} 1, & \text{if } \ i \in K_j \\ 0, & \text{if } \ i \notin K_j \end{cases}, \tag{4.12}$$

where K_j is the set of indices of stocks in sector j. Then, the assumed factor model is given by

$$\begin{aligned} \frac{dS_{i,t}}{S_{i,t}} &= (r+\alpha_i)dt + \sum_{j=1}^{k} \beta_j \mathbf{1}_{\{i\in K_j\}} dZ_t + \sum_{j=1}^{k} \gamma_j \mathbf{1}_{\{i\in K_j\}} dB_{j,t} \\ &\quad + \sum_{j=1}^{k} \delta_j \mathbf{1}_{\{i\in K_j\}} dB_t^i + \sum_{j=1}^{k} \xi_j \mathbf{1}_{\{i\in K_j\}} P_t dN_t, \end{aligned} \tag{4.13}$$

where β_j is the factor sensitivity towards the market risk factor of stocks belonging to sector j; γ_j the factor sensitivity towards the sector risk factor[4]; δ_j the idiosyncratic risk factor sensitivity of stocks belonging to sector j; and ξ_j the jump process sensitivity of stocks belonging to sector j. dZ, dB_j, and dB^i denote the increments of standard Brownian motions being pairwise orthogonal. As before, P_t denotes the stochastic jump amplitude with domain $(-1, \infty)$; and dN the increment of the systemic Poisson process with intensity λ.

The covariance of the pure diffusion part (i.e. $\lambda = 0$ in (4.13)) is then given by

[4]We commit a slight misuse of notation here, as γ already denotes the risk aversion coefficient. No confusion should arise, as the meaning will be clear from the context.

$$Cov\left[\frac{dS_{i_1}}{S_{i_1}}, \frac{dS_{i_2}}{S_{i_2}}\right] = \begin{cases} (\beta_{j_1}^2 + \gamma_{j_1}^2 + \delta_{j_1}^2)dt & \text{if} \quad i_1 \in K_{j_1} \wedge i_1 = i_2 \\ (\beta_{j_1}^2 + \gamma_{j_1}^2)dt & \text{if} \quad i_1 \in K_{j_1} \ \wedge \ i_2 \in K_{j_1} \wedge i_1 \neq i_2 \\ (\beta_{j_1}\beta_{j_2})dt & \text{if} \quad i_1 \in K_{j_1} \ \wedge \ i_2 \in K_{j_2} \wedge j_1 \neq j_2 \end{cases} . \tag{4.14}$$

The portfolio choice problem can be greatly simplified in the case of a covariance matrix having a structure like (4.14), as described by Aït-Sahalia et al. (2009). The basic idea is to decompose the optimization problem in two orthogonal spaces, one spanned by the jump component, and one being orthogonal to this space. Doing so, it is possible to significantly reduce the optimization problem which has to be solved numerically. In what follows, we briefly describe the decomposition technique applying it to the simple case of two sectors with two companies each. We choose this simple example to demonstrate the main idea as clear as possible. The solution for k sectors, with m_k firms each, is structurally similar.
For convenience, we define

$$\vartheta_j^2 = \beta_j^2 + \gamma_j^2 + \delta_j^2, \tag{4.15}$$

and

$$\kappa_j^2 = \beta_j^2 + \gamma_j^2. \tag{4.16}$$

Then, the covariance matrix of the diffusion term is given by

$$\mathbf{\Sigma} = \begin{bmatrix} \vartheta_1^2 & \kappa_1^2 & \beta_1\beta_2 & \beta_1\beta_2 \\ \kappa_1^2 & \vartheta_1^2 & \beta_1\beta_2 & \beta_1\beta_2 \\ \beta_1\beta_2 & \beta_1\beta_2 & \vartheta_2^2 & \kappa_2^2 \\ \beta_1\beta_2 & \beta_1\beta_2 & \kappa_2^2 & \vartheta_2^2 \end{bmatrix}.$$

This matrix is now decomposed into two matrices, one spanned by the same basis as the jump vector and one spanning the orthogonal space

$$\mathbf{\Sigma} = \bar{\mathbf{\Sigma}} + \mathbf{\Sigma}^{\perp(B)}, \tag{4.17}$$

where B denotes the basis spanned by the jump vector. In the case of two sectors with two companies each, the basis is given by $B = \{[1,1,0,0]', [0,0,1,1]'\}$. Thus, $\mathbf{\Sigma}$ can be decomposed into

$$\bar{\mathbf{\Sigma}} = \begin{bmatrix} \frac{1}{2}(\vartheta_1^2 + \kappa_1^2) & \frac{1}{2}(\vartheta_1^2 + \kappa_1^2) & \beta_1\beta_2 & \beta_1\beta_2 \\ \frac{1}{2}(\vartheta_1^2 + \kappa_1^2) & \frac{1}{2}(\vartheta_1^2 + \kappa_1^2) & \beta_1\beta_2 & \beta_1\beta_2 \\ \beta_1\beta_2 & \beta_1\beta_2 & \frac{1}{2}(\vartheta_2^2 + \kappa_2^2) & \frac{1}{2}(\vartheta_2^2 + \kappa_2^2) \\ \beta_1\beta_2 & \beta_1\beta_2 & \frac{1}{2}(\vartheta_2^2 + \kappa_2^2) & \frac{1}{2}(\vartheta_2^2 + \kappa_2^2) \end{bmatrix}, \tag{4.18}$$

and

$$\mathbf{\Sigma}^{\perp(\boldsymbol{B})} = \begin{bmatrix} \frac{1}{2}(\vartheta_1^2 - \kappa_1^2) & -\frac{1}{2}(\vartheta_1^2 - \kappa_1^2) & 0 & 0 \\ -\frac{1}{2}(\vartheta_1^2 - \kappa_1^2) & \frac{1}{2}(\vartheta_1^2 - \kappa_1^2) & 0 & 0 \\ 0 & 0 & \frac{1}{2}(\vartheta_2^2 - \kappa_2^2) & -\frac{1}{2}(\vartheta_2^2 - \kappa_2^2) \\ 0 & 0 & -\frac{1}{2}(\vartheta_2^2 - \kappa_2^2) & \frac{1}{2}(\vartheta_2^2 - \kappa_2^2) \end{bmatrix}. \tag{4.19}$$

The return vector $\boldsymbol{\alpha}$ and the portfolio weights vector $\boldsymbol{\omega}$ are decomposed on the same basis, i.e. in this case:

$$\boldsymbol{\alpha} = \underbrace{\overline{\alpha}_1 \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \end{bmatrix} + \overline{\alpha}_2 \begin{bmatrix} 0 \\ 0 \\ 1 \\ 1 \end{bmatrix}}_{\equiv \overline{\boldsymbol{\alpha}}} + \boldsymbol{\alpha}^{\perp(B)}, \tag{4.20}$$

and

$$\boldsymbol{\omega} = \underbrace{\overline{\omega}_1 \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \end{bmatrix} + \overline{\omega}_2 \begin{bmatrix} 0 \\ 0 \\ 1 \\ 1 \end{bmatrix}}_{\equiv \overline{\boldsymbol{\omega}}} + \boldsymbol{\omega}^{\perp(B)}. \tag{4.21}$$

Plugging these decompositions into the part of (4.10) which is concerned with $\boldsymbol{\omega}$, we get the following maximization problem

$$\begin{aligned}\max_{\{\overline{\boldsymbol{\omega}},\boldsymbol{\omega}^{\perp(B)}\}} \quad & (\boldsymbol{\omega}^{\perp(B)})'\boldsymbol{\alpha}^{\perp(B)} - \frac{\gamma}{2}(\boldsymbol{\omega}^{\perp(B)})'\boldsymbol{\Sigma}^{\perp(B)}\boldsymbol{\omega}^{\perp(B)} \\ & + \overline{\boldsymbol{\omega}}'\overline{\boldsymbol{\alpha}} - \frac{\gamma}{2}\overline{\boldsymbol{\omega}}'\overline{\boldsymbol{\Sigma}}\overline{\boldsymbol{\omega}} + \frac{\lambda}{1-\gamma}E[(1+\overline{\boldsymbol{\omega}}'\boldsymbol{\xi}P_t)^{1-\gamma} - 1]. \qquad (4.22)\end{aligned}$$

As can be seen from (4.22), the problem separates into two problems; one for $\boldsymbol{\omega}^{\perp(B)}$ which is given by the first line, and one for $\overline{\boldsymbol{\omega}}$, which is given by the second.
By construction, the first problem with respect to $\boldsymbol{\omega}^{\perp(B)}$ does not involve any jump components. Thus, the first order condition coincides with the case of no jump risk and we have

$$\mathbf{0} = \boldsymbol{\alpha}^{\perp(B)} - \gamma\boldsymbol{\Sigma}^{\perp(B)}\boldsymbol{\omega}^{\perp(B)*}. \qquad (4.23)$$

As the elements s_{ij} of $\boldsymbol{\Sigma}^{\perp(B)}$ are zero if i and j belong to different sectors, the system of linear equations can be solved sector by sector. The second optimization problem lies in the jump vector space and must be solved numerically. The first order condition is given by

$$\mathbf{0} = \overline{\boldsymbol{\alpha}} - \gamma\overline{\boldsymbol{\Sigma}}\overline{\boldsymbol{\omega}} - \lambda E[\boldsymbol{\xi}P_t(1+\overline{\boldsymbol{\omega}}'\boldsymbol{\xi}P_t)^{-\gamma}]. \qquad (4.24)$$

Solving this equation numerically, we make use of the assumption that $\ln(1+P_t)$ is normally distributed.
At this point, the merits of applying the orthogonal decomposition of the portfolio problem become obvious: compared to the first order condition (4.11) which has to be solved for the 'full' model, the structural assumptions regarding the factor structure of the stock price dynamics allow us to reduce the numerical burden significantly. Precisely, the problem reduces from solving a system of n non-linear equations, to a problem where we have to solve only a system of k equations, where n is the number of stocks and k the number of sectors. Of course, this relief comes at the price of the rather restrictive assumptions regarding the parameters of the

price processes. As it is possible to refine the sector classification used one can increase k up to n - at this point one arrives at the original 'full' problem. Thus, deciding on the number of sectors is always a trade-off between computational feasibility and more realistic structural assumptions.

