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Wewel, Claudio (2013). Are earthquakes less contagious than bank failures? Comparative impact assessment of the Tohoku earthquake 2011 and the Lehman bankruptcy 2008. Working Paper.

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“*No book can ever be finished. While working on it we learn just enough to find it immature the moment we turn away from it.*”

“*The game of science is, in principle, without end. He who decides one day that scientific statements do not call for any further test, and that they can be regarded as finally verified, retires from the game.*”

– Sir Karl R. Popper

1 Introduction

The recent Subprime and Euro Crises have stressed the vulnerability of the international banking system and the adverse impact that bank defaults have on the macro-economy. Over the last decades, financial markets (and in particular banks) have become increasingly interconnected as a result of financial liberalization, growing international trade, and increasingly global supply chains. In this effect, the understanding of systemic risk and financial contagion that pose a threat to both the international financial system and to the real economy (through its dependence on the financial sector) is of vital interest to both researchers and economic policy makers.

Over the years, various definitions of systemic risk and contagion have emerged. According to the 2001 Report on Consolidation in the Financial Sector, the Group of Ten (2001) defines systemic risk as follows:

> *Systemic financial risk is the risk that an event will trigger a loss of economic value or confidence in, and attendant increases in uncertainly about, a substantial portion of the financial system that is serious enough to quite probably have significant adverse effects on the real economy. Systemic risk events can be sudden and unexpected, or the likelihood of their occurrence can build up through time in the absence of appropriate policy responses. The adverse real economic effects from systemic problems are generally seen as arising from disruptions to the payment system, to credit flows, and from the destruction of asset values.*

The previous definition provides a general and intuitive insight to the notion of systemic risk. Thus, more concisely, systemic risk can be subsumed as the *risk or the probability of breakdowns in an entire system, as opposed to breakdowns in individual parts or components, and is evidenced by comovements (correlation) among most or all the parts* (Kaufman and Scott, 2003).

In literature, there is consesus that two alternate main mechanisms cause systemic risk: common shocks (e.g., Kaufmann, 2000; Helwege, 2010) and contagion (e.g., Lando and Nielsen, 2010; Longstaff, 2010). Contagion requires strong interconnectedness between financial institutions such as mutual credit exposures or derivatives transactions entailing counterparty risk and may occur if an institution I defaults on payments to another institution J (that is closely connected to I) causing J to default on its own payments and thereby potentially causing financial distress of further institutions. More generally, Kaminsky and Reinhart (2000) refer to contagion as *channels through which disturbances are transmitted* and mention trade links and (largely ignored) financial sector links such as bilateral exposures and interbank loans as examples.

Whereas contagion refers to a direct causation mechanism, causation by *common shocks* is rather indirect. Moreover, causation by common shocks necessitates sufficiently homogenous risk factors, i.e., similarities in the financial institutions' portfolios. Thus, if insitutions' risk exposures are alike, a shock resulting in severe losses to an asset could result in uncertainty about similar traded assets potentially subject to the same shock (Kaufmann, 2000). Given that these assets constitute a substantial portion in a multitude of financial institutions' portfolios, such a shock could potentially trigger simultaneous losses to a wide range of institutions with similar exposures across the financial industry.

Research on systemic risk can be separated into various branches. One branch focuses on general systemic risk measurement and can furthermore be systemized as follows:

(i) *Asset price based measurement.* Over the past years, the *Conditional Value at Risk* (Adrian and Brunnermeier, 2011) and the *Marginal Expected Shortfall* (Acharya et al., 2010) have emerged as the most prominent asset price based measures. The latter measures are applied by the U.S. Treasury Department (Financial Stability Oversight Council, 2013) and the European Systemic Risk Board (European Systemic Risk Board, 2013) and have triggered numerous studies proposing extensions.[1] Other approaches proposed by academia are based on extreme value theory (De Jonghe, 2010; Zhou, 2010), principal component analysis (Billio et al., 2012; Kritzman et al., 2011), and default probabilities (Lehar, 2005; Huang et al., 2009; Segoviano and Goodhart, 2009; Huang et al., 2012; Gray and Jobst, 2010).

(ii) *Network analysis based measurement.* This strand of literature analyzes systemic risk modeling institutions' mutual exposures (e.g., Elsinger et al., 2006a; Allen et al., 2010; Tarashev et al., 2010; Halaj and Kok Sorensen, 2013).

An advantage of network based modelling is that such an analysis may even incorporate institutions whose stock is not traded on stock markets.[2] However, this comes at the cost

[1] Several studies implement the Marginal Expected Shortfall (Acharya and Steffen, 2012; Idier et al., 2013), related measures (Engle et al., 2012; Acharya et al., 2012), and the Conditional Value at Risk (López-Espinosa et al., 2012; Van Oordt and Zhou, 2011; Roengpitya and Rungcharoenkitkul, 2011; Gauthier et al., 2010). Other studies propose various extensions to the latter approaches (Hong, 2011; Girardi and Ergün, 2013; Cao, 2013).

[2] This concern particularly applies to economies with few publicly traded banks such as Germany or Austria.

of employing balance sheet data with much lower sampling frequency than stock prices. Thus, asset price based measures are capable of reflecting the daily dynamics at the stock markets. Moreover, asset price based measures are less likely to be prone to national particularities in accounting practices and hence allow for broad analyses and comparisons within the international banking system. Bisias et al. (2012) provide an extensive survey on the literature on systemic risk measurement.

Another branch investigates common shocks and contagion in an event study setup. Research on contagion is abundant with literature covering financial crises such as the Mexican Peso Crisis in 1994 (e.g., Calvo and Reinhart, 1996; Edwards, 1998) or the Subprime Crisis including the bankruptcy of Lehman Brothers (e.g., Longstaff, 2010; Hwang et al., 2010; Bekaert et al., 2011) as well as contagion following Black Swan events such as the 1987 Black Monday (e.g., King and Wadhwani, 1990; Hamao et al., 1990; Bertero and Mayer, 1990) and the September 11, 2011 terrorist attacks (e.g., Hon et al., 2004) or natural disasters (e.g., Lee et al., 2007; Asongu, 2012).

This thesis consists out of three essays on systemic risk in the banking system and stock market contagion. The first essay (Trapp and Wewel, 2013, "Transatlantic systemic risk") investigates which type of systemic risk – common shocks or contagion – dominated in the banking system at the onset of the Subprime Crisis and thus contributes to the literature on the distinction of contagion and common shocks.

Applying a Copula approach, we measure bivariate upper tail dependence between CDS premia of 550 firms based in the US and Europe. We show that banks' exposures to common risk factors are crucial for systemic risk in the banking sector. We come to this conclusion by showing that dependencies are generally higher within the US and Europe than between these regions. At the onset of the Subprime Crisis, however, systemic risk in Europe increases much more strongly than in the US. Given that intra-regional dependencies are stronger than transatlantic dependencies, we argue that the steep increase of systemic risk in Europe is unlikely to arise from contagion but rather from common risk factors in the banks' portfolios.

We furthermore find that dependence between banks and real sector firms is limited, however, European banks are more closely connected to real sector firms of the same region than their US counterparts. This finding is likely to result from a relatively higher importance of bank loans as a means of funding to European real sector firms when compared to US firms that rely on capital market-based funding to a greater extent (see, e.g., Demirguc-Kunt and Levine, 1999).

Our results indicate that in the Subprime Crisis, common factors played a much more important role than contagion, which is in line with the findings of Kaufmann (2000). Our results have important implications for regulatory authorities stressing the importance of monitoring international bank dependencies arising from common risk factors. Moreover, the limited dependencies between banks and real sector firms imply that while regulators should pay particular attention to large banks providing a substantial share of loans to real-sector firms, they should improve real sector firms' access to the capital markets.

The second essay (Döring, Hartmann-Wendels, and Wewel, 2013, "What can systemic risk measures predict?") contributes to the literature on the assessment of systemic risk measures and to the literature on CoVaR (Adrian and Brunnermeier, 2011), MES (Acharya et al., 2010), and the related SRISK measure (Brownlees and Engle, 2012).[3] In a first step, we implement these three prominent systemic risk measures in a DCC GARCH framework.

Systemic risk measures should be able of capturing distress in the banking system that subsequently leads to substantial downturns in the real economy. Hence, in a second step, we compare the measures evaluating their adequacy as a tool for regulatory authorities on the basis of their predictive power for various market, balance sheet related, and macroeconomic variables investigating directionalities at the bank as well as at the banking system level. We apply the measures to a sample of stock prices of European banks with total assets above €30*bn* in the period from July 2005 to June 2013.[4] As European banks are likely to be affected by both the recent international financial crisis and the European sovereign debt crisis, the European banking system constitutes a unique setting for the assessment of systemic risk measures. Moreover, we ensure that the systemic risk measures are not exclusively evaluated by their performance during the Subprime Crisis.

Overall, we find that systemic risk measures are capable of capturing early symptoms of distress in the financial markets. Furthermore, we find that at the banking system level systemic risk measures possess substantial forecasting power for a variety of

[3] Literature on the CoVaR, MES, and SRISK measures can be systemized as follows: (i) studies employing CoVaR (López-Espinosa et al., 2012; Van Oordt and Zhou, 2011; Roengpitya and Rungcharoenkitkul, 2011; Gauthier et al., 2010) and MES related measures (Acharya and Steffen, 2012; Idier et al., 2013; Engle et al., 2012; Acharya et al., 2012) to analyze distress in the financial markets (ii) extentions of the latter measures (Hong, 2011; Girardi and Ergün, 2013; Cao, 2013), and comparisons between the latter (Jiang, 2012; Benoit et al., 2013; Löffler and Raupach, 2013).

[4] According to the European Commission's proposal for a Single Supervisory Mechanism (SSM) for the European Banking Union, banks with total assets above €30*bn* are supervised directly by the ECB due to their potential systemic relevance (European Commission, 2013).

financial market variables (EURIBOR-OIS spread and volatility), balance sheet variables (leverage, market-to-book ratio, and profitability), and macro-economic variables (GDP, housing prices, and economic sentiment). Whereas balance sheet characteristics determine an individual bank's systemic importance, they cannot explain or predict systemic risk at the banking system level. Comparing the predictive power of the analyzed measures, we find that the CoVaR's forcasting power is dominated by MES related measures' predictive power and conclude that the latter are thus most suitable for regulatory purposes.

The third essay (Wewel, 2013, "Are earthquakes less contagious than bank failures? Comparative impact assessment of the Tohoku earthquake 2011 and the Lehman bankruptcy 2008") contributes to the literature on international stock market contagion. Employing a data set of 4,350 international stocks in 13 countries, we investigate pre-and post-event cross-market correlation on national and international stock markets following the Japanese Tohoku[5] earthquake on March 11, 2011, the subsequent tsunami and the nuclear disaster at Fukushima Daiichi. To better evaluate the degree of contagion, we employ the bankruptcy of Lehman Brothers on September 15, 2008 as benchmark event. Contrary to previous studies (Lee et al., 2007; Asongu, 2012), we analyze contagion by industry and country at the individual share price level which allows us to explore potential geographical patterns of how contagion propagates through global stock markets.