4.4 Estimation

In this section, we describe our estimation approach for the presented model capturing systemic risk via a common Poisson jump process. Various approaches to estimate the parameters of jump-diffusion models have been proposed in the literature. Press (1967) is one of the first to estimate the jump parameters of univariate stock price series using the method of cumulants.

Ball and Torous (1983) suggest to estimate the parameters employing the method of maximum likelihood.

If data is discretely sampled every change of value is a discrete jump. Thus, it is an obvious question, whether it is possible to disentangle the continuous Brownian motion components from that of the jump components employing likelihood-based statistical methods without using additional information, e.g. derivatives prices. This question is answered by Aït-Sahalia (2004), who shows that it is indeed asymptotically possible to distinguish continuous and jump parts with perfect accuracy.[5]

As we cannot observe the continuous and jump factor separately, we need to estimate a factor model with latent factors. To do so, we conduct a Kalman filter-based maximum likelihood approach, which has been proposed by Kim et al. (1994). The Kalman filter has the advantageous property of combining time-series and cross-sectional information in an efficient way. For a detailed derivation and

[5] Honoré (1998) points out, that without restrictions on the parameter space, the likelihood function is unbounded. This issue is solved by constraining the optimization problem.

discussion of the Kalman filter, see e.g. the standard references Harvey (1989) or Hamilton (1994).

In general, we observe n stock returns $y_{i,t}$, $i = 1, ..., n$, at each point in time t (with possible missing values at the beginning of the sample period for some i). A classification into k sectors results in $k+2$ common risk factors. Precisely, we have one market wide diffusion risk factor, k sector specific factors, and one market wide jump risk factor. Note that we deviate from the previous convention to print vectors and matrices bold, as all variables in the subsequent definitions are multivariate. The definitions of these vectors and matrices are given thereafter. The measurement equation for n observables and $k+2$ latent factors, respectively, can be written as

$$\underset{(n\times 1)}{y_t} = \underset{(n\times(k+2))}{H} \underset{((k+2)\times 1)}{x_t} + \underset{(n\times 1)}{d} + \underset{(n\times 1)}{\varepsilon_t} . \tag{4.25}$$

The vector d contains the expected returns for the n stocks; the matrix H contains the sensitivities of each stock towards the $k+2$ risk factors; ε_t captures the idiosyncratic risk of each stock with

$$\varepsilon_t \sim N(0, \Xi), \qquad \Xi = diag(\delta).$$

For the transition equation we have

$$\underset{((k+2)\times 1)}{x_t} = \underset{((k+2)\times(k+2))}{G} \underset{((k+2)\times 1)}{x_{t-1}} + \underset{((k+2)\times 1)}{c} + \underset{((k+2)\times 1)}{\psi_t} , \tag{4.26}$$

with

$$\psi_t \sim N(0, W), \qquad W = diag(\sigma).$$

The types of variables x, y, d, δ, G, c, σ, and H are specified as:

$$
\begin{aligned}
y_t &= [y_{1,t}, ..., y_{n,t}]' \\
x_t &= [\Delta Z_t, \Delta B_t^1, ..., \Delta B_t^k, \Delta J_t]' \\
d &= [d_1, ..., d_n]' \\
\delta &= [\delta_1^2, ..., \delta_1^2, \delta_2^2, ..., \delta_{k-1}^2, \delta_k^2, ..., \delta_k^2]' \\
G &= 0_{k+2} \\
c &= [0, ..., 0, j\eta]' \\
\sigma &= [1, ..., 1, j\nu^2]'
\end{aligned}
$$

$$
H = \begin{bmatrix}
\beta_1 & \gamma_1 & 0 & \cdots & 0 & \xi_1 \\
\vdots & \vdots & \vdots & & \vdots & \vdots \\
\beta_1 & \gamma_1 & 0 & & & \xi_1 \\
\beta_2 & 0 & \gamma_2 & & & \xi_2 \\
\vdots & \vdots & \vdots & \cdots & \vdots & \vdots \\
\vdots & \vdots & \vdots & \cdots & \vdots & \vdots \\
\beta_{k-1} & & & & 0 & \xi_{k-1} \\
\beta_k & & & & \gamma_k & \xi_k \\
\vdots & \vdots & \vdots & & \vdots & \vdots \\
\beta_k & 0 & 0 & \cdots & \gamma_k & \xi_k
\end{bmatrix}
$$

The matrix G is specified as $(k+2) \times (k+2)$ zero matrix, as we assume no autocorrelation present in the stock returns. The variable $j = 0, 1, ..., N$ in the definitions of c and σ represents the possible number of jumps occurred in one observation step. Its role will become more clear after writing down the likelihood function.

Note that, in order to avoid excessive notation, we have dropped the time subscribed. However, in order to deal with missing observations we implement the Kalman filter with time varying size of H, d, and Ξ. Reducing the size of the matrices whenever an observation is missing conveniently deals with the problem of gaps in the time series.

Collecting all parameters to be estimated in the set $\Psi = (H, d, \delta, c, \sigma)$, we can now write down the (log-)likelihood function which needs to be maximized:

$$\mathcal{L}(y;\Psi) = \sum_{t=1}^{T} \log \sum_{j=1}^{N} \frac{e^{-\lambda}\lambda^{j}}{j!}(2\pi)^{-n/2}|F_{t,j}|^{-1/2} e^{-\frac{1}{2}v_{t,j}' F_{t,j}^{-1} v_{t,j}}. \tag{4.27}$$

The variable $v_{t,j}$ denotes the prediction error, i.e. $v_{t,j} = y_t - E_{t-1}[y_t]$, and $F_{t,j}$ the corresponding covariance matrix. Both quantities directly emerge from the Kalman filter iterations.[6]

Since our data is sampled discretely, the theoretical likelihood function would involve an infinite sum. We thus have to decide on a cut-off point, N, for practical implementation of the estimation. Increasing the value of N improves the finite approximation but also increases the computational burden.

In their univariate setting, Ball and Torous (1985) used $N = 10$, corresponding to a maximum number of ten shocks per month for one stock. As systemic shocks occur less frequent than individual shocks (as every systemic shock affects every company, but not vice versa), we use $N = 3$ in the subsequent analysis.[7]

---

[6] For the precise iteration through prediction and updating equations in the filtering algorithm see Harvey (1989), p. 104-106.

[7] As a robustness check we have also estimated our model with $N = 4$ for several data sets yielding very similar results to $N = 3$ not improving the fit statistically significant. Thus, one could expect small marginal value of increasing N further.

4.5 Data

We analyze the effects of systemic risk for the case of an investor whose investment universe comprises the stocks listed in the German DAX 30. For instance, this investor could be a mutual fund investing in German blue chips.

We sample end of month price data, which is adjusted for dividends, stock splits, and right issues.[8] As sample period we use the time spanning from January, 1998 to December, 2007. This means we cover a time span of 10 years, yielding a maximum number of 120 observations per stock. The price series are transformed to log return series by $y_t = \log(S_t/S_{t-1})$ where S_t denotes the stock price and y_t the return at time t. Table 4.1 reports descriptive summary statistics of the return data used. For 24 companies, we obtain a complete time series, whereas for Hypo Real Estate, Daimler, Deutsche Postbank, Deutsche Post, Deutsche Börse and Infineon we must rely on a smaller number of observations.

For most stocks, we observe a positive mean return during our sample period. Allianz shows a mean return which is slightly below zero; the only stock with a strong negative mean return is Infineon. The standard deviations of most of the log returns lie between 25 % and 40 %. Only Postbank and Eon show lower dispersion, whereas Commerzbank, SAP, and Infineon exhibit a higher volatility, the latter with the maximum observed value of 61 %. All but the return series of Hypo Real Estate, SAP, and Fresenius, show a negative skew, i.e. exhibiting a longer left tail, making large negative returns more likely than large positive returns. The kurtosis, is mostly larger than three, indicating leptokurtic return distributions. Only Linde and Volkswagen exhibit tails which are slightly lighter compared to the Normal distribution. The highest kurtosis is observed for Münchner Rück, Lufthansa, and Commerzbank. The last column shows the p-value of the Jarque-Bera test of normality. For 18 series we can reject the null hypothesis of normality at the 5 % significance level. For two additional stocks this can be done at the 10 %

[8]The data source is Thomson Financial Datastream.

Table 4.1: **Descriptive Summary Statistics of DAX Company Returns**

This table reports summary statistics for the return data used. The mean and standard deviation are on an annualized basis. The last column reports the p-value of the Jarque-Bera test of normality.