Overall, we find that contagion arising from both events is substantial. Whereas the Lehman bankruptcy affected stocks from all industries globally, the Tohoku earthquake only significantly affected insurance and utilities stocks. We argue that the degree of global stock markets' response is explained by distinct contagion mechanisms. Events such as the Lehman bankruptcy have the potential to result in panics at the global stock markets, which emerge as a consequence of anticipated future losses resulting from financial exposures or future liquidity freezes. As global stock markets are higly integrated, such panics are easily transmitted. Contrary, natural disasters are less likely to be followed by panics because stock market participants will anticipate price effects to have fully materialized after the disaster. Moreover, the destruction of (real) assets will be most severe in the event country itself. International supply chain disruptions arising from destroyed production facilities impact global stock only to a lesser degree.

[5] The term *Tohoku* refers to the Northeast of Japan's main island *Honshu* and represents the region that was most severely affected by the earthquake.

2 Transatlantic systemic risk

2.1 Introduction

Where does systemic risk come from, and how should we regulate it? The first, most commonly cited mechanism causing banks to default jointly is contagion: Banks can be connected with one another because of direct bilateral exposures, e.g., through interbank loans or derivatives transactions entailing counterparty risk. In this case, regulation must specify limits to the exposure one bank can have towards another to prevent one default from causing a meltdown of the entire banking system. Second, if banks hold similar portfolios, a common shock may simultaneously affect all banks and also lead to the joint default of multiple banks. Then, the main role of regulation is to ensure that there is sufficient variation across the portfolios of different banks, or at least variation in the sensitivities of the portfolio values towards joint risk factors.

Both of these channels for systemic risk, contagion and conditional independence, have been discussed in the literature on joint defaults (see, e.g., Lando and Nielsen, 2010; Longstaff, 2010). However, evidence on which type of systemic risk dominates in the banking system is extremely scarce for three reasons. First, information at the portfolio level is, if at all, only available to supervisory authorities. Second, even supervisors often do not have disaggregate information on mutual exposures at the international level. Hence, the only study differentiating between common shocks and bilateral exposures that we are aware of analyzes US data (Helwege, 2010). An international setting, however, is crucial because distinguishing between a common shock and one originating within an individual bank is almost impossible at the national level. Third, even if they were available, portfolio-level information may not sufficiently reflect interbank exposures. Given most banks' limited exposures[1] towards Lehman, it is unlikely that balance-sheet based measures of systemic risk could have quantified the resulting declines of bank stocks and defaults of numerous financial institutions.

In this study, we explore whether systemic risk arises from common shocks or contagion in an international setting. We focus on the two largest integrated economic regions in the world, the United States of America and Europe, because each constitutes an integrated

[1] While Bank of America filed a 5.3 bn USD claim against Lehman, followed by Goldman with 2.5 bn USD, Bloomberg estimated the aggregate exposure for European banks *and* insurers to lie below 7.3 bn USD shortly after Lehman filed for bankruptcy on September 15, 2008. "European Banks, Insurers Have $7.3 Billion Exposure to Lehman", Fabio Benedetti-Valentini and Elisa Martinuzzi, September 18, 2008.

banking market with homogenous regulation and a single predominant currency. We avoid the issue of obtaining portfolio exposures or balance sheet information by using the prices of traded assets, and directly infer systemic risk by adapting the copula approach of Buehler and Prokopczuk (2010) to credit default swap (CDS) premia.

We explore the importance of common shocks vs. contagion for the banking sector in two steps. First, we document that connections between US and European banks are low compared to those within each region. Second, we show that the onset of the Subprime Mortgage Crisis increased systemic risk in Europe much more strongly than in the US. This effect strongly points at a prevalence of common shocks: An increase in subprime mortgage loan defaults in the US is a local shock (as, for that matter, the Lehman bankruptcy). Since the connection between US banks is stronger than between US and European banks, a transmission of this shock through contagion would imply that systemic risk should increase *less* strongly in Europe than it does in the US.

We then turn to the implications of banking risk for the real sector. During the recent financial crisis, banks received financial support under the troubled asset relief program (TARP), the European Financial Stability Facility (EFSF), and the European Financial Stabilisation Mechanism (EFSM) due to concerns about a recession arising from another bank's default. This concern was well-grounded in historical experience, even prior to the Lehman bankrupcty: As Reinhart and Rogoff show in a series of papers (2009c, 2009a, 2009b), banking crises are regularly followed by a drop in equity prices, output, and employment levels since real-sector firms rely on banks as a source of external funding. We therefore determine how strongly banks and firms from a wide range of real sectors are connected, again by applying the copula approach to CDS premia for these firms. This allows us to base our analysis on a large range of firms besides banking and insurance, for which regulatory guidelines demand publication of balance sheet information at an extremely detailed level (see, e.g., Furfine, 2003; Wells, 2004; Gauthier et al., 2010).

Interestingly, we find that banks do not play a central role: Firms from a given real sector are more strongly connected to both firms from the same real sector and to firms from any other real sector than they are to banks. Only other banks and non-bank financial firms are more strongly connected to banks than to real-sector firms. At first sight, this result appears surprising, because of the established role of banks in supplying loans to the real sector. However, the importance of banks in this respect can vary substantially. For example, a large group of small banks on average provides more loans than a small group of large banks, and banks with a larger focus on investment banking provide fewer loans than banks with a strong focus on commercial banking (Altunbas et al., 2002; Jia, 2009). Most banks in our sample are large, international banks. Therefore, our results imply that the default of a single large real-sector firm is more likely to lead to a recession than the default of a large, international bank.

In addition to the differentiation between common shocks and contagion, our study contributes to several strands of literature. First, we extend the broad body of literature on systemic risk for financial institutions. Studies that compare banks to other financial institutions (see, e.g., Billio et al., 2012; Bosma et al., 2012) mostly find that systemic risk is highest for banks. Very few studies (see, e.g., Harmon et al., 2010; Muns and Bijlsma, 2011; Buehler and Prokopczuk, 2010) compare systemic risk in the banking sector to systemic risk for non-financial firms, and come to the same conclusion: systemic risk is highest in the banking sector. We extend this literature by showing that the interdependence between banks and non-banks is low, compared to systemic risk within and between real sectors.

Studies analyzing the determinants of systemic risk identify bank size, interbank loan ratio, and the bank's country of origin (Elsinger et al., 2006a), linkages at the asset level and mutual credit relations (Elsinger et al., 2006b), and the bank's default probability (Huang et al., 2012) at the individual level as significant factors. We contribute to this literature by showing that the link between non-banks and banks is higher in Europe than in the US. This is in line with the greater importance of banks as a source of external financing in Europe (see, e.g., Demirguc-Kunt and Levine, 1999; Dermine, 2002; Kwok and Tadesse, 2006).

From a macro perspective, Kaminsky and Reinhart (1999) argue that a typical banking crisis begins with a period of financial liberalization, leading to an economic boom and an overvaluation of the local currency, which leads to a recession and a reinforcing banking and currency crisis. Multiple studies have explored this mechanism empirically, and come to the conclusion that adverse economic conditions coincide with higher systemic risk (see, e.g., Buehler and Prokopczuk, 2010; Bartram et al., 2007), and regions differ significantly regarding their susceptibility to contagion (Bae et al., 2003). In contrast, Bosma et al. (2012) study global relations between financial firms, and find that systemic risk has uniformly decreased since the onset of the financial crisis. We contribute on this macro perspective by showing how the financial crisis has intensified systemic risk in the US and Europe.

Second, we contribute to the literature on international relations between financial firms. The global banking system has become more integrated within the last 30 years (Garratt et al., 2011) for a variety of reasons: In addition to the active interbank markets, banks have branched out from their domestic to foreign markets, and the liberalization of financial markets has led to the creation of new financial products. As a result, banks are exposed to similar risk factors globally. However, these global factors do not obliterate the importance of regional factors (Bartram et al., 2007). Consistent with evidence by Hartmann et al. (2006) for banks in different EMU countries, we find higher financial integration within the US and within Europe than between the two regions. We also document the evolution of these differences over time, and show that they drastically decrease during the financial crisis.

Last, our results have implications for the structure of international financial regulation. For example, Went (2010) discusses the implications of the new focus on systemic risk in the Basel III framework, and Hanson et al. (2011) develop a framework for macroprudential instead of microprudential regulation. Blackmore and Jeapes (2009) study the consequences of one global financial regulator compared to a multi-regulator approach under international guidelines. Our results have two implications for this body of literature. First, monitoring exposures towards common shocks at the international level is a central issue no less important than monitoring bilateral exposures. Second, bailouts for large international banks which are termed "too big to fail" are not necessary to avoid spillovers to the real sector if the bilateral exposures between these banks and smaller banks supplying the majority of loans are properly monitored.

The remainder of the paper is structured as follows: In Section 2.2, we give an overview over the CDS time series used to compute systemic risk. We motivate and develop our systemic risk measures in Section 2.3, and present the empirical results of our study in Section 2.4. Section 2.5 summarizes and concludes.

2.2 Data

In our analysis, we use CDS premia to determine systemic risk. Clearly, the use of CDS premia instead of stock returns or equity option data has advantages and disadvantages. On the one hand, the CDS premium has a closer link to a firm's default than stock returns. For example, stocks frequently trade at a non-zero price even after the underlying firm has defaulted on debt payments. This effect points at violations of the absolute priority rule, which has been documented by Unal et al. (2003). On the other hand, CDS might also reflect factors other than the underlying entity's default risk. We believe that illiquidity, the delivery option, and counterparty risk play a particular role:

(i) Lower liquidity in the CDS market will be associated with lower bid quotes. Hence, our systemic risk estimate which is derived via the *upper* tail dependence is unlikely to be upwards-biased due to deteriorating liquidity conditions in the CDS market.

For CDS ask quotes, the opposite effect prevails. Buehler and Trapp (2010) show that the effect of CDS liquidity on CDS quotes can be substantial.

(ii) Both CDS bid and ask quotes may be biased upwards or downwards because of counterparty risk, depending on whether the protection seller's or the protection buyer's default is more likely.[2] As Arora et al. (2012) show, counterparty risk has a very limited effect on CDS premia of around 1 bp.[3] Hence, fluctuations of counterparty risk are likely to have almost no effect on CDS premia overall.

(iii) A protection buyer has the option to deliver the cheapest out of a range of bonds after a default of the underlying reference entity. This cheapest-to-deliver option should increase both CDS bid and ask quotes.

Overall, CDS bid quotes are less likely to increase for reasons other than fundamental default risk, compared to CDS ask quotes. An upper tail dependence estimate derived from CDS bid quotes will thus be more conservative than an estimate derived from CDS ask quotes. We attempt to minimize the impact of these alternative sources of CDS premium variation by focusing on the CDS bid quote.

We obtain our CDS data from Bloomberg. We focus on the five-year maturity and use Credit Market Analysis (CMA) as our price source, since Mayordomo et al. (2010) show that new information seems to be reflected most quickly for this maturity-provider combination. To ensure comparability between the CDS contracts, we focus on CDS written on senior unsecured debt.

Overall, Bloomberg specifies the following sectors: Basic Materials, Communication, Consumer (Cyclical), Consumer (Non-cyclical), Diversified, Energy, Financial, Sovereign, Industrial, Technology, Utilities. We perform four modifications: First, we merge the cyclical and the non-cyclical consumer sectors.[4] Second, we manually verify whether firms with the "Financial" sector tag are banks or non-banks,[5] and split the "Financial" sector accordingly. Third, we drop CDS contracts written on firms from the "Diversified" sector since only twelve firms, mostly holding companies, fall into this category. Last, we drop

[2] To be precise, both the univariate default risk of protection buyer and seller as well as their joint default risk with the underlying reference entity matter for the total effect.

[3] This is likely due to the margin payments that are regularly made in most CDS contracts as the contract value changes over time.

[4] This merge ensures comparability between Bloomberg and Industry Classification Benchmark (ICB) sectors.

[5] We define a bank as a financial institution with the authority to accept deposits and grant loans. Such an institution may of course also operate outside of this area, e.g., offer asset management services.

all CDS contracts written on reference entities termed "Sovereign", since the economic rationale behind joint defaults of sovereign reference entities (such as municipalities or states) is likely to be different than for non-sovereign firms. This leaves us with 1,323 firms.

We split our sample into the following two (regulatory) regions: the United States of America (US) and Europe. For 957 of the 1,323 firms, we are able to identify the country of the firms' headquarters. 550 out of the 957 firms are headquartered either in the US or in Europe. The subsample used for the following analysis contains 335 firms for the US and 215 firms for Europe, including the UK.[6] For these 550 firms, we collect daily CDS bid quotes, denominated in basis points per annum, via Bloomberg from October 2004 to October 2009, omitting all zero quotes.[7] Table 2.1 reports descriptive statistics of all CDS contracts in our final sample.

As Panel A of Table 2.1 shows, the number of firms is not evenly distributed across sectors with only 19 firms in the technology sector, and 173 firms in the consumer sector. The joint financial sector (bank and non-bank) is the second-largest sector with 103 firms, of which 35 are banks. With a total of 65,950 observations for these banks, we are confident that the CDS premia with a mean of 95 bp and a standard deviation of 305 bp are a reliable indicator of default risk in the banking sector. The strongly skewed distribution of CDS premia (the median on average amounts to one third of the mean) indicates that a symmetric dependence measure would severely underestimate upper tail dependence.[8]

[6] The exact composition of the subsample (i.e., the distribution of firms among countries within both considered regions) is as follows:
US (335 firms) ; *Europe* (215 firms) – Austria (2), Belgium (3), Denmark (5), Finland (5), France (39), Germany (29), Greece (2), Ireland (3), Italy (12), Netherlands (11), Norway (2), Portugal (2), Spain (10), Sweden (14), Switzerland (13), United Kingdom (63). We include Norway and Switzerland in the region *Europe* even though they are not members of the European Union since they implemented Basel II along the Directives 2006/48/EC and 2006/49/EC of the European Parliament and the Council, and are adopting the new Basel III directives, such that the region *Europe* has a homogenously regulated banking sector.

[7] To explore whether our results are affected by possibly stale premia, we repeat our analyses on a subset of CDS premia where all quotes that do not exhibit a change within a week are omitted. The results are virtually identical.

[8] The high maximum values in our sample are due to the fact that a number of firms default during the observation interval. For example, Clear Channel Communications, Inc., a media and entertainment company, experienced a distressed exchange default in August 2009. Loss given default estimates from Moody's for senior unsecured bonds were as high as 92%. Consequently, CDS premia for Clear Channel Communications increased to 9,580.20 bp.

Panel A – Complete Sample			CURRENCY (in %)				MOMENTS		QUANTILES				
Sector	(abbr.)	#firms	EUR	GBP	USD	#obs	mean	sdev	min	$q = 0.25$	$q = 0.50$	$q = 0.75$	max
Basic Materials	Basi	47	34.04	2.13	63.83	77,668	156.09	399.71	6.81	28.00	53.33	130.51	5,316.67
Communication	Comm	52	53.85	3.85	42.31	82,245	192.29	421.99	6.95	39.55	72.75	193.40	9,580.20
Consumer	Cons	173	32.95	2.89	64.16	287,118	190.26	509.57	1.67	29.36	60.00	164.21	9,135.45
Energy	Ener	35	11.43	–	88.57	55,795	95.97	128.50	2.36	26.50	41.11	101.85	1,009.25
Financial (Bank)	Bank	35	65.71	–	34.29	65,950	95.47	305.03	2.17	11.25	22.00	80.52	5,886.42
Financial (Non-Bank)	Fina	68	32.35	2.94	64.71	106,490	184.45	417.48	3.63	23.84	43.27	138.87	6,274.24
Industrial	Indu	78	39.74	–	60.26	133,761	97.17	186.43	5.75	25.38	45.00	106.00	5,165.69
Technology	Tech	19	10.53	–	89.47	25,918	168.38	365.08	4.00	24.77	61.70	120.33	4,632.01
Utilities	Util	43	48.84	2.33	48.84	75,583	69.82	95.96	4.35	23.50	38.50	68.32	1,011.13
ALL		550	37.09	2.00	60.91	910,528	149.91	389.30	1.67	25.50	49.36	127.70	9,580.20
Panel B – United States Sample													
Basic Materials	Basi	29	–	–	100.00	44,823	193.55	502.66	6.81	32.25	64.30	172.77	5,316.67
Communication	Comm	22	–	–	100.00	29,090	267.10	621.95	8.87	44.53	91.51	234.00	9,580.20
Consumer	Cons	112	0.89	–	99.11	179,717	227.98	624.67	3.00	29.04	62.56	179.99	9,135.45
Energy	Ener	31	–	–	100.00	47,515	106.39	134.87	5.00	28.25	45.15	119.75	1,009.25
Financial (Bank)	Bank	12	–	–	100.00	23,461	167.88	484.16	5.03	20.23	32.17	114.70	5,886.42
Financial (Non-Bank)	Fina	44	–	–	100.00	63,779	228.47	488.55	6.06	27.58	49.33	192.50	6,274.24
Industrial	Indu	47	–	–	100.00	74,545	88.84	128.92	5.75	23.67	45.49	105.25	1,965.16
Technology	Tech	17	–	–	100.00	21,869	184.52	394.65	4.00	23.00	60.03	125.09	4,632.01
Utilities	Util	21	–	–	100.00	33,408	80.24	99.50	7.10	33.57	45.45	75.86	760.10
ALL		335	0.30	–	99.70	518,207	182.01	483.76	3.00	28.00	53.95	144.50	9,580.00
Panel C – European Sample													
Basic Materials	Basi	18	88.89	5.56	5.56	32,845	104.98	168.75	6.99	23.68	43.33	85.00	1,855.30
Communication	Comm	30	93.33	6.67	–	53,155	151.36	243.12	6.95	38.31	62.33	162.50	3,076.72
Consumer	Cons	61	91.80	8.20	–	107,401	127.16	186.62	1.67	29.70	57.19	146.70	2,352.70
Energy	Ener	4	100.00	–	–	8,280	36.20	52.00	2.36	8.44	20.96	41.22	483.23
Financial (Bank)	Bank	23	100.00	–	–	42,489	55.49	102.45	2.17	9.33	13.60	70.43	1,113.75
Financial (Non-Bank)	Fina	24	91.67	8.33	–	42,711	118.72	266.32	3.63	18.12	31.00	95.25	4,341.46
Industrial	Indu	31	100.00	–	–	59,216	107.65	239.56	7.00	27.50	44.50	108.43	5,165.69
Technology	Tech	2	100.00	–	–	4,049	81.22	54.42	19.56	30.11	72.50	115.00	283.64
Utilities	Util	22	95.45	4.55	–	42,175	61.57	92.24	4.35	19.54	28.73	62.98	1,011.13
ALL		215	94.42	5.12	0.47	392,321	107.51	198.65	1.67	22.54	44.00	107.80	5,165.69

Table 2.1 – Summary statistics of the sample of CDS premia
The above table presents descriptive statistics on the time series of daily CDS premia used in our analysis. All CDS data are obtained via Bloomberg; the time series of observations ranges from October 2004 to October 2009.

Table 2.1 – continued:
To minimize the impact of factors other than the underlying reference entity's default risk, we only consider bid quotes. In total, we have 5-year CDS contracts on 550 firms in our sample, all of which are on senior unsecured debt. Panel A presents descriptive statistics of the entire sample and Panels B and C provide statistics by region. Column two gives the sectoral abbreviations used in the remainder of this paper, column three the number of available firms for each sector, columns four to six the relative distribution of CDS contracts across currencies; column seven gives the number of observations used to compute mean and standard deviation in columns eight and nine; columns ten to fourteen present the quantiles. Appendix-Table 2.16 presents the names of the US and European banks in our sample and Appendix-Table 2.17 provides supplementary information on the CDS market.

Regarding the US and European sub-samples in Panels B and C of Table 2.1, we find that CDS contracts for US firms are almost exclusively denominated in US-Dollar (USD). Our sample contains 12 US banks, which have a significantly higher average CDS premium of 168 bp compared to their 23 European counterparts with an average of 55 bp. We take this difference as an indication that aggregate risk (not dependence) is higher for US banks than for European ones.

In Figures 2.1 and 2.2, we present the time series of CDS premia, taking cross-sectional averages across all CDS premia for firms in the same sector on each observation date. We separately display the averages for the US and Europe.

Figures 2.1 and 2.2 allow for two main observations. First, CDS premia in the different sectors evolve similarly over time both in the US and in Europe until mid-2008. Around the time of the Lehman default, CDS premia begin to evolve very differently in the US and in Europe. In the US, we observe a drastic increase for banks and non-bank financial firms. In Europe, the increase is strongest for non-bank financial and industrial firms. For the latter, we attribute the increase to automotive firms subsumed in the industrial sector. Banks, on the other hand, exhibit CDS premia in the intermediate range.

Our second observation concerns the comovement of CDS premia for different sectors. As Figure 2.1 shows, the comovement of banks and firms from other sectors appears limited for the US, as the banks' time series exhibits spikes at dates which differ greatly from the other sectors. For European banks, Figure 2.2 implies a higher comovement between banks and non-bank sectors such as the industrial or the technology sector. The two latter time-series almost appear as scaled versions of the banks' time series. This observation is in line with the higher importance of banks in Europe as a source of external financing compared to the US (see, e.g., Demirguc-Kunt and Levine, 1999; Dermine, 2002; Kwok and Tadesse, 2006). We further explore the dependencies between banks and non-banks in Section 2.4.4.