	Mnemonic	NOBS	Mean	Std.	Skewness	Kurtosis	Jarque-Bera
ALLIANZ	D:ALV	120	-0.0042	0.3847	-0.4846	6.0063	0.0000
BASF	D:BAS	120	0.1419	0.2513	-0.2335	3.5668	0.3085
BAYER	D:BAY	120	0.0909	0.3395	-0.5207	4.5431	0.0003
ADIDAS	D:ADS	120	0.0467	0.3026	-0.4155	3.5693	0.0969
HYPO REAL ESTATE HLDG.	D:HRX	50	0.2448	0.2405	0.6652	3.8709	0.1144
BMW	D:BMW	120	0.0936	0.3093	-0.4600	3.7940	0.0334
COMMERZBANK	D:CBK	120	0.0076	0.4272	-0.9241	7.0830	0.0000
MUENCHENER RUCK.	D:MUV2	120	0.0194	0.3873	-0.6013	8.1834	0.0000
DAIMLER	D:DAI	100	0.0450	0.3220	-0.5170	3.6235	0.0480
DEUTSCHE POSTBANK	D:DPB	41	0.1691	0.2043	-0.4853	3.4231	0.4577
SAP	D:SAP	120	0.0591	0.5164	0.1053	6.0545	0.0000
DEUTSCHE BANK	D:DBK	120	0.0646	0.3246	-0.5921	4.0928	0.0024
DEUTSCHE LUFTHANSA	D:LHA	120	0.0500	0.3429	-1.2125	7.2068	0.0000
CONTINENTAL	D:CON	120	0.1721	0.3031	-0.7899	4.2872	0.0001
HENKEL PREF.	D:HEN3	120	0.0937	0.2553	-0.4132	3.7602	0.0560
FRESENIUS MED.CARE	D:FME	120	0.0663	0.3697	0.2261	5.6568	0.0000
DEUTSCHE POST	D:DPW	85	0.0132	0.2858	-0.3581	3.8851	0.1437
METRO	D:MEO	120	0.0694	0.3314	-0.0488	4.6376	0.0022
LINDE	D:LIN	120	0.0808	0.2490	-0.2845	2.9109	0.4331
MAN	D:MAN	120	0.1837	0.3685	-0.7302	5.6831	0.0000
DEUTSCHE BOERSE	D:DB1	82	0.2841	0.2675	-0.1359	3.2281	0.8563
RWE	D:RWE	120	0.1162	0.2627	-0.5941	3.2866	0.0280
MERCK KGAA	D:MRK	120	0.1194	0.3194	-0.4096	3.6655	0.0781
SIEMENS	D:SIE	120	0.1063	0.4083	-0.2881	3.5780	0.2273
THYSSENKRUPP	D:TKA	120	0.1118	0.3561	-0.1464	3.0862	0.8089
E ON	D:EOA	120	0.1293	0.2297	-0.7022	3.7277	0.0027
INFINEON TECHNOLOGIES	D:IFX	93	-0.2310	0.6135	-0.7066	6.7603	0.0000
VOLKSWAGEN	D:VOW	120	0.1488	0.3554	-0.3174	2.5612	0.2098
DEUTSCHE TELEKOM	D:DTE	120	0.0043	0.3735	-0.1862	5.0252	0.0001
TUI	D:TUI1	120	0.0186	0.3732	-0.3415	5.9082	0.0000

Table 4.2: **Sector Classification**

This table displays the sector classification. It is based on the Industry Classification Benchmark (on the first level) and was slightly modified by merging the sectors basic materials and healthcare, as well as telecommunications and technology.

I Basic Materials / Healthcare	IV Consumer Services
1 BASF	16 DEUTSCHE LUFTHANSA
2 BAYER	17 METRO
3 FRESENIUS MED.CARE	18 TUI
4 LINDE	
5 MERCK KGAA	V Telecommunications / Technology
	19 SAP
II Industrials	20 INFINEON TECHNOLOGIES
	21 DEUTSCHE TELEKOM
6 DEUTSCHE POST	
7 MAN	VI Utilities
8 SIEMENS	
9 THYSSENKRUPP	22 RWE
	23 E ON
III Consumer Goods	VII Financials
10 ADIDAS	24 ALLIANZ
11 BMW	25 HYPO REAL ESTATE HLDG.
12 DAIMLER	26 COMMERZBANK
13 CONTINENTAL	27 MUENCHENER RUCK.
14 HENKEL PREF.	28 DEUTSCHE POSTBANK
15 VOLKSWAGEN	29 DEUTSCHE BANK
	30 DEUTSCHE BOERSE

level. Thus, we conclude that the usually observed stylized facts of stock returns, namely a negative skew and heavy tails, are also present in our data set. It is also well established that these facts are less pronounced for data sampled with a lower frequency. It is worth noting that the negative skewness and positive excess kurtosis cannot be explained in a linear factor model if we consider Brownian motions only. However, a Poisson jump process with negative expected jump amplitude is able to generate returns showing exactly the features observed. As the statistics in Table 4.1 are solely based on an univariate analysis, we cannot distinguish between idiosyncratic and systemic jumps in the data at this point.

To implement our factor model, we have to define the sectors. Basically, one can imagine two main approaches to do this. First, one could group the stocks based on some economic criterion, e.g. the sector in which the company operates. Second, one could imagine to follow a data driven strategy, and group the stocks by some statistical approach aiming to best match the structural assumptions imposed in the proposed model. As the latter proposal could be characterized as data mining and is without intuition, we decided to follow the first approach and group the stocks according to their sector belongings.

The grouping of the companies is done according to the Industry Classification Benchmark (ICB)[9] which classifies all companies into one of the 10 industries: oil & gas, basic materials, industrials, consumer goods, health care, consumer services, telecommunications, utilities, financials, and technology. For the oil & gas sector, we do not have any observations. For the healthcare, telecommunication, and technology sectors, we have, at maximum, two companies each. Thus, we decided to group these sectors further to have a sufficient amount of observations for each class. As most of the companies of the basic materials sector operate in the healthcare sector as well,[10] we decided to assign the health care companies to the basic materials sector. Regarding the technology sector, we think that it is most closely related to the telecommunications sector, and we thus merge these two industry sectors. In the utilities sector we also only observe two companies. However, as we have the entire time series available for both companies and as the utilities sector is special amongst the other sectors we decided not to merge it with another industry. The final sector classification is displayed in Table 4.2. We use the numerical sector identifiers I through VII in the following discussion. The numbering 1 through 30 of the individual companies is used to identify individual stocks.

[9] See www.icbenchmark.com.

[10] Pharmaceuticals & biotechnology is a subsector of the healthcare industry sector.

4.6 Estimation Results

First, we estimate the complete model including a market wide jump factor as described in the previous section. Additionally, we estimate the standard pure diffusion model, i.e. without the existence of Poisson jumps to have a comparison and benchmark at hand. Table 4.3 displays the results of this estimation.

The estimated average returns per month from the continuous part of the model are reported in the left part of the table. Compared with the pure diffusion model, all drift estimates are higher in the jump diffusion model. The reason for this becomes immediately visible by examining the parameters of the jump component. The expected mean jump size η is clearly below zero with a value of -11.23 %. Thus, in order to compensate for the existence of negative jumps, the individual drift parameters must be adjusted upwards (see also equation 4.4) to fit the time series. Interestingly, the drift parameter of Allianz (d_{24}), which is negative in the purely continuous model, changes its sign by introducing systemic jumps, indicating that the negative mean return observed for this company can be attributed to systemic events.

To get an impression of the importance of the systemic jumps, we report the mean jump return η and its volatility ν scaled by the respective sensitivities ξ_j in Table 4.4. The sensitivity of the financial sector (VII) towards the systemic jump factor is among the highest of all sectors. The expected jump size upon the arrival of a systemic event is -5.48 % with a standard deviation of 15.11 %. According to the large standard deviation, it is very likely not only to observe joint negative jumps, but also joint upwards movements. Taking into account the large variability of the jump returns, a heavy shock, causing the jump return realizing two standard deviations below its mean would cause all financial stock prices to drop by 36 % simultaneously.

The arrival rate of systemic events is estimated as 0.1583. This means we expect the occurrence of such an event every 7 months on average. Estimating a jump diffusion model with perfectly correlated jumps for six countries, Das and Uppal

Table 4.3: **Estimated Parameters**

This table reports the estimation results of of the systemic jump model for the DAX stocks as well as for the same data, neglecting the possibility of a systemic jump. The left part gives the results for the average returns per month d_i of each stock, the right reports the estimation results for the volatility and jump process parameters. β_j denotes the sensitivities towards the market wide continuous factor; γ_j the sensitivities towards the sector factors; δ_j the sensitivities towards the idiosyncratic factors; η and ν the mean and standard deviation of the jump factor; and λ the jump intensity.

Parameter	Systemic Jump	Diffusion	Parameter	Systemic Jump	Diffusion
d_1	0.0165	0.0113	β_1	0.0410	0.0548
d_2	0.0120	0.0070	β_2	0.0622	0.0760
d_3	0.0116	0.0059	β_3	0.0544	0.0564
d_4	0.0118	0.0063	β_4	0.0394	0.0694
d_5	0.0147	0.0099	β_5	0.0543	0.0839
d_6	0.0074	0.0019	β_6	0.0281	0.0332
d_7	0.0214	0.0152	β_7	0.0455	0.0737
d_8	0.0155	0.0092	γ_1	0.0207	0.0214
d_9	0.0149	0.0091	γ_2	0.0047	0.0001
d_{10}	0.0080	0.0039	γ_3	0.0231	0.0305
d_{11}	0.0110	0.0073	γ_4	0.0047	0.0001
d_{12}	0.0065	0.0034	γ_5	0.0473	0.0476
d_{13}	0.0176	0.0139	γ_6	0.0489	0.0487
d_{14}	0.0101	0.0065	γ_7	0.0291	0.0337
d_{15}	0.0168	0.0128	δ_1	0.0671	0.0671
d_{16}	0.0107	0.0033	δ_2	0.0719	0.0716
d_{17}	0.0139	0.0055	δ_3	0.0624	0.0623
d_{18}	0.0087	0.0006	δ_4	0.0706	0.0728
d_{19}	0.0127	0.0046	δ_5	0.1065	0.1069
d_{20}	-0.0067	-0.0147	δ_6	0.0378	0.0384
d_{21}	0.0079	-0.0003	δ_7	0.0654	0.0653
d_{22}	0.0119	0.0084	ξ_1	0.3023	-
d_{23}	0.0143	0.0102	ξ_2	0.3642	-
d_{24}	0.0076	-0.0009	ξ_3	0.2184	-
d_{25}	0.0193	0.0110	ξ_4	0.4853	-
d_{26}	0.0081	0.0005	ξ_5	0.5227	-
d_{27}	0.0087	0.0005	ξ_6	0.2029	-
d_{28}	0.0120	0.0022	ξ_7	0.4881	-
d_{29}	0.0140	0.0054	η	-0.1123	-
d_{30}	0.0345	0.0266	ν	0.3095	-
			λ	0.1583	-

Table 4.4: **Jump Amplitudes**

This table reports the estimated jump amplitudes as well as their estimated standard deviations. Each column corresponds to one of the sectors considered, using the numerical identifiers introduced in Table 4.2.

	I	II	III	IV	V	VI	VII
mean jump return	-0.0339	-0.0409	-0.0245	-0.0545	-0.0587	-0.0228	-0.0548
standard deviation	0.0936	0.1127	0.0676	0.1502	0.1618	0.0628	0.1511

(2004) report a jump arrival rate of 5 %, which corresponds to a systemic event every 20 months. Naturally, the arrival of a systemic event in one country should be more likely than in six countries simultaneously. Thus, we conclude that the estimated value for λ is of reasonable size.

Surprisingly, the consumer services sector (IV) also shows a high exposure to systemic risk. The sector with the largest sensitivity, and therefore the largest jump component, is the telecommunications / technology sector (V), which is less unexpected. The lowest sensitivity towards the systemic shock is carried by the utilities sector (VI), exhibiting an expected return upon the arrival of abnormal news of only -2.28 %.

Inspecting the volatility parameters β_j, γ_j, δ_j of the continuous part of the model, we can observe smaller values for the systematic risk factors β_j in the jump diffusion case, which, as in the case of the drift parameters, compensate for the existence of the systemic jump factor (see equation (4.5)). The sector specific continuous part γ_j changes slightly between the two models, with no clear direction of sign. The coefficients for the industrials, as well as for the consumer services sector, γ_2 respectively γ_4, are very close to zero for both models. On the other hand, the corresponding idiosyncratic sensitivities δ_2 and δ_4 are relatively high, which may be a sign for a rather weak link between the companies of these two sectors. For all sectors the idiosyncratic risk does not change considerably.

4.7 Optimal Portfolios

In this section, we present the results of the portfolio choice problem and discuss their implications. First, we analyze the changes of optimal portfolio weights when considering or neglecting the presence of systemic risk in the German market. We then disentangle the different effects caused by optimization and estimation. In the third part, we study the consequences of neglecting systemic risk in an historical simulation approach. As a robustness check, we then repeat the analysis for the US stock market.

4.7.1 Optimal Portfolio Weights

For the first static analysis, we assume that the portfolio of stocks to be invested in consists of all DAX companies at the beginning of 2008. Using the methodology presented in the previous sections, we compute the optimal portfolio weights given the estimated parameters for an investor incorporating the risk of systemic events vis-à-vis an investor neglecting this possibility. We call the former the crisis conscious investor, whereas the latter is called the crisis ignorant investor. Note that the crisis ignorant investor already neglects the possibility of systemic jumps when estimating the model's parameters. The risk-free rate used is the one month Libor rate on the euro, which is 4.28 % on an annual basis at the end of our estimation period, December 2007, which is the hypothetical investment date of our DAX investor.

Table 4.5 reports the results for risk aversion coefficients of three, five, and seven. For each stock, we report the optimal portfolio weights for the systemic crisis conscious investor in the left column and the optimal weights for an investor neglecting potential systemic risk, the crisis ignorant investor, in the right column. In the penultimate row, the table displays the overall investment in risky assets for the respective cases. Considering the case for $\gamma = 3$ first, we see that the crisis conscious investor optimally invests slightly more than their entire wealth into stocks.[11] The same is true for the crisis ignorant investor, who invests only minimally more than the former one. This result is in line with the finding of Das and Uppal (2004, p. 2823), who report only minimal changes in the overall risky portions invested. When increasing the level of risk aversion the decrease of the risky investment fraction is of almost equal relative size for both cases. For a γ of five, the investor puts around 60 % of his wealth at risk, for a γ of seven around 42 % remain invested in the stocks.[12]

The last row of Table 4.5 reports the similarity across strategies considering the risky part of the investment, computed as

$$\Delta_\omega = \frac{\sum_{i=1}^{30} |\omega^i_{conscious} - \omega^i_{ignorant}|}{\frac{1}{2}\sum_{i=1}^{30} |\omega^i_{conscious} + \omega^i_{ignorant}|}. \tag{4.28}$$

The value of this similarity measure increases from 0.38 to 0.45 when increasing the risk aversion coefficient from three to seven. Thus, one can observe a bigger difference in portfolio selection for increasing risk aversion. Consequently, the influence of the systemic risk component on portfolio selection is increasing in γ.

Inspecting the individual portfolio weights, we observe that in most instances, as one would expect, the absolute weights decrease for the crisis conscious portfolio. In 12 cases this can be observed for long, in 15 cases for short positions. Three positions do not behave according to this general pattern. First, we can observe the fraction of wealth invested in BMW changing from a long to a short position, although on a very small scale. Second, and more pronounced, the investment in the stock of Metro is changing from a short position of -5.49 % to a long position

[11] Note that, a levered position of the crisis conscious investors can occur due to the employed finite approximation of the normal distribution when computing optimal portfolio weights. Theoretically, a levered or short overall position is never chosen by the investor, in order to avoid negative wealth. See Liu et al. (2003) on this issue.

[12] For the crisis ignorant investor, this effect has to hold as the optimal portfolio weights are inversely proportional related to the risk aversion coefficient. For the crisis conscious investor, it is, however, less clear what to expect.

Table 4.5: **Portfolio Weights**

This table reports the optimal portfolio weights computed for both, the case considering systemic risk and the case neglecting systemic risk. The former was determined numerically as described in Section 4.3 and is reported in the left columns. The later can be computed analytically and is reported in the right columns.

		$\gamma = 3$		$\gamma = 5$		$\gamma = 7$	
		$\omega_{conscious}$	$\omega_{ignorant}$	$\omega_{conscious}$	$\omega_{ignorant}$	$\omega_{conscious}$	$\omega_{ignorant}$
1	D:BAS	0.2548	0.3474	0.1490	0.2085	0.1044	0.1489
2	D:BAY	0.0025	0.0321	0.0045	0.0192	0.0031	0.0137
3	D:FME	-0.0249	-0.0487	-0.0112	-0.0292	-0.0079	-0.0209
4	D:LIN	-0.0118	-0.0230	-0.0037	-0.0138	-0.0026	-0.0098
5	D:MRK	0.1511	0.2444	0.0895	0.1466	0.0627	0.1047
6	D:DPW	-0.2503	-0.3166	-0.1347	-0.1900	-0.0950	-0.1357
7	D:MAN	0.3506	0.5488	0.2032	0.3293	0.1401	0.2352
8	D:SIE	0.0962	0.1552	0.0602	0.0931	0.0406	0.0665
9	D:TKA	0.0689	0.1526	0.0448	0.0915	0.0299	0.0654
10	D:ADS	-0.1592	-0.2771	-0.0873	-0.1663	-0.0602	-0.1188
11	D:BMW	-0.0002	0.0144	0.0014	0.0086	0.0013	0.0062
12	D:DAI	-0.2378	-0.3257	-0.1312	-0.1954	-0.0907	-0.1396
13	D:CON	0.3504	0.5767	0.1971	0.3460	0.1370	0.2472
14	D:HEN3	-0.0512	-0.0552	-0.0270	-0.0331	-0.0184	-0.0237
15	D:VOW	0.3108	0.4848	0.1750	0.2909	0.1217	0.2078
16	D:LHA	-0.1129	-0.1973	-0.0719	-0.1184	-0.0446	-0.0846
17	D:MEO	0.0624	-0.0549	0.0297	-0.0330	0.0269	-0.0235
18	D:TUI1	-0.2293	-0.3680	-0.1394	-0.2208	-0.0921	-0.1577
19	D:SAP	0.0983	0.1224	0.0546	0.0735	0.0380	0.0525
20	D:IFX	-0.3405	-0.4420	-0.1969	-0.2652	-0.1383	-0.1894
21	D:DTE	-0.0105	-0.0223	-0.0077	-0.0134	-0.0057	-0.0095
22	D:RWE	0.1615	0.0366	0.0988	0.0220	0.0687	0.0157
23	D:EOA	0.3771	0.4349	0.2143	0.2610	0.1477	0.1864
24	D:ALV	-0.3745	-0.5813	-0.2110	-0.3488	-0.1469	-0.2491
25	D:HRX	0.2589	0.3528	0.1467	0.2117	0.1023	0.1512
26	D:CBK	-0.3460	-0.4670	-0.1949	-0.2802	-0.1357	-0.2001
27	D:MUV2	-0.3097	-0.4667	-0.1744	-0.2800	-0.1214	-0.2000
28	D:DPB	-0.1336	-0.3328	-0.0750	-0.1997	-0.0521	-0.1426
29	D:DBK	-0.0240	-0.0823	-0.0131	-0.0494	-0.0090	-0.0353
30	D:DB1	1.0732	1.5663	0.6065	0.9398	0.4226	0.6713
	Σ	1.0003	1.0085	0.5959	0.6050	0.4264	0.4324
	Δ_ω		0.3801		0.4218		0.4480

of 6.24 %, which means it does not only change the sign but also increases in absolute terms. Third, the portfolio weight of the investment in the stock of RWE increases from 3.66 % to 16.15 %. As for the entire risky investment, an increase in risk aversion leads to a pure scaling effect - not changing the overall results. The only qualitative differences observable are that the portfolio weight of BMW changes to a long position for the crisis conscious case and that the weight of Bayer increases to 0.0045 for $\gamma = 5$ and falling back to 0.0031 for $\gamma = 7$.