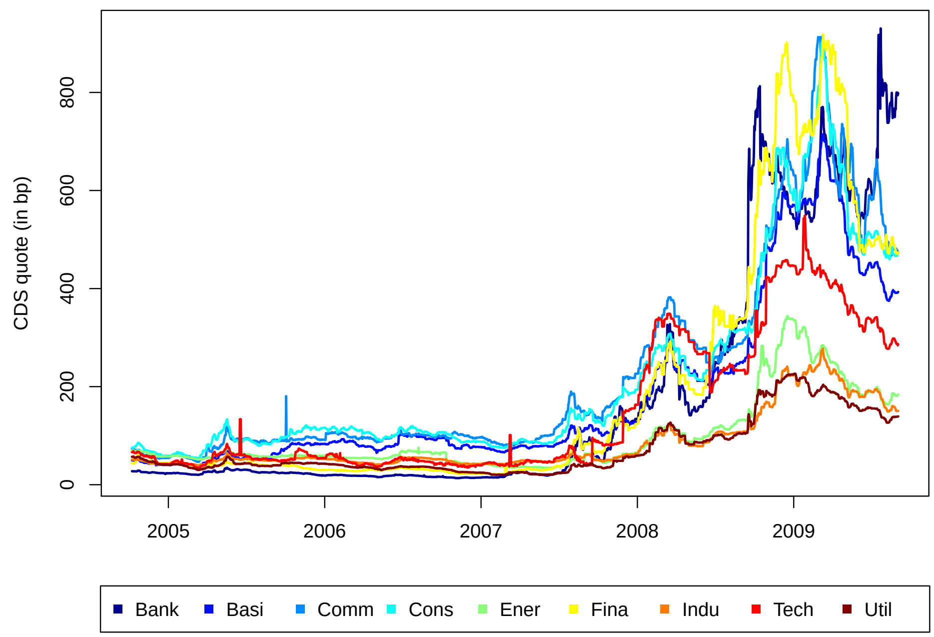

Figure 2.1 – Time evolution of CDS premia averaged across sectors (United States)
The figure presents sector-averaged time series of daily CDS bid quotes used in our analysis. All CDS data are obtained from Bloomberg; the time series of observations ranges from October 2004 to October 2009. Daily averages are taken across all firms belonging to the given sector.

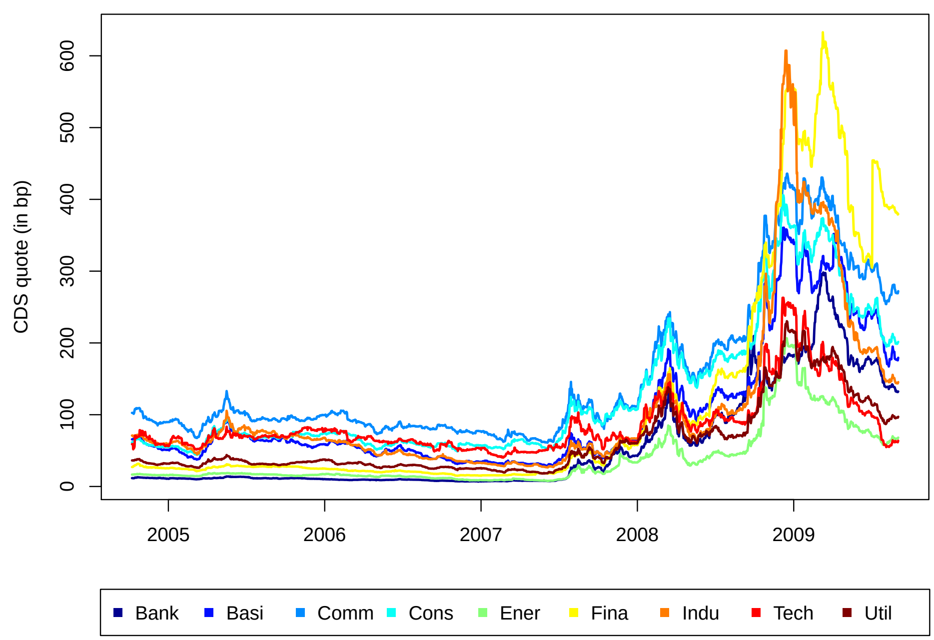

Figure 2.2 – Time evolution of CDS premia averaged across sectors (Europe)
The figure presents sector-averaged time series of daily CDS bid quotes used in our analysis. All CDS data are obtained from Bloomberg; the time series of observations ranges from October 2004 to October 2009. Daily averages are taken across all firms belonging to the given sector.

2.3 Measuring systemic risk

We measure systemic risk applying a copula approach to focus on downside risk. Multiple studies, such as Schneider et al. (2010), document that CDS premia are non-normally distributed. Although earlier studies such as De Nicolo and Kwast (2002) use correlation as a dependence measure, symmetric dependence measures cannot capture prevailing non-normal distribution features as different behavior in the upper (right) and the lower (left) tail of the distribution. Therefore, recent approaches use copulas (see, e.g., Buehler and Prokopczuk, 2010; Chan-Lau et al., 2004; Rodriguez, 2007), extreme value theory (see, e.g., Bae et al., 2003; Gropp and Moerman, 2004) or conditional measures such as CoVaR and marginal expected shortfall (see, e.g., Acharya et al., 2010; Adrian and Brunnermeier, 2011). We combine the first two approaches of extreme value theory and copulas to model the full dependence structure.

Since the upper tail of the CDS premium distribution reflects joint default risk, we apply marginal distributions and a copula which allow for extreme positive values and upper tail dependence.[9] Hence, we use an upside risk measure derived using extreme value theory.

As the marginal distribution function for a firm's CDS premia, we consider the extreme value distribution G characterized by

$$G\left(x\right) = \exp\left[-\left(1+\frac{c\left(x-a\right)}{b}\right)^{-\frac{1}{c}}\right], \tag{2.1}$$

with location parameter a, scale parameter b, and shape parameter c. For a shape parameter $c<0$, the distribution function corresponds to the Weibull distribution, for $c=0$, the Gumbel distribution, and $c>0$ the Fréchet distribution. The probability of firm i

[9] When stock returns are used to measure a firm's default, default (asymptotically) corresponds to an infinite negative stock return if the absolute priority rule is observed. This approach is taken by Buehler and Prokopczuk (2010), who estimate lower tail dependence parameters from stock returns. Our approach is similar, but adjusts for the fact that CDS premia behave slightly differently as a company approaches default. If default occurs, a protection seller pays the difference between the face value of the underlying and its post-default price, or loss given default, to the protection buyer. Hence, if default occurs with certainty one year after the CDS contract's inception, the fair *per annum* CDS premium equals the expected loss given default. If default occurs with certainty one day, or one hour, after the inception, the fair CDS premium *payment* still equals the expected loss given default, which is limited to the face value. However, due to the per annum quoting convention, this *finite* premium payment corresponds to a quoted premium of 360 times the loss given default, or 360·24 the loss given default, where time is measured in hours, etc. Asymptotically, the fair per annum quoted CDS premium for a certain default event after one infinitesimally small time step thus approaches infinity.

defaulting is given by $\lim_{y\to\infty} P(s_i > y) = \lim_{y\to\infty} 1 - G(y)$, where s_i denotes the CDS premium of firm i.

In analogy to the marginal distribution, the joint default probability of two firms is the probability of a joint extreme upwards movement of their quoted per annum CDS premia. The copula framework allows us to characterize such a joint upwards movement through the upper tail dependence coefficient as follows. For two firms i and j belonging to sectors $\boldsymbol{I}$ and $\boldsymbol{J}$ with marginal distribution functions G_i and G_j of their respective CDS premia s_i and s_j, the upper tail dependence coefficient is given by

$$\mathrm{UTDC}(i,j) = \lim_{x\uparrow 1} P\left[s_i > G_i^{-1}(x)\,\middle|\, s_j > G_j^{-1}(x)\right], \tag{2.2}$$

where $P[\cdot|\cdot]$ denotes the conditional joint probability function of s_i and s_j. Hence, $\mathrm{UTDC}(i,j)$ measures the probability of an extremely large CDS premium for firm i, given that such a high premium (in the upper tail of firm j's premium distribution) is observed for firm j. In other words, $\mathrm{UTDC}(i,j)$ measures the probability of distress for firm i, given that firm j is in distress.

We model the joint probability function of firms i and j as the Gumbel copula

$$C_{i,j}(x_i, x_j) = \exp\left(-\left[(-\ln x_i)^{d(i,j)} + (-\ln x_j)^{d(i,j)}\right]^{\frac{1}{d(i,j)}}\right), \tag{2.3}$$

where $d(i,j) > 1$ measures the degree of dependence between firm i and firm j, $x_i = G_i(s_i)$ is the value of the marginal distribution function G_i evaluated at s_i, and $x_j = G_j(s_j)$ the value of the marginal distribution function G_j evaluated at s_j. Taking the limit of the Gumbel copula for $x_i = x_j = x \uparrow 1$, the UTDC for firms i and j thus becomes

$$\mathrm{UTDC}(i,j) = 2 - 2^{\frac{1}{d(i,j)}}. \tag{2.4}$$

We calibrate the above copula model to the data in three steps: First, we determine the parameter vector (a_i, b_i, c_i) of the marginal generalized extreme value distribution defined in Equation (2.1) for each firm i via maximum likelihood.[10] Second, we determine the

[10] Since we estimate constant parameters for the marginal distributions, it is important that the time series from which we estimate the parameters is stationary. We test all CDS premia time series intervals which we use in the following for stationarity, and are unable to reject that the time series are stationary in the majority of the cases. Moreover, we find that the majority of the CDS premia time series intervals exhibit significant auto-correlation, heteroscedasticity, and non-normality. Auto-correlation becomes important only when we analyze UTDC in Section 2.4 and is addressed there. The two latter properties are accommodated by the chosen marginal distribution. For detailed figures we refer to Appendix-Table 2.18.

value of the firm-specific distribution function for each CDS premium quote $s_{i,t}$ observed for firm i on date t. As a result, we obtain values $(\hat{x}_{i,1}, \ldots, \hat{x}_{i,t})$ on the unit interval. Third, we determine the copula parameter $d\,(i,j)$ for each firm-combination (i,j) using the Gumbel copula in Equation (2.3) by maximum likelihood, and compute the upper tail coefficient $\mathrm{UTDC}\,(i,j)$ according to Equation (2.4).

We perform this estimation using a rolling window with a window width of three months, which is rolled forward one week in each step, and let t denote the end point of the time interval. We thus obtain a time series of firm-specific parameter vectors $(a_i, b_i, c_i)_t$ as well as copula parameters $d\,(t;i,j)$ and upper tail dependence coefficients $\mathrm{UTDC}\,(t;i,j)$.[11]

Since our hypotheses regarding systemic risk are on the *aggregate* level, we must aggregate the firm-specific UTDC into sector- and region-specific UTDC. We perform this aggregation in two ways, and then compute test statistics from these pooled samples.

In the first aggregation, we simply pool all estimates $\mathrm{UTDC}(t;i,j)$ over time t and *across* all firms from sector $\boldsymbol{I}$ *and* region $\boldsymbol{R}$ and firms from sector $\boldsymbol{J}$ and region $\bar{\boldsymbol{R}}$:

$$\bigcup_{t,i,j} \mathrm{UTDC}(t;i,j), \tag{2.5}$$

where $i \in \boldsymbol{I}^R \equiv \{\boldsymbol{I} \cap \boldsymbol{R}\}$, $j \in \boldsymbol{J}^{\bar{R}} \equiv \{\boldsymbol{J} \cap \bar{\boldsymbol{R}}\}$, and $\boldsymbol{R}, \bar{\boldsymbol{R}} \in \{\text{US, Europe}\}$. For these pooled observations, we compute two types of test statistics. First, we compute the mean, which we denote by $\widetilde{\mathrm{UTDC}}\left(\boldsymbol{I}^R, \boldsymbol{J}^{\bar{R}}\right)$, standard deviation, and percentiles of this aggregate.[12] In Section 2.4, we present these results in Panel A of each table. Second, we compute ranks for the mean of the pooled observations within and across the different regions. We do this to account for the fact that dependence between firms could be generally higher in the US than in Europe, or vice versa, because of an unobservable country-specific effect. For example, if the CDS market is dominated by US banks, the upper tail dependence measure could be uniformly higher for US reference entities because their relation to US banks is

[11] We also compute statistics that allow us to evaluate the goodness of fit of the marginal distributions and the copula (see Appendix-Tables 2.19–2.22). Overall, we find that the parameters a_i and b_i are very precisely estimated, with p-values below 10^{-12} for all firms and all time windows. The shape parameters c_i are mostly negative, but we obtain a small subset of 0.3% to 0.5% of estimates with p-values larger than 1% for all 9 sectors we consider. A similar result holds for the copula: all p-values for the parameters describing the dependence between two firms within the same sector, and between a bank and a non-bank, lie below 1%.