To examine the consequences on a sectorial level, we report the aggregated portfolio weights for each sector in Table 4.6. As for the case of the weights for single stocks, we can observe different reactions when changing from crisis ignorant to crisis conscious portfolio weights. The weights for the basic materials / healthcare, industrials, and consumer goods sectors are positive and decrease when changing to the crisis conscious strategy. The consumer services and telecommunications / technology sectors exhibit short positions which decrease on an absolute basis. The investment fraction in the utilities sector is positive and increases when changing strategies which is due to the sharp increase of the weight of the RWE investment. The portfolio weight of the financial sector, in contrast, changes from a small negative position of -1.10 % to a positive position of 14.43 %.

We thus conclude, although the overall position in risky stocks does not differ substantially under the two different approaches, in most instances the crisis conscious investor chooses less extreme portfolio weights but might also decide to hold bigger position in stocks, which are less exposed to systemic risk compared to the other investment alternatives.

4.7.2 Disentangling Estimation and Optimization Effects

So far we have compared the portfolio weights of the crisis conscious investor with the weights of the crisis ignorant investor obtained by estimating the processes parameters already assuming the nonexistence of jumps for the crisis ignorant

Table 4.6: **Sector Weights**

This table reports the optimal portfolio weights for each sector considered, computed as the sum of the weights in Table 4.5.

	$\gamma = 3$		$\gamma = 5$		$\gamma = 7$	
	$\omega_{conscious}$	$\omega_{ignorant}$	$\omega_{conscious}$	$\omega_{ignorant}$	$\omega_{conscious}$	$\omega_{ignorant}$
I Basic Materials / Healthcare	0.3717	0.5522	0.2281	0.3313	0.1597	0.2366
II Industrials	0.2654	0.5400	0.1735	0.3239	0.1156	0.2314
III Consumer Goods	0.2128	0.4179	0.1280	0.2507	0.0907	0.1791
IV Consumer Services	-0.2798	-0.6202	-0.1816	-0.3722	-0.1098	-0.2658
V Telecommunications / Technology	-0.2527	-0.3419	-0.1500	-0.2051	-0.1060	-0.1464
VI Utilities	0.5386	0.4715	0.3131	0.2830	0.2164	0.2021
VII Financials	0.1443	-0.0110	0.0848	-0.0066	0.0598	-0.0046

investor. Thus, we cannot be sure whether the differences in the individual weights are due to the fact that the investor takes the possibility of systemic events into account when choosing their optimal portfolio weights or due to differences arising from the consideration of systemic jump events when estimating the parameters. To disentangle these two effects, we recalculate the optimal portfolio weights of the crisis ignorant investor by using the process parameters obtained from the estimation of the systemic jump diffusion model, adjusting these to match the mean vector and covariance matrix of a pure diffusion model. This is achieved by using formula (4.4) and (4.5). We call the strategy using these portfolio weights the 'moment matching' strategy. Overall, we now compare three different strategies: (a) the crisis conscious strategy, considering systemic risk in estimation and optimization. (b) the crisis ignorant strategy, neglecting systemic risk in estimation and optimization. (c) the moment matching strategy, considering systemic risk in estimation but not optimization.

The portfolio weights for the case of a risk aversion coefficient of $\gamma = 3$ are provided in Table 4.7. In the first two columns, ω_C (crisis conscious) and ω_I (crisis ignorant), the results of the original optimizations are displayed. The third column ω_{MM}, contains the optimal portfolio weights of the moment matching strategy which matches the mean and covariance of the pure diffusion model to the estimated model including jumps. This allows us to decompose the estimation and the optimization effect. The column Δ_{Syst} reports the difference of ω_C and ω_I, and equates the overall effect of ignoring systemic risk in the estimation, as well as during optimization when choosing optimal portfolio weights. This difference is decomposed in the columns Δ_{Opt} and Δ_{Est} using the identity

$$\Delta_{Syst} = \Delta_{Est} + \Delta_{Opt}. \tag{4.29}$$

The quantity Δ_{Opt} captures the difference of the crisis conscious ω_C and the moment matching strategy ω_{MM} and is thus attributable to the portfolio optimization. It remedies any effect from the estimation as the same parameters

Table 4.7: **Effects of Estimation**

This table reports the optimal portfolio weights for the pure diffusion case computed using the parameters from the pure diffusion estimation and the ones using the parameters from the jump-diffusion estimation adjusted by moment matching. The risk aversion coefficient is set to $\gamma = 3$. The columns ω_C, ω_I, and ω_{MM} denote the optimal portfolio weights of the crisis conscious, crisis ignorant, and the moment matching strategies. Δ_{Syst} is the difference of crisis conscious and crisis ignorant ($\omega_C - \omega_I$), Δ_{Opt} the difference of crisis conscious and moment matching ($\omega_C - \omega_{MM}$), and Δ_{Est} the difference of the moment matching and crisis ignorant strategy ($\omega_{MM} - \omega_I$).

		ω_C	ω_I	ω_{MM}	Δ_{Syst}	Δ_{Opt}	Δ_{Est}
1	D:BAS	0.25	0.35	0.36	-0.09	-0.11	0.01
2	D:BAY	0.00	0.03	0.03	-0.03	-0.03	0.00
3	D:FME	-0.02	-0.05	0.00	0.02	-0.02	0.04
4	D:LIN	-0.01	-0.02	0.01	0.01	-0.02	0.03
5	D:MRK	0.15	0.24	0.22	-0.09	-0.07	-0.02
6	D:DPW	-0.25	-0.32	-0.38	0.07	0.13	-0.06
7	D:MAN	0.35	0.55	0.52	-0.20	-0.17	-0.03
8	D:SIE	0.10	0.16	0.14	-0.06	-0.04	-0.02
9	D:TKA	0.07	0.15	0.10	-0.08	-0.03	-0.05
10	D:ADS	-0.16	-0.28	-0.25	0.12	0.10	0.02
11	D:BMW	0.00	0.01	0.00	-0.01	0.00	-0.01
12	D:DAI	-0.24	-0.33	-0.38	0.09	0.14	-0.05
13	D:CON	0.35	0.58	0.56	-0.23	-0.21	-0.01
14	D:HEN3	-0.05	-0.06	-0.08	0.00	0.03	-0.02
15	D:VOW	0.31	0.48	0.50	-0.17	-0.19	0.01
16	D:LHA	-0.11	-0.20	-0.23	0.08	0.12	-0.04
17	D:MEO	0.06	-0.05	-0.02	0.12	0.08	0.04
18	D:TUI1	-0.23	-0.37	-0.37	0.14	0.14	0.00
19	D:SAP	0.10	0.12	0.11	-0.02	-0.01	-0.01
20	D:IFX	-0.34	-0.44	-0.46	0.10	0.12	-0.02
21	D:DTE	-0.01	-0.02	-0.03	0.01	0.02	-0.01
22	D:RWE	0.16	0.04	-0.02	0.12	0.18	-0.06
23	D:EOA	0.38	0.43	0.52	-0.06	-0.14	0.08
24	D:ALV	-0.37	-0.58	-0.56	0.21	0.18	0.02
25	D:HRX	0.26	0.35	0.35	-0.09	-0.09	0.00
26	D:CBK	-0.35	-0.47	-0.52	0.12	0.18	-0.05
27	D:MUV2	-0.31	-0.47	-0.48	0.16	0.17	-0.01
28	D:DPB	-0.13	-0.33	-0.22	0.20	0.08	0.12
29	D:DBK	-0.02	-0.08	-0.06	0.06	0.04	0.02
30	D:DB1	1.07	1.57	1.54	-0.49	-0.46	-0.03

are used. Δ_{Est} is the difference of ω_{MM} and ω_I, representing the difference due to estimating different models. Note that as the difference due to the portfolio optimization may be bigger than the overall difference, the difference due to estimation effects might have a different sign than the difference due to optimization. Actually, this is observed in 17 instances meaning that in these cases the differences due to different estimation procedures are mitigated and not enhanced. In 22 cases the absolute difference originating from portfolio optimization is bigger than the differences due to estimation, indicating that the former effect is dominant. However, it is difficult to make out any general pattern. Thus, we conclude that the differences due to the estimation procedure seem not to cause a systematic bias, yet alter the optimal portfolio weights quite substantially and should also be taken into account.

4.7.3 Consequences of Neglecting Systemic Risk

To investigate the consequences of following the crisis ignorant strategy - opposed to the crisis conscious strategy - we conduct an historical simulation study. More precisely, we repeat the estimation and optimization analysis procedure for the past 17 years on a monthly basis.
We first obtain the composition of the DAX at the beginning of each month from 1991 to 2007.[13] The DAX was first published on December 30th, 1987. The composition changed 20 times due to mergers, take-overs, IPOs, or because of normal changes due to revised rankings with regard to the selection criteria.[14] An

[13]This information is freely available on the website of the Deutsche Börse AG.