[12] Note that we distinguish between firms $i \in \boldsymbol{I}^R$ and $j \in \boldsymbol{J}^{\bar{R}}$. This distinction is most important for Section 2.4.4, where we analyze inter-sectoral systemic risk between banks $\boldsymbol{I}^R$ and non-banks $\boldsymbol{J}^R$ within one region as well as systemic risk *between* two regional banking sectors $\boldsymbol{I}^R$ and $\boldsymbol{I}^{\bar{R}}$.

more important than to European banks. Hence, we evaluate upper tail dependence in a sector $\boldsymbol{I}$ relative to upper tail dependence in all other sectors $\boldsymbol{J}$ ($\boldsymbol{J} \cap \boldsymbol{I} = \emptyset$), and upper tail dependence between sectors $\boldsymbol{I}$ and $\boldsymbol{J}$ relative to upper tail dependence between sector $\boldsymbol{J}$ and all other sectors $\boldsymbol{H}$ ($\boldsymbol{H} \cap \boldsymbol{I}, \boldsymbol{J} = \emptyset$). Since our focus is on banks, we calculate the mean upper tail dependence coefficient for each bank and non-bank sector (in Section 2.2, we give a detailed overview of the nine sectors) and define the rank of systemic risk in the regional banking sectors as

$$\# \left\{ \text{sectors } J : \quad \widetilde{\text{UTDC}} \left(\boldsymbol{J}^R, \boldsymbol{J}^R \right) > \widetilde{\text{UTDC}} \left(\text{Bank}^R, \text{Bank}^R \right) \right\}. \tag{2.6a}$$

The rank of systemic risk between a regional banking sector and a non-bank sector $\boldsymbol{I}^R$ of the same region is determined as follows:

$$\# \left\{ \text{sectors } J : \quad \widetilde{\text{UTDC}} \left(\boldsymbol{I}^R, \boldsymbol{J}^R \right) > \widetilde{\text{UTDC}} \left(\boldsymbol{I}^R, \text{Bank}^R \right) \right\}. \tag{2.6b}$$

We thus assign rank 1 to the most systemic sector and rank 9 to the least systemic sector. In Section 2.4, we present these results in Panel C of each table.

In our second aggregation, we take the time dimension into account. Since our observations constitute an unbalanced panel, where the number of observations differs during different time intervals, the statistics computed from Expression (2.5) are biased towards intervals for which more UTDC estimates are available. We therefore pool only observations made during the three months interval that ends at date t, $\text{UTDC}(t; i, j)$, for firms $i \in \boldsymbol{I}^R$ and $j \in \boldsymbol{J}^{\bar{R}}$:

$$\bigcup_{i,j} \text{UTDC}(t; i, j). \tag{2.7}$$

Again, we compute means (denoted by $\overline{\text{UTDC}} \left(t; \boldsymbol{I}^R, \boldsymbol{J}^{\bar{R}} \right)$), standard deviations, and percentiles, which allows us to analyze the evolution over time. For ease of exposition, we also calculate statistics based on the set of these means across all t. Thus, we weigh all observation dates equally by pooling the mean values over time:

$$\bigcup_{t} \overline{\text{UTDC}} \left(t; \boldsymbol{I}^R, \boldsymbol{J}^{\bar{R}} \right). \tag{2.8}$$

We display the corresponding means, standard deviations, and percentiles in Panel B1 in all tables of Section 2.4. As a second test statistic, we check whether the average relation between two sectors $\boldsymbol{I}$ and $\boldsymbol{J}$ is higher in one region $\boldsymbol{R}$ than in the alternative region $\bar{\boldsymbol{R}}$.

We then count the time intervals during which the proposed relation holds:

$$\text{countstat}\left(\text{UTDC}^{R}_{\boldsymbol{I},\boldsymbol{J}}\right) = \frac{\#\left\{t: \quad \overline{\text{UTDC}}\left(t;\boldsymbol{I}^{R},\boldsymbol{J}^{R}\right) > \overline{\text{UTDC}}\left(t;\boldsymbol{I}^{\bar{R}},\boldsymbol{J}^{\bar{R}}\right)\right\}}{T}. \tag{2.9}$$

For ease of interpretation, we report the count statistics in percentage terms, i.e., the absolute number of upward (downward) deviations in relation to the total sample. In Section 2.4, Panel B2 (B3) displays the corresponding results in each table. Finally, we also compute time-t specific ranks in analogy to the statistics in Expression (2.6). Applying the following rank count statistic, we count the number of time intervals where $\overline{\text{UTDC}}\left(t;\text{Bank}^{R},\text{Bank}^{R}\right)$ is ranked lower (i.e., more systemically important) than $\overline{\text{UTDC}}\left(t;\text{Bank}^{\bar{R}},\text{Bank}^{\bar{R}}\right)$, i.e., where the rank of systemic risk in the banking sector in one region is lower than the rank of systemic risk in the alternative region's banking sector:

$$\text{rankcount}\left(\text{UTDC}^{R}_{\text{Bank}}\right) = \frac{\#\left\{t: \quad \text{rank}_t\left(\overline{\text{UTDC}}\left(t;\text{Bank}^{R},\text{Bank}^{R}\right)\right) < \text{rank}_t\left(\overline{\text{UTDC}}\left(t;\text{Bank}^{\bar{R}},\text{Bank}^{\bar{R}}\right)\right)\right\}}{T}. \tag{2.10a}$$

Again, we report the count statistics in percentage terms. Analogously, we determine the number of time intervals where $\overline{\text{UTDC}}\left(t;\boldsymbol{I}^{R},\text{Bank}^{R}\right)$ is ranked lower (i.e., more systemically important) than $\overline{\text{UTDC}}\left(t;\boldsymbol{I}^{\bar{R}},\text{Bank}^{\bar{R}}\right)$, i.e., where the rank of systemic risk between the banking sector and a non-bank sector $\boldsymbol{I}^{R}$ in one region is lower than between the alternative region's banking and non-bank sector $\boldsymbol{I}^{\bar{R}}$:

$$\text{rankcount}\left(\text{UTDC}^{R}_{\boldsymbol{I},\text{Bank}}\right) = \frac{\#\left\{t: \quad \text{rank}_t\left(\overline{\text{UTDC}}\left(t;\boldsymbol{I}^{R},\text{Bank}^{R}\right)\right) < \text{rank}_t\left(\overline{\text{UTDC}}\left(t;\boldsymbol{I}^{\bar{R}},\text{Bank}^{\bar{R}}\right)\right)\right\}}{T}. \tag{2.10b}$$

The corresponding results are displayed in Panel D of each table in Section 2.4.

2.4 Results

We commence our analysis with an investigation of systemic risk for the US and the European banking system, and proceed in three steps to show that common risk factors are central for systemic risk. In Section 2.4.1, we determine systemic risk among US and among European banks. Then, we explore the relation between US and European banks in Section 2.4.2. Third, we determine the increase in systemic risk among and between US and European banks during the financial crisis in Section 2.4.3. We find that (i) systemic risk is on average higher in the US than in Europe, (ii) the relation between the US and Europe is weaker than systemic risk within each region, and (iii) systemic risk increases *more* in Europe than it does in the US. We then explore the relation between the banking sector and a wide range of real sectors in Section 2.4.4, where we find that the relation between banks and non-banks is comparatively low, especially when we consider large banks.

2.4.1 Systemic risk within the US and Europe

The regulatory frameworks in the US and Europe vary substantially. European banks are mostly regulated according to the Basel II framework. US banks are regulated according to rules determined by the Federal Reserve Board. A standard finding in the literature is that the regulation of European banks is more effective compared to the more fragmented regulation in the US due to shared responsibilities at the state and the federal level for the latter. Thus, European regulation is likely to coincide with lower systemic risk. Figure 2.3 depicts the evolution of upper tail dependence in the US and European banking sectors.

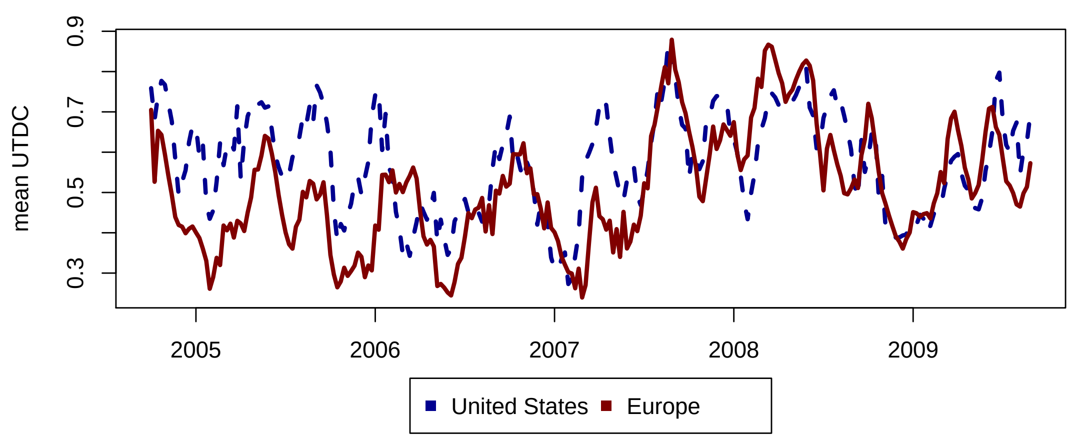

Figure 2.3 – Time evolution of upper tail dependence within the regional banking sectors
Upper tail dependence coefficients are estimated from a rolling time window consisting of data of the previous 12 weeks, which is rolled across a series of daily CDS bid quotes ranging from October 2004 to October 2009 one week in each step. The above figure displays the evolution of mean upper tail dependence, calculated as the average of all available upper tail dependence coefficients between banks *within* the same region.

We observe that systemic risk in the US is mostly higher than in Europe. Especially in the first half of the sample, systemic risk is substantially lower for Europe. However, at the onset of the Subprime Crisis, systemic risk increases sharply in both regions. To test whether this relation is statistically significant, we formulate the following null hypothesis[13]:

Hypothesis 1a *Systemic risk within the European banking sector is higher than within the US banking sector.*

Table 2.2 presents the results of our analysis of the regional banking sectors. Panels A and B1 are organized as follows: The first column shows the region, the second column the number of observations used for the calculation of the mean, quantiles, and standard deviations in columns three to seven. The last two columns report the results of a t-test with the null hypothesis that systemic risk in Europe is higher than in the US. Statistics exhibited in Panel A are calculated according to Expression (2.5); statistics in Panel B1 are determined according to Expressions (2.7) and (2.8).

From Panel A, we observe that with a mean UTDC of 0.5872, systemic risk in the US is higher than in Europe (mean UTDC of 0.5375) by 9%.[14] This means that in the US banking sector, a bank's probability of distress, given that another bank is in distress, is on average by 9% higher than in the European banking sector. This relation is confirmed by the values for the median UTDC (0.6362 for the US and 0.5729 for the European banking sector) as well as the aggregate figures of Panel B1, which are determined weighing all $\overline{\mathrm{UTDC}}\left(t; \boldsymbol{I}^R, \boldsymbol{J}^{\bar{R}}\right)$ equally. Upper tail dependence in the US (0.5748) substantially exceeds upper tail dependence in Europe (0.5107). Applying t-difference tests of means reveals that the figures for the US are significantly higher than for Europe in both panels.[15]

Panel B2 reports results obtained applying the count statistic from Expression (2.9). During more than half of the observation period, systemic risk in the US is significantly higher than in Europe. In 65% of all dates t, we observe a higher mean UTDC in the US. Approximately 80% of these upward deviations are statistically significant at the 5%-level.

[13] Throughout this paper, we formulate the null hypotheses such that rejecting it confirms the economic intuition.

[14] Alternatively, we compute UTDC not in a rolling window approach, but using the entire time series CDS bid premia. We find that the average UTDC estimates are higher, but that our main results still hold. The detailed figures are presented in Appendix-Table 2.7.

[15] By construction, the series of UTDC exhibit significant auto-correlation (see Appendix-Table 2.23). Second, they exhibit substantial cross-correlation. Thus, the application of t-tests might not be justified. To verify if our results still hold when applying an alternative non-parametric median-test, we conduct the Wilcoxon test for each of our main results in Panel A of Tables 2.2 to 2.5. For each of our calculations, we obtain highly significant p-values below 0.01%. The results are presented in Appendix-Table 2.8.

Panel A	#obs	mean	min	median	max	sdev	t-value	p-value
United States	11,040	0.5872	0.0029	0.6362	0.9738	0.2109		
Europe	29,219	0.5375	0.0028	0.5729	0.9680	0.2329		
Δ%(US/Europe)		9.25					-19.5929	0.0000
Panel B1	#obs	mean	min	median	max	sdev	t-value	p-value
United States	256	0.5748	0.2729	0.5788	0.8721	0.1266		
Europe	256	0.5107	0.2393	0.4983	0.8792	0.1449		
Δ%(US/Europe)		12.56					-5.3326	0.0000
Panel B2	#obs	signif	>	=	<	signif		
United States	256	51.56	64.84	–	35.16	16.80		
Europe	256	16.80	35.16	–	64.84	51.56		
Δ%(US/Europe)		206.98	84.44		-45.78	-67.42		
Panel C	#obs	rank						
United States	11,040	1						
Europe	29,219	6						
Δ(US/Europe)		-5						
Panel D	#obs		>	=	<		mean	sdev
United States	256		65.62	16.80	17.58		3.17	2.76
Europe	256		17.58	16.80	65.62		5.16	2.59
Δ%(US/Europe)			273.33	–	-73.21		-38.65	

Table 2.2 – Upper tail dependence within the United States and European banking sectors All figures are estimated from the full sample of daily CDS bid quotes ranging from October 2004 to October 2009 applying the methodology outlined in Section 2.3. We present aggregate statistics of the upper tail dependence coefficients for banks within the same region. Panels A and B provide figures associated with Hypothesis 1a stating that *systemic risk within the European banking sector is higher than within the US banking sector*. The statistics presented in Panel A (Panel B1) are calculated according to Expression (2.5) (Expressions (2.7) and (2.8)); the count statistics in Panel B2 are determined according to Expression (2.9). Panels C and D present figures associated with Hypothesis 1b stating that *systemic risk within the European banking sector is higher than systemic risk within the US banking sector when evaluated relative to the corresponding regions' non-bank sectors*. The rank (count) statistics of Panel C (Panel D) are computed according to Expressions (2.6a) and (2.10a). Appendix-Table 2.9 provides detailed statistics supplementary to the determination of ranks in Panel C. Panels A and B1 are organized as follows: Column one gives the region to which the statistics in the following columns refer. Column two reports the number of estimates used to compute the statistics given in columns three to seven. The last two columns report the result of a t-test with the null hypothesis that the banks' mean upper tail dependence coefficients for the US and Europe are identical. Panels B2 and D read as follows: Column two reports the number of estimates used to compute the count statistics given in columns three to seven. The figures in the fourth (third) column of Panel B2 present the number of dates where the banks' mean upper tail dependence coefficient in the row-name region is (significantly) larger than in the alternative region, relative to the total number of dates in the sample. Conversely, the figures in the sixth (seventh) column of Panel B2 present the number of dates where the upper tail dependence coefficient within the row-name region is (significantly) lower than within the alternative region, relative to the total number of dates in the sample. Columns three to five of Panel D are organized accordingly but refer to the dynamic ranks where a low rank indicates high upper tail dependence. Columns six and seven of Panel D report the mean and standard deviation of the dynamic ranks. Each panel's last row reports the deviations of the regional statistics from each other – either expressed in percentage (Δ%) or in absolute (Δ) terms.

Conversely, in only 17% of all dates t, systemic risk is significantly higher in Europe. Therefore, we are able to reject Hypothesis 1a.

As stated in Section 2.3, a direct comparison of systemic risk levels prevailing in the respective regions may not be appropriate since systemic risk could be generally higher in either the US or in Europe as a result of unobservable country factors. To account for this possibility, we evaluate systemic risk in the banking sector relative to systemic risk in all sectors of the same region.

Figures 2.4 and 2.5 show how systemic risk in the banking sectors compares to systemic risk in non-bank sectors. In the US, systemic risk in the banking sector is mostly higher than in non-bank sectors. In Europe, systemic risk in the banking sector is not higher than in non-bank sectors, even in the period following the default of Lehman Brothers. To evaluate the significance of this observation, we test Hypothesis 1b:

Hypothesis 1b *Systemic risk within the European banking sector is higher than systemic risk within the the US banking sector when evaluated relative to the corresponding regions' non-bank sectors.*

Panels C and D of Table 2.2 exhibit the results obtained applying Expressions (2.6a) (pooling over firms and time) and (2.10a) (pooling across firms for each date t). The numbers show that systemic risk in the US banking sector remains high when benchmarked against US non-bank sectors. When measured across the entire observation period, systemic risk for US banks ranks first among all sectors. In Europe, systemic risk in the banking sector ranks only sixth.[16] In the (time) dynamic ranking exhibited in Panel D, the banking sector is ranked 3.17 on average in the US and 5.16 in Europe. In 66% of all dates, the rank of the US banking sector is lower than the rank of the European banking sector. Therefore, we reject Hypothesis 1b and conclude that the US banking sector contains more systemic risk.

The low systemic risk in the European banking sector, compared to European non-bank sectors, seems striking at first. Due to interbank exposures, we would expect systemic risk in the banking sector to be substantially higher than in other sectors. However, regulation is likely to lower systemic risk in the regional banking sectors. Our systemic risk estimates incorporate these regulatory effects as they are reflected in asset prices.

[16] We present more detailed results of the sectoral ranking in Appendix-Table 2.9.

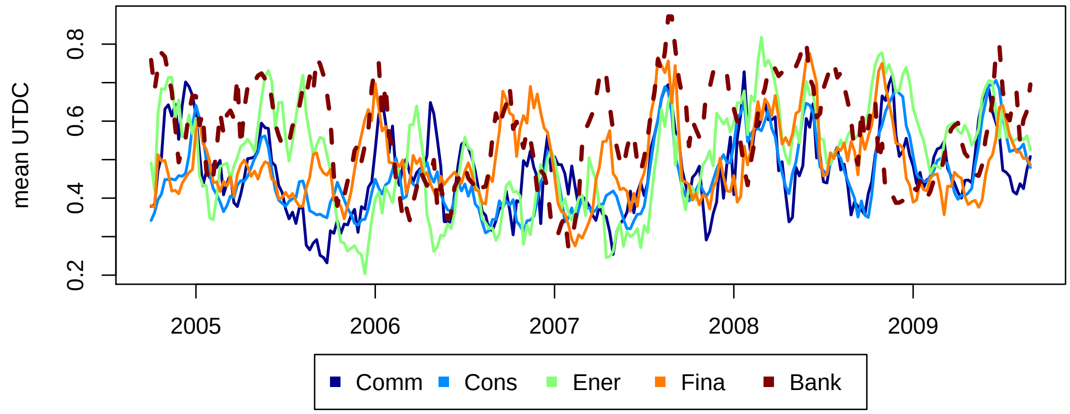

Figure 2.4 – Time evolution of intra-sectoral upper tail dependence (United States)
Upper tail dependence coefficients are estimated from a rolling time window consisting of data of the previous 12 weeks, which is rolled across a series of daily CDS bid quotes ranging from October 2004 to October 2009, one week in each step. The above figure displays the evolution of mean *intra-sectoral* upper tail dependence, calculated as the average of all available upper tail dependence coefficients between firms *within* one sector.

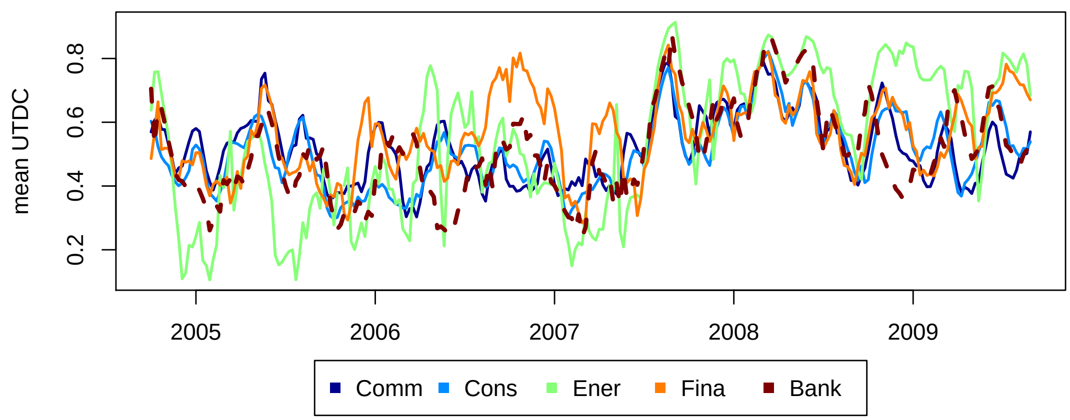

Figure 2.5 – Time evolution of intra-sectoral upper tail dependence (Europe)
Upper tail dependence coefficients are estimated from a rolling time window consisting of data of the previous 12 weeks, which is rolled across a series of daily CDS bid quotes ranging from October 2004 to October 2009, one week in each step. The above figure displays the evolution of mean *intra-sectoral* upper tail dependence, calculated as the average of all available upper tail dependence coefficients between firms *within* one sector.

2.4.2 Systemic risk between the US and Europe

So far, our analysis has been constrained to systemic risk in the US and in Europe. Over the last two decades, the global connectedness among businesses has increased. This particularly applies to the banking industry: First, banks are connected via mutual exposures in the interbank market. Second, both the number and volume of international transactions have greatly increased, as banks extend the geographic range of their activity. Third, liberalization of financial markets has triggered the origination and trade of new products, thereby leading to an increased exposure to similar risk factors globally.