[14]To be included in the DAX, the following prerequisite must be fulfilled (see website of the Deutsche Börse AG for more detailed information): The stock must be listed in the Prime Standard segment, be traded continuously on Xetra, show a free float portion of at least 5 percent and be headquartered (operating or registered headquarter) in Germany. Among all companies fulfilling these prerequisites, 30 are selected based on the two main criteria, order book turnover on Xetra and in Frankfurt floor trading, and free float market capitalization as at a certain reporting date.

overview about the DAX composition as of 01/01/1991 is given in Table 4.13 in Appendix B.

The deletions and additions until 31/12/2007 are reported in Table 4.15. In total we consider 47 companies. Additionally, we sample stock price information for each of these 47 companies during our sample period. Continuously compounded returns are again calculated adjusting for dividends, stock splits, and right issues. We commence the historical simulation in 1991 for two reasons. First, we need sufficient historical data to estimate the parameters of our model and therefore need time series information prior to the first investment date. Second, before 1991 two companies were listed in the DAX, for which we could not obtain historical data (Feldmühle Nobel and Nixdorf).

The details of our historical simulation are as follows: at the end of each month, we estimate the parameters of the crisis conscious as well as the crisis ignorant model for the 30 stocks, currently listed in the DAX at this point in time. We use up to ten years of data for each stock, and require at least five years to be available. If less than five years are available, we exclude the stock from the portfolio until the required amount of data is available (this occurs mainly for IPOs directly entering the DAX). The minimal number of stocks considered is 23, on average 27.8 stocks enter into the investor's portfolio. Additionally, we compute the moment matching parameters for the jump-diffusion model to yield a pure diffusion distribution with identical first and second moments as described in the previous section.

Using these parameter sets, we compute the optimal portfolio weights for the three different cases: (a) crisis-conscious, (b) crisis-ignorant, and (c) moment matching, i.e. crisis-conscious in the estimation but crisis-ignorant in the optimization. As risk-free rate we employ the prevailing one month Libor rate for the euro obtained from the British Banker's Association.[15] Using these portfolio weights $\omega_{i,t,s}$ of the n_t stocks considered, we obtain for each month t the portfolio return of the

[15]See http://www.bba.org.uk.

respective portfolios $y_{t,s}$, $s \in \{a, b, c\}$, by

$$y_{t,s} = \sum_{i=0}^{n_t} \omega_{i,t,s} y_{i,t}, \tag{4.30}$$

where $y_{i,t}$, $i = 1, ..., n_t$, is the return of the ith stock; $y_{0,t}$ is the risk-free rate; and $\omega_{0,t,s} = 1 - \sum_{i=1}^{n_t} \omega_{i,t,s}$.

In total we obtain 194 monthly return observations for each strategy.[16] Table 4.8 reports the summary statistics of these realized portfolio returns for risk aversion coefficients between three and seven.

The mean monthly return of the crisis conscious strategy lies between 0.24 % and 0.41 % for the different levels of risk aversion. The dispersion is comparatively high. In contrast, the mean return of the crisis ignorant strategy is smaller, ranging from -0.90 % to -0.34 % and thus, is even negative. The dispersion is higher compared to the crisis conscious case and thus, amplifying the difference of returns per unit risk calculated as μ/σ compared with simple returns. Higher median than mean returns indicate a skew of the distributions to the left. The lower and upper quartile are much more extreme in the crisis ignorant case. The third case, estimating the parameters using the jump-diffusion model, matching the first two moments to a diffusion model and choosing weights ignoring the possibility of systemic risk, yields very similar results to the crisis ignorant strategy.[17]

[16] As we consider 17 years of monthly data we started with 204 observations. However, 10 months were discarded as the numerical optimization were notoriously unstable in these instances.

[17] We do not want to conceal a caveat applying to our study. It is well known in the literature that *optimal* portfolio choices do not perform well in practice. Very simple heuristical rules, like the naive $1/N$ strategy continue to outperform vast varieties of *optimal* strategies - beginning from Markowitz mean-variance portfolios throughout more complex strategies. Recent and detailed evidence on this observation is given by DeMiguel et al. (2007) who implement and benchmark a broad range of strategies to finally concluding that $1/N$ outperforms for most data sets considered. This is mainly due to the difficulties when estimating the correct parameters of complex models. The same is true for our strategies, including the crisis conscious strategy. The naive approach of investing equal fractions of wealth into the available stocks yields better results in terms of expected return, risk adjusted return as well as expected utility. Therefore, we emphasize that we do not want to argue that the presented strategy should be used for managing a real investment portfolio. The goal of our study is to analyze the effects of neglecting systemic risk relative to considering systemic risk when forming investment portfolios. Thus our results are important, as they show that systemic risk can deteriorate investment results substantially.

To get a better impression of the overall distribution of returns, we plot in Figure 4.1 the histograms of the three cases for a risk aversion coefficient of three. One can clearly observe the consequence of neglecting the existence of possible systemic events. Extreme returns in the upper and lower tails become much more likely where returns close to the mean return decrease in quantity. Thus, even though having an equal degree of risk aversion, the investor who ignores systemic jumps suffers under a much higher dispersion of monthly portfolio returns.

The portfolio choice optimization in our study is based on an investor choosing portfolio weights in order to maximize expected utility. Thus, it is most appropriate to compare the results of the strategies with respect to the utility realized by the investors. Having an empirical distribution of realized wealth at hand, we can compute the utility right away. As utility numbers are difficult to interpret, we calculate the mean relative utility using the crisis conscious case as benchmark. These numbers are given in the last column of Table 4.8. For each case of γ, the expected utility loss of the crisis ignorant investor is bigger than 20 % and up to 32 % for the lowest value of γ. A loss of more than 20 % of expected utility can be seen as economically significant.

To see whether the found loss in mean return and utility is also statistically significant, we conduct a paired t-test with the null hypothesis of a mean difference between the crisis conscious and the crisis ignorant strategy equal to zero. The results are reported in Table 4.9. The mean returns are different at a moderate level of significance between 1.29 % and 5.25 %. The significance levels decrease for the differences in expected utility to p-values very close to zero. Therefore, we can conclude that the loss an investor suffers from ignoring the possibility of systemic crises is also statistically significant.

In the previous section, we have seen a very similar portion of wealth invested into the risky assets for the main cases, crisis conscious and crisis ignorant. One could imagine that this observation was pure coincidence and the results presented in this section are driven by the fact that one of the two investors takes on more

Table 4.8: **DAX Investment - Results of Historical Simulation**

This table reports selected statistics of the monthly returns obtained by the historical simulation using DAX data from 1991 to 2007 and three different investment strategies: (a) the crisis conscious strategy employing the systematic jump diffusion model, (b) the crisis ignorant strategy employing the pure diffusion model, and (c) the moment matching strategy based on the jump diffusion estimates and the pure diffusion optimization. μ *denotes the average return,* σ *the standard deviation of returns. The column* $q_{0.50}$ *reports the median, whereas* $q_{0.25}$ *and* $q_{0.75}$ *the respective quantiles of the return distribution. The last column reports expected utility of the respective strategy relative to the strategy of the crisis concious investor.*

	$\gamma = 3$						
	μ	σ	μ/σ	$q_{0.5}$	$q_{0.25}$	$q_{0.75}$	$E[U]$
(a) crisis conscious	0.0024	0.1660	0.0142	0.0061	-0.0607	0.0875	1.0000
(b) crisis ignorant	-0.0098	0.2279	-0.0430	0.0052	-0.1022	0.1028	0.6833
(c) moment matching	-0.0090	0.2183	-0.0414	0.0015	-0.1081	0.0999	0.7478
	$\gamma = 5$						
	μ	σ	μ/σ	$q_{0.5}$	$q_{0.25}$	$q_{0.75}$	$E[U]$
(a) crisis conscious	0.0040	0.0996	0.0399	0.0066	-0.0294	0.0501	1.0000
(b) crisis ignorant	-0.0067	0.1350	-0.0493	0.0035	-0.0580	0.0566	0.7771
(c) moment matching	-0.0060	0.1290	-0.0464	-0.0011	-0.0612	0.0552	0.8272
	$\gamma = 7$						
	μ	σ	μ/σ	$q_{0.5}$	$q_{0.25}$	$q_{0.75}$	$E[U]$
(a) crisis conscious	0.0041	0.0706	0.0578	0.0069	-0.0202	0.0382	1.0000
(b) crisis ignorant	-0.0038	0.0968	-0.0391	0.0019	-0.0416	0.0431	0.7826
(c) moment matching	-0.0034	0.0925	-0.0369	-0.0013	-0.0437	0.0426	0.8281

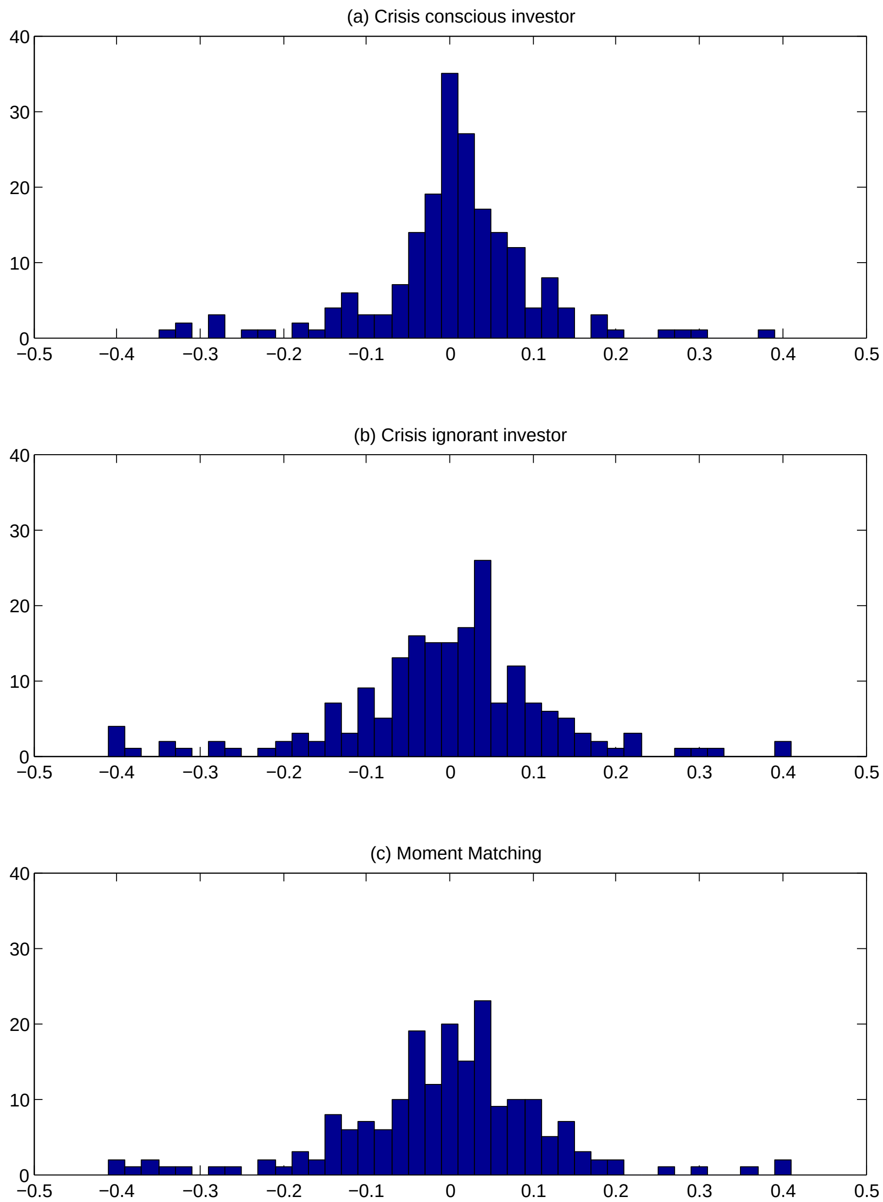

Figure 4.1: **Monthly Returns of Historical Simulation**

This figure shows the monthly returns histograms of the historical simulation for (a) the crisis conscious strategy employing the systematic jump diffusion model, (b) the crisis ignorant strategy employing the pure diffusion model, and (c) the moment matching strategy based on the jump diffusion estimates and the pure diffusion optimization.

Table 4.9: **DAX - Results of the Paired T-Test**

This table reports the results of the paired t-test of the differences in mean return and expected utility between the crisis conscious and the crisis ignorant strategy investing in the DAX. The null hypothesis is equal values for the two strategies.

γ	$\Delta(\mu)$	p-value	$\Delta(E[U])$	p-value
3	0.0122	0.0525	0.1788	0.0122
5	0.0106	0.0169	0.0623	0.0005
7	0.0079	0.0129	0.0402	0.0002

risky positions in general. To check whether this is true, we calculate the mean of the risky fractions over all periods $\hat{\omega} = \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{n_t}\omega_{i,t}$, as well as its standard deviation and report them in Table 4.10. It can be clearly seen, that the differences are small and very unlikely the reason of the observed loss in expected utility and return.

4.7.4 US-Investment

As a final robustness test, we repeat the historical simulation study for a second market. We take the perspective of an US investor allocating their wealth among the 30 stocks comprising the Dow Jones Industrial Average (DJIA). We use the same sample period as for the German market. Table 4.14 in Appendix B lists the stocks of the DJIA as of January 1991, Table 4.16 reports subsequent changes. Note that in contrast to the inclusion into the DAX, there are no technical rules for the DJIA. Here, the 30 included stocks are selected at the discretion of The Wall Street Journal. No strict criteria apply except that the chosen companies should be established US companies and leaders in their field. Continuity is desired and thus, changes occur rarely.[18] Due to this features, data availability is very good and we are able to include at least 29 stocks at each point in time, and 29.75 stocks in the portfolio on average. As risk-free rate we employ the one month US dollar

[18]See webpage of Dow Jones Indexes www.djindexes.com.

Table 4.10: **Fraction of Risky Investment**

This table reports the average fraction of wealth invested into the risky assets $\hat{\omega}$ as well as its standard deviation of the risky fraction for various levels of risk aversion.

	crisis conscious		crisis ignorant	
γ	$\hat{\omega}$	σ	$\hat{\omega}$	σ
3	1.0800	0.3484	1.0344	0.3593
5	0.6646	0.2412	0.6265	0.2342
7	0.4671	0.1783	0.4475	0.1592

Libor rate.

The results for the US market are reported in Table 4.11. Compared with the results for the German market the return realizations are bigger for a γ equal to three and smaller for larger risk aversion coefficients. When comparing the crisis conscious and the crisis ignorant strategy, one can observe similar patterns as for the case of Germany. Mean returns and mean returns per unit risk are higher for the crisis conscious case. The expected utility loss is - with values between 9 % and 18 % - lower than in the German case but still notable. Table 4.12 reports the results of the corresponding paired t-test. Again, we find moderate levels of significance for the differences in mean returns, but highly significant results for the differences in expected utility. Overall, the results do not change qualitatively, indicating robustness with respect to the market considered.

4.8 Conclusion

We have analyzed the consequences of systemic risk on optimal portfolio choice and subsequent portfolio return realizations. To do this, we have taken the perspective of an investor, allocating their wealth across the risky assets of a major domestic stock market index as well as a risk-free asset. In contrast to the results of Das and Uppal (2004) who consider an investment into six stock indices on a global basis, we have found much bigger negative consequences of ignoring the presence of

Table 4.11: **DJIA Investment - Results of Historical Simulation**

This table reports selected statistics of the monthly returns obtained by the historical simulation using DJIA data from 1991 to 2007 and three different investment strategies: (a) the crisis conscious strategy employing the systematic jump diffusion model, (b) the crisis ignorant strategy employing the pure diffusion model, and (c) the moment matching strategy based on the jump diffusion estimates and the pure diffusion optimization. μ denotes the average retruns, σ the standard deviation of returns. The column $q_{0.50}$ reports the median, whereas $q_{0.25}$ and $q_{0.75}$ the respective quantiles of the return distribution. The last column reports expected utility of the respective strategy relative to the strategy of the crisis concious investor.

	$\gamma = 3$						
	μ	σ	μ/σ	$q_{0.5}$	$q_{0.25}$	$q_{0.75}$	$E[U]$
(a) crisis conscious	0.0110	0.1376	0.0803	-0.0011	-0.0527	0.0851	1.0000
(b) crisis ignorant	-0.0016	0.1675	-0.0095	-0.0097	-0.0680	0.0897	0.9101
(c) moment matching	-0.0061	0.1648	-0.0373	-0.0111	-0.0760	0.0786	0.9110
	$\gamma = 5$						
	μ	σ	μ/σ	$q_{0.5}$	$q_{0.25}$	$q_{0.75}$	$E[U]$
(a) crisis conscious	-0.0109	0.1086	-0.1005	-0.0116	-0.0632	0.0447	1.0000
(b) crisis ignorant	-0.0186	0.1367	-0.1360	-0.0173	-0.0760	0.0641	0.8211
(c) moment matching	-0.0195	0.1333	-0.1463	-0.0126	-0.0789	0.0549	0.8227
	$\gamma = 7$						
	μ	σ	μ/σ	$q_{0.5}$	$q_{0.25}$	$q_{0.75}$	$E[U]$
(a) crisis conscious	-0.0060	0.0789	-0.0760	-0.0067	-0.0418	0.0372	1.0000
(b) crisis ignorant	-0.0112	0.0990	-0.1133	-0.0114	-0.0545	0.0471	0.8412
(c) moment matching	-0.0121	0.0964	-0.1252	-0.0087	-0.0576	0.0403	0.8433

Table 4.12: **DJIA - Results of the Paired T-Test**

This table reports the results of the paired t-test of the differences in mean return and expected utility between the crisis conscious and the crisis ignorant strategy investing in the DJIA. The null hypothesis is equal values for the two strategies.

γ	$\Delta(\mu)$	p-value	$\Delta(E[U])$	p-value
3	0.0126	0.0535	0.0465	0.0074
5	0.0077	0.0256	0.0534	0.0088
7	0.0052	0.0523	0.0316	0.0044

systemic risk when making portfolio decisions on a domestic level. Depending on the degree of risk aversion and the market considered, the investor loses between 9 % and 32 % of their expected utility. These differences are also highly statistically significant. The losses in expected utility and expected return are mainly due to more extreme weights in stocks with significant exposure towards systemic risk, and smaller weights in stocks less sensitive towards systemic risk when following the crisis ignorant strategy. Errors due to the disregard of systemic risk during the estimation procedure do not have a systematic effect on these results.

We admit that the considered strategies perform poorly compared to simple heuristics as $1/N$. However, the purpose of our study is not to find superior trading strategies, but to analyze the consequences of neglecting systemic risk. The negligence of this type of risk in portfolio decisions can cause painful losses to the investor. As a consequence, this type of risk should be incorporated in any kind of portfolio strategy, be it a simple or sophisticated one.