Therefore, we now focus on the connectedness of US and European banks. We argue that systemic risk between them is governed by two competing effects: On the one hand, the regulator's influence to tackle systemic risk is mainly restricted to the respective regulatory region. Hence, systemic risk across regions could be higher than within a region, potentially harming the transatlantic banking system. On the other hand, (i) banks' loan portfolios across regions are likely to be less similar than within regions, (ii) interbank exposures for banks of different regions are potentially smaller than for banks in the same region. This leads to natural diversification and lower systemic risk (see Hartmann et al., 2006 for systemic risk between different European countries).

We now examine whether the first or the second effect dominates by testing Hypothesis 2a:

Hypothesis 2a *Systemic risk between the US and European banking sectors is higher than systemic risk within the regions' banking sectors.*

In analogy to the previous sections, we benchmark systemic risk between banks in the US and Europe with the figures obtained for systemic risk between non-banks:

Hypothesis 2b *Systemic risk between the US and European banking sectors is higher than systemic risk within the regions' banking sectors when evaluated relative to systemic risk between non-banks.*

To evaluate systemic risk between the US and European banking sectors, we calculate UTDC$(t; i, j)$ between *all* US and *all* European banks, where i denotes any European and j any US bank.[17] The aggregate results are exhibited in Table 2.3.

The figures in Panel A reveal that systemic risk between US and European banks (mean UTDC of 0.5031) is lower than within the US (0.5872) and Europe (0.5375). The result is statistically significant and confirmed by the figures obtained by applying the alternative aggregation method (Panel B1) and the count statistics (Panel B2). In 92% (63%) of all dates, systemic risk in the US (Europe) exceeds systemic risk between

[17] Asynchronicity is not an issue in our analysis, since all our CDS premia are end-of-day CDS bid quotes recorded at New York close.

Panel A	#obs	mean	min	median	max	sdev	t-value	p-value
Transatlantic	35,635	0.5031	0.0029	0.5397	0.9418	0.2209		
Δ%(US/Trans)		16.71					-35.3142	0.0000
Δ%(Europe/Trans)		6.83					-19.2415	0.0000
Panel B1	#obs	mean	min	median	max	sdev	t-value	p-value
Transatlantic	256	0.4759	0.2033	0.4818	0.8574	0.1410		
Δ%(US/Trans)		20.78					-8.3483	0.0000
Δ%(Europe/Trans)		7.30					-2.7519	0.0030
Panel B2	#obs	signif	>	=	<	signif		
Δ%(US/Trans)	256	72.66	91.80	–	8.20	–		
Δ%(Europe/Trans)	256	45.31	63.28	–	36.72	13.28		
Panel C	#obs	rank						
Transatlantic	35,635	2						
Δ(US/Trans)		-1						
Δ(Europe/Trans)		4						
Panel D	#obs		>	=	<		mean	sdev
Transatlantic	256						4.18	3.01
United States			48.83	36.33	14.84			
Europe			22.27	21.09	56.64			

Table 2.3 – Upper tail dependence coefficients between US and European banking sectors All figures are estimated from the full sample of daily CDS bid quotes ranging from October 2004 to October 2009 applying the methodology outlined in Section 2.3. We present aggregate statistics of upper tail dependence coefficients *between* US and European banks. Panels A and B provide figures associated with Hypothesis 2a stating that *systemic risk between the US and European banking sectors is higher than systemic risk within the individual regions' banking sectors*. The statistics presented in Panel A (Panel B1) are calculated according to Expression (2.5) (Expressions (2.7) and (2.8)); the count statistics in Panel B2 are determined according to Expression (2.9). Panels C and D present figures associated with Hypothesis 2b stating that *systemic risk between the US and European banking sectors is higher than systemic risk within the individual regions' banking sectors when evaluated relative to systemic risk between non-banks*. The rank (count) statistics of Panel C (Panel D) are computed according to Expressions (2.6a) and (2.10a). Appendix-Table 2.10 provides detailed statistics supplementary to the determination of ranks in Panel C. Panels A and B1 report the upper tail dependence coefficients between US and European banks as well as the deviations of these figures from the ones within the individual regions. Column two reports the number of estimates used to compute the statistics given in columns three to seven. The last two columns report the result of a t-test with the null hypothesis that the transatlantic mean upper tail dependence coefficient and the mean upper tail dependence coefficient for the row-name region is identical. Panels B2 and D read as follows: Column two reports the number of estimates used to compute the count statistics given in columns three to seven. The figures in the fourth (third) column of Panel B2 present the number of dates where the mean upper tail dependence coefficient for banks within the row-name region is (significantly) larger than the transatlantic mean upper tail dependence coefficient, relative to the total number of dates. Conversely, the figures in the sixth (seventh) column of Panel B2 present the number of dates where the mean upper tail dependence coefficient within the row-name region is (significantly) lower than the transatlantic mean upper tail dependence coefficient, relative to the total number of dates in the sample. Columns three to five of Panel D are organized accordingly but refer to the dynamic ranks where a low rank indicates a high mean upper tail dependence coefficient. Columns six and seven of Panel D report the mean and standard deviation of the dynamic ranks.

US and European banks. In both cases, the majority of these upward deviations are statistically significant at the 5%-level. Hence, we can reject Hypothesis 2a.

Panels C and D evaluate systemic risk between the US and European banks relative to systemic risk between US and European firms from non-bank sectors. Compared to the figures for the non-bank sectors, the mean UTDC between European and US banks is ranked second. The count statistics of Panel D confirm this finding: Systemic risk between US and European banks is mostly larger than systemic risk in the European banking sector. However, the *level* of upper tail dependence between US and European banks is below the level of upper tail dependence in the individual regions' banking sectors, and we reject Hypothesis 2b. Our findings imply that systemic risk is stronger within regions than between them. The diversification effect appears to outweigh the regulatory effect. However, when evaluated relative to systemic risk between US and European non-banks, systemic risk between US and European banks is high. Thus, regulators should be aware of substantial transatlantic linkages between US and European banks.

2.4.3 Pre-crisis and crisis levels of systemic risk

In the course of the recent financial crisis with its origin in the subprime mortgage market[18], the adverse effects of systemic risk became visible. In this section, we analyze pre-crisis and crisis systemic risk within and across the individual regions' banking sectors. We do so by specifying a *pre-crisis* and a *crisis* sample for which we calculate separate figures. On June 22, 2007 Bear Stearns announced the bankruptcy of two of its hedge funds.[19] We specify this date as the beginning of the Subprime Crisis and construct a pre-crisis sample comprising all UTDC estimated for dates t from October 2004 to June 2007 and a crisis sample comprising all UTDC estimated for dates t from July 2007 to October 2009.[20]

We conjecture that systemic risk in both regions' banking sectors increases substantially as a result of the losses incurred in the subprime mortgage market. In contrast to European banks, US banks are more integrated with the US mortgage market. This is likely to be reflected in the pre-crisis systemic risk figure for the US banking sector.

[18] On February 27, 2007 Freddie Mac was one of the first financial firms to announce that it would cease buying subprime adjustable rate mortgage with borrowers of inferior credit standing.

[19] *High Grade Structured Credit Strategies Enhanced Fund* and *High Grade Structured Credit Strategies Fund*.

[20] The UTDC of the first twelve dates t in the crisis sample is based partly based on data from the pre-crisis time interval, because UTDC are estimated on basis of daily CDS bid quotes of the prior three months.

Panel A	#obs	mean	min	median	max	sdev	t-value	p-value
pre-crisis								
United States	6,246	0.5580	0.0031	0.6053	0.9195	0.2131		
Europe	11,823	0.4499	0.0028	0.4687	0.9196	0.2280		
Δ%(US/Europe)		24.01					-30.9728	0.0000
Transatlantic	17,046	0.4381	0.0029	0.4618	0.8971	0.2090		
Δ%(US/Trans)		27.36					-38.5725	0.0000
Δ%(Europe/Trans)		2.70					-4.5571	0.0000
crisis								
United States	4,794	0.6252	0.0029	0.6738	0.9738	0.2019		
Europe	17,396	0.5970	0.0028	0.6428	0.9680	0.2168		
Δ%(US/Europe)		4.74					-8.1100	0.0000
Transatlantic	18,589	0.5627	0.0030	0.6156	0.9418	0.2146		
Δ%(US/Trans)		11.11					-18.2036	0.0000
Δ%(Europe/Trans)		6.09					-15.0621	0.0000
Panel B1	#obs	mean	min	median	max	sdev	t-value	p-value
pre-crisis								
United States	144	0.5472	0.2729	0.5484	0.7770	0.1235		
Europe	144	0.4319	0.2393	0.4215	0.7050	0.1022		
Δ%(US/Europe)		26.70					-8.6337	0.0000
Transatlantic	144	0.4186	0.2321	0.4096	0.7021	0.1034		
Δ%(US/Trans)		30.71					-9.5792	0.0000
Δ%(Europe/Trans)		3.17					-1.0938	0.1370
crisis								
United States	112	0.6103	0.3878	0.6208	0.8721	0.1222		
Europe	112	0.6120	0.3607	0.6062	0.8792	0.1278		
Δ%(US/Europe)		-0.28					-0.1014	0.4596
Transatlantic	112	0.5496	0.2033	0.5575	0.8574	0.1490		
Δ%(US/Trans)		11.05					-3.3372	0.0004
Δ%(Europe/Trans)		11.36					-3.3668	0.0004
Panel B2	#obs	signif	>	=	<	signif		
pre-crisis								
United States	144	70.14	83.33	–	16.67	6.94		
Europe	144	6.94	16.67	–	83.33	70.14		
Δ%(US/Europe)		910.00	400.00		-80.00	-90.10		
crisis								
United States	112	27.68	41.07	–	58.93	29.46		
Europe	112	29.46	58.93	–	41.07	27.68		
Δ%(US/Europe)		-6.06	-30.30		43.48	6.45		

Table 2.4 – continued on the next page

– continued –

Panel C	pre-crisis		crisis		Δ(crisis − pre-crisis)	
	#obs	rank	#obs	rank	#obs	rank
United States	6,246	1	4,794	1	11,040	0
Europe	11,823	7	17,396	5	29,219	-2
Δ(US/Europe)		-6		-4		2

Panel D	#obs	>	=	<	mean	sdev
pre-crisis						
United States	144	72.92	10.42	16.67	3.02	2.52
Europe	144	16.67	10.42	72.92	5.54	2.44
Δ%(US/Europe)		337.50	–	-77.14	-45.49	
crisis						
United States	112	56.25	25.00	18.75	3.36	3.04
Europe	112	18.75	25.00	56.25	4.68	2.70
Δ%(US/Europe)		200.00	–	-66.67	-28.24	