4.9 Appendix A

In this appendix, we provide a brief derivation of the optimal portfolio weights in the spirit of Merton (1969).[19]

Following Merton (1969), we solve the portfolio choice problem by applying the dynamic programming approach. Define the indirect utility function J as:

$$J(W_t, t) = \max_{\{\boldsymbol{\omega}_t\}} \; E_t \left[U(W_T) \right]. \tag{4.31}$$

This can be rewritten as:

$$\begin{aligned} J(W_t, t) &= \max_{\{\boldsymbol{\omega}_t\}} \; E_t \left[J(W_{t+dt}, t + dt) \right] && (4.32) \\ &= \max_{\{\boldsymbol{\omega}_t\}} \; E_t \left[J(W_t + dW, t + dt) \right]. && (4.33) \end{aligned}$$

Applying Ito's lemma on J, taking expectations, subtracting $J[W_t, t]$ from both sides and dividing by dt one can obtain the following Hamilton-Jacobi-Bellman equation:

$$\begin{aligned} 0 \;=\; \max_{\{\boldsymbol{\omega}_t\}} & \left\{ \frac{\partial J}{\partial t} + \frac{\partial J}{\partial W} [rW_t + \boldsymbol{\omega}_t' \boldsymbol{\alpha} W_t] + \frac{1}{2} \frac{\partial^2 J}{\partial W^2} W_t^2 \boldsymbol{\omega}_t' \boldsymbol{\Sigma} \boldsymbol{\omega}_t \right. \\ & \left. \lambda E\big[J(W_t + W_t \boldsymbol{\omega}_t' \boldsymbol{\xi} P_t, t) - J(W_t, t) \big] \right\}. && (4.34) \end{aligned}$$

Take as a trial solution for the indirect utility function:

$$J(W_t, t) = b(t) \frac{W_t^{1-\gamma}}{1-\gamma}. \tag{4.35}$$

We have:

$$\frac{\partial J}{\partial W} = b(t) W^{-\gamma}; \qquad \frac{\partial^2 J}{\partial W^2} = -b(t) \gamma W^{-1-\gamma}; \qquad \frac{\partial J}{\partial t} = b'(t) \frac{W_t^{1-\gamma}}{1-\gamma}. \tag{4.36}$$

---

[19] For a more detailed exposition see e.g. Korn (1997) or Duffie (2001).

Thus, we can rewrite (4.34) to:

$$
\begin{aligned}
0 &= \max_{\{\boldsymbol{\omega}_t\}} \Big\{ b'(t)\frac{W_t^{1-\gamma}}{1-\gamma} + b(t)W_t^{-\gamma}W_t[r+\boldsymbol{\omega}_t'\boldsymbol{\alpha}] - \frac{1}{2}b(t)\gamma W_t^{-1-\gamma}W_t^2\boldsymbol{\omega}_t'\boldsymbol{\Sigma}\boldsymbol{\omega}_t \\
&\quad +\lambda E\big[b(t)\frac{(W_t+W_t\boldsymbol{\omega}_t'\boldsymbol{\xi}P_t)^{1-\gamma}}{1-\gamma} - b(t)\frac{W_t^{1-\gamma}}{1-\gamma}]\Big\}. \qquad (4.37)
\end{aligned}
$$

Simplifying yields the desired result:

$$
\begin{aligned}
0 &= \max_{\{\boldsymbol{\omega}_t\}} \Big\{ \frac{b'(t)}{b(t)} + (1-\gamma)[r+\boldsymbol{\omega}_t'\boldsymbol{\alpha}] - \frac{1}{2}\gamma(1-\gamma)\boldsymbol{\omega}_t'\boldsymbol{\Sigma}\boldsymbol{\omega}_t \\
&\quad +\lambda E\big[(1+\boldsymbol{\omega}_t'\boldsymbol{\xi}P_t)^{1-\gamma}-1\big]\Big\}. \qquad (4.38)
\end{aligned}
$$

4.10 Appendix B

Table 4.13: **Companies Listed in the DAX**

This table reports the 30 companies listed in the DAX as of 01/01/1991.

Allianz	Deutsche Babcock	Mannesmann
BASF	Deutsche Bank	Metallgesellschaft
Bayer	Deutsche Lufthansa	Preussag
Bayer. Hypo.- und Wechselbank	Dresdner Bank	RWE
Bayerische Vereinsbank	Henkel	Schering
BMW	Hoechst	Siemens
Commerzbank	Karstadt	Thyssen
Continental	Kaufhof	Veba
Daimler-Benz	Linde	Viag
Degussa	MAN	Volkswagen

Table 4.14: **Companies Listed in the DJIA**

This table reports the 30 companies listed in the DJIA as of 01/01/1991.

Allied-Signal	Exxon	Philip Morris
Aluminum Comp. of America	General Electric	Primerica
American Express	General Motors	Procter & Gamble
American Tel. & Tel.	Goodyear	Sears Roebuck
Bethlehem Steel	Int. Business Machines	Texaco
Boeing	International Paper	Union Carbide
Chevron	McDonald's	United Technologies
Coca-Cola	Merck & Company, Inc.	USX
Du Pont	Minesota Mining & Mfg	Westinghouse Electric
Eastman Kodak	Navistar International	Woolworth

Table 4.15: **Changes in the Composition of the DAX**

This table reports the changes in the composition of the DAX between 01/01/1991 and 31/12/2007 as well as a brief reason for the change.

Date	Deletion	Addition	Reason
18/09/1995	Deutsche Babcock	SAP	Higher market cap. of SAP
22/07/1996	Kaufhof	METRO	Merger
23/09/1996	Continental	Münchener Rück	
18/11/1996	Metallgesellschaft	Deutsche Telekom	IPO of Deutsche Telekom
22/06/1998	Bayerische Hypotheken- und Wechselbank	Adidas	Merger
	Bayerische Vereinsbank	HypoVereinsbank	
21/12/1998	Daimler-Benz	Daimler	Merger
22/03/1999	Degussa	Degussa-Hüls	Take-over
25/03/1999	Thyssen	ThyssenKrupp	Merger
20/09/1999	Hoechst	Fresenius Medical Care	Merger
14/02/2000	Mannesmann	Epcos	Take-over
19/06/2000	Veba	E.ON	Merger
	VIAG	Infineon	
18/12/2000	Degussa-Hüls	Degussa	Change of name
19/03/2001	KarstadtQuelle	Deutsche Post	IPO of Deutsche Post
23/07/2001	Dresdner Bank	MLP Vz.	Take-over
23/09/2002	Degussa	Altana	Higher market cap. of Altana
23/12/2002	Epcos	Deutsche Börse	
22/09/2003	MLP Vz.	Continental	
19/12/2005	HypoVereinsbank	Hypo Real Estate	Take-over
18/09/2006	Schering	Postbank	Take-over
18/06/2007	Altana	Merck	Higher market cap. of Merck

Table 4.16: **Changes in the Composition of the DJIA**

This table reports the changes in the composition of the DJIA between 01/01/1991 and 31/12/2007.

Date	Deletion	Addition
06/05/1991	Navistar International	Caterpillar
	USX	Walt Disney
	Primerica	JP Morgan
17/03/1997	Westinghouse Electric	Travelers Group
	Texaco	Hewlett-Packard
	Bethlehem Steel	Johnson & Johnson
	Woolworth	Wal-Mart Stores
01/01/1999	Chevron	Microsoft
	Goodyear	Intel
	Union Carbide	SBC Communications
	Sears Roebuck	Home Depot
08/04/2004	AT&T	American International
	Eastman Kodak	Pfizer
	International Paper	Verizon

Chapter 5

Concluding Remarks

In this thesis, we have presented three papers dealing with systemic risk. Chapter 1 has laid the foundation of the topic by introducing the concept of systemic risk, employing a general working definition applicable to any economic system of companies, and discussed the special situation of the banking sector.

The empirical study presented in Chapter 2 was devoted to the question of whether systemic risk is indeed higher in the banking sector, compared with other sectors of the economy. By using a novel approach, interpreting the multivariate tail coefficient of stock returns as joined conditional default probability, we found empirical evidence for a higher systemic crisis probability in the banking sector. Furthermore, we found that the risk of experiencing a crisis significantly rises during adverse economic conditions. When comparing the US and German banking systems, it became apparent that the German system is less exposed to systemic risk.

The approach taken in Chapter 2, measuring systemic risk at the outer tail of the distribution, has the great advantage of focusing directly on the events that are most important when dealing with systemic threats, i.e. joined extreme downward movements of the system. The fact that it is impossible to disentangle systemic risk in the narrow and in the broad sense can be seen as a disadvantage of this methodology.

As the different types of systemic risk demand different policy reactions, the issue of narrow systemic risk is investigated in more detail in Chapter 3 by analyzing the abnormal stock price reactions of companies upon a negative earnings surprise at a competitor firm. The main result of this study is empirical evidence of contagion effects in the banking sector, in contrast to non-banking sectors, which do not show any signs of contagion. The degree of contagion increases with the importance of both the bank experiencing a negative earnings surprise as well as the banks being affected.

The last paper of this thesis, presented in Chapter 4, focused on a different aspect of systemic risk. By taking the position of a stock market investor, we empirically analyzed the consequences of neglecting the presence of systemic risk in the process of forming optimal portfolios. Failure to take systemic threats into account yielded significant losses in expected returns and expected utility for a German as well as a US-based stock market investor during the last two decades. Therefore, systemic risk should be taken into account when forming investment portfolios.

Systemic risk has become a very present theme in economic research as well as political discussions. The currently prevailing financial crisis has conjured up this issue in a striking way. Beside the aspects of systemic risk dealt with in this thesis, many others must be considered.

First, in the first two studies, we have focused on the measurement of systemic risk, without analyzing the microstructural origin of this threat. This is an important point and should also be addressed and studied when striving towards a crises robust economy.

Second, we have analyzed how a stock market investor should react to systemic risk without being able to mitigate this threat. However, this task of crisis prevention lies with policy makers and regulators, who consequently ask for measures against systemic risk. They should be able to apply these instruments in the best possible way, in order to receive optimal results. Thus, the issue of prevention and abatement of systemic risk is another important topic for further research.

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