Table 2.4 – Pre-crisis and crisis upper tail dependence within and between the US and European banking sectors
The figures are estimated from our sample of daily CDS bid quotes ranging from October 2004 to October 2009 applying the methodology outlined in Section 2.3. The time series of banks' mean upper tail dependence coefficients is divided in two sub-series: The *pre-crisis series* contains upper tail dependence coefficients for all dates from October 2004 to June 2007; the *crisis series* consists of upper tail dependence coefficients for all dates from July 2007 to October 2009. We present aggregate statistics of upper tail dependence coefficients for banks within the same region during the pre-crisis and crisis time regimes. Panels A and B provide figures associated with Hypothesis 3a stating that *in the course of the crisis, the increase in systemic risk is higher for the US banking sector than for the European banking sector*. The statistics presented in Panel A (Panel B1) are calculated according to Expression (2.5) (Expressions (2.7) and (2.8)); the count statistics in Panel B2 are determined according to Expression (2.9). Panels C and D present figures associated with Hypothesis 3b stating that *when evaluated relative to systemic risk within the corresponding non-bank sectors, the increase in systemic risk is higher for the US banking sector than for the European banking sector in the course of the crisis.* The rank (count) statistics of Panel C (Panel D) are computed according to Expressions (2.6a) and (2.10a). Appendix-Table 2.11 provides detailed statistics supplementary to the determination of ranks in Panel C. Panels A and B1 are organized as follows: Column one gives the region to which the statistics in the following columns refer. Column two reports the number of estimates used to compute the statistics given in columns three to seven. The last two columns report the result of a t-test with the null hypothesis that the mean upper tail dependence coefficient during the given time regime between US banks is identical to the mean upper tail dependence coefficient between European banks. Panels B2 and D read as follows: Column two reports the number of estimates used to compute the count statistics given in columns three to seven. The figures in the fourth (third) column of Panel B2 present the number of dates where the mean upper tail dependence coefficient during the given time interval between banks within the row-name region is (significantly) larger than the mean upper tail dependence coefficient between banks in the alternative region, relative to the total number of dates. Conversely, the figures in the sixth (seventh) column of Panel B2 present the number of dates where the mean upper tail dependence coefficient between banks in the row-name region is (significantly) lower than within the alternative region, relative to the total number dates. Columns three to five of Panel D are organized accordingly but refer to the (time) dynamic ranks where a low rank indicates a high upper tail dependence coefficient. Columns six and seven of Panel D report the mean and standard deviation of the (time) dynamic ranks. Each panel's last row reports the deviations of the regional statistics from each other – either expressed in percentage (Δ%) or in absolute (Δ) terms.

As explained above, our hypothesis is that the increase of systemic risk in Europe does not arise via interbank exposures, but through exposures to common risk factors. Therefore, we conjecture that the increase of systemic risk is larger for the European banking sector than for the US. If we find this to be the case, we can reject the hypothesis that the increase in systemic risk arises through interbank exposures. We formulate the following null hypothesis:

Hypothesis 3a *In the course of the crisis, the increase in systemic risk is higher for the US banking sector than for the European banking sector.*

Table 2.4 reports the results. Panel A is calculated in the same fashion as Panel A of Table 2.2. From Panel A, we observe that *prior* to the crisis, systemic risk in both regions differs strongly. Whereas the mean UTDC between banks amounts to 0.5580 in the US, it is much lower in Europe with an average value of 0.4499. The difference between these two values is statistically significant and confirmed by the quantiles. In the course of the Subprime Crisis, systemic risk in Europe rises much more sharply than in the US. The mean UTDC rises to 0.5970 in Europe and to 0.6252 in the US. Even though it remains statistically significant, the absolute difference between both values decreases drastically. Thus, systemic risk in the individual regions' banking sectors converges during the crisis, which is in line with our initial expectation. Interestingly, transatlantic systemic risk between US and European banks also increases at large scale from 0.4381 to 0.5627.

The figures in Panel B1 confirm the findings from Panel A. During the crisis, systemic risk in the US is no longer significantly different from systemic risk in Europe, while it differs significantly prior to the crisis. The count statistics in Panel B2 complement this picture: Prior to the crisis, upper tail dependence in Europe is significantly higher than in the US in only 7% of all dates but 70% vice versa. During the crisis, upper tail dependence in Europe is significantly higher than in the US in 29% of all dates and 28% vice versa. Thus, systemic risk in both individual regions' banking sectors converged, and we reject Hypothesis 3a.

Again, we compare systemic risk in the regional banking sectors to that in the respective regions' non-bank sectors, applying the rank methodology from the previous sections. Hence, we reformulate Hypothesis 3a:

Hypothesis 3b *When evaluated relative to systemic risk within the corresponding regions' non-bank sectors, the increase in systemic risk is higher for the US banking sector than for the European banking sector in the course of the crisis.*

Panels C and D of Table 2.4 present the results. The figures confirm the main results of Panels A and B. Prior to the crisis period, systemic risk in the banking sector is highest in the US, but ranks at 7 in Europe. US banks remain most systemic during the crisis period at rank 1, and European banks rank at 5, which is two ranks lower (i.e. more systemic) than their pre-crisis rank. Panel D confirms this finding: Prior to the crisis, the European banking sector is ranked 5.54 on average; during the crisis, however, the rank is 4.68 and thus more systemic. We therefore reject Hypothesis 3b.

To check whether the Subprime Crisis is responsible for these differences in systemic risk in Europe, we perform an attribution analysis. We collect the proportion of past-due conventional subprime fixed-rate mortgages, which is published quarterly by the Mortgage Bankers Association of America, from Datastream. We then compute the correlation between the mean UTDC of the regional banking sectors (calculated according to Expression (2.7)) and this index in the time interval from October 2004 to June 2007 and from July 2007 to October 2009. In the pre-crisis interval, the correlation is substantially higher for US banks with a value of -3.03% than for the European banks with a value of -0.39%. In the crisis period, the correlation value rises much more sharply to -19.92% for the European banking sector compared to -26.23% for the US banking sector.

The results provide evidence that systemic risk increases more sharply in Europe than in the US. Interestingly, this increase is also visible for transatlantic systemic risk in the banking sectors. We again attribute this to common shocks; see Kaufmann (2000).

This result allows us to make two conjectures. In light of the low pre-crisis correlation between the European banking sector and the US mortgage market, it seems likely that investors were mostly unaware of the European banks' high exposure to US subprime mortgage backed assets. However, the awareness of the exposure rose with the beginning of the Subprime Crisis. Second, we identify the mortgage market as a major driver of systemic risk in the banking sector. Substantial exposures in mortgage-backed securities resulted in a high risk concentration. Regulators could improve their monitoring of risk concentration by analyzing banks' portfolios with respect to the type of obligors.

2.4.4 The relation between banks and non-banks

In this section, we measure systemic risk *between* the banking and non-bank sectors. This relation is a vital concern for financial stability, since banks act as major credit suppliers to the real economy. Therefore, regulators are especially concerned about the possibility of negative spillovers. These spillovers can originate either from the banking sector or the non-bank sectors: On the one hand, banks may default because their non-bank obligors default (e.g., as a result of adverse economic conditions). On the other hand, banks may decrease their loan supply to lower their risk exposures and cause a credit crunch, which adversely affects the real sectors.

To quantify the importance of banks, we compare systemic risk between the banking sector and a real sector to systemic risk between that real sector and another real sector. In addition to this pure industry comparison, we again distinguish between the US and Europe. In most European economies, banks play a more important role in the provision of capital to non-banks than in the US.[21] Thus, we expect systemic risk between the banking sector and non-bank sectors to be higher in Europe than in the US. As in the previous section, we formulate the null hypothesis in the opposite direction:

Hypothesis 4a *Systemic risk between the banking and any non-bank sector is lower in Europe than in the US.*

Table 2.5 presents the results of the analysis of systemic risk between the banking sector $\boldsymbol{I}^R$ and the non-bank sectors $\boldsymbol{J}^R$ for $R \in \{\text{US}, \text{Europe}\}$. Panels A and B1 read as follows: The second column contains the mean UTDC calculated for systemic risk in the US and European banking sectors (as in Table 2.2) for reference purposes. Columns three to ten present the regional mean UTDC between the banking sector and the respective non-bank column-sector (given in the header).

From Panel A, we observe that dependence between non-banks and banks is higher in Europe than in the US. E.g., the mean UTDC between the European banking and basic materials sectors is 0.4879, whereas the mean UTDC between the US banking and basic materials sectors is 0.4670. All deviations between the US and European figures are significant. The figures obtained for the dynamic calculation in Panel B1, which we include to demonstrate robustness with respect to the method of aggregation, mainly confirm these results.

We provide the results for the count statistics in Panels B2 (B3), which read as follows: The %-figures give the number of dates t in which the mean UTDC between the banking sector and the column-sector in the row-region is (significantly) higher than in the alternative region, relative to the number of dates in the entire sample period T. In 57% (42%) of all dates, the mean UTDC between the European banking and basic materials sector is (significantly) higher than its US counterpart and in 43% (29%) of all dates vice versa. We reject Hypothesis 4a, and our earlier result holds: systemic risk between the banking sector and a non-bank sector is higher in Europe than in the US.

As in Section 2.4.1, we conduct the above analysis relative to the relation between any two non-bank sectors:

Hypothesis 4b *Systemic risk between the banking and a given non-bank sector is lower in Europe than in the US when evaluated relative to systemic risk between the given non-bank sector and any other non-bank sector.*

[21] See Sections 2.1 and 2.2 for references.

	Bank	Basi	Comm	Cons	Ener	Fina	Indu	Tech	Util
Panel A									
United States	0.5872	0.4670	0.4647	0.4631	0.4673	0.4853	0.4642	0.4637	0.4762
Europe	0.5375	0.4879	0.4840	0.4811	0.4999	0.5183	0.4889	0.4582	0.4913
Δ%(US/Europe)	9.25***	-4.28***	-3.97***	-3.74***	-6.53***	-6.36***	-5.06***	1.21***	-3.08***
Panel B1									
United States	0.5748	0.4391	0.4417	0.4452	0.4323	0.4709	0.4435	0.4395	0.4547
Europe	0.5107	0.4511	0.4515	0.4511	0.4473	0.4912	0.4503	0.4249	0.4474
Δ%(US/Europe)	12.56***	-2.67	-2.16	-1.31	-3.34	-4.13**	-1.51	3.44*	1.64
Panel B2									
United States	64.84	42.97	44.53	47.27	41.90	35.55	46.48	49.41	47.27
Europe	35.16	57.03	55.47	52.73	58.10	64.45	53.52	50.59	52.73
Δ%(US/Europe)	84.44	-24.66	-19.72	-10.37	-27.89	-44.85	-13.14	-2.33	-10.37
Panel B3									
United States	51.56	29.30	27.34	37.50	28.46	25.78	31.25	25.10	35.16
Europe	16.80	41.80	40.23	41.41	42.29	47.66	42.19	21.57	37.50
Δ%(US/Europe)	206.98	-29.91	-32.04	-9.43	-32.71	-45.90	-25.93	16.36	-6.25
Panel C									
United States	1	9	9	9	9	3	9	9	9
Europe	1	9	9	9	9	7	9	9	9
Δ(US/Europe)	–	–	–	–	–	-4	–	–	–
Panel D1									
United States	50.78	55.08	59.77	60.94	42.97	41.02	53.91	45.70	49.22
Europe	12.11	23.83	24.61	19.92	30.47	18.75	26.17	38.67	31.25
Δ%(US/Europe)	319.35	131.15	142.86	205.88	41.03	118.75	105.97	18.18	57.50
Panel D2									
United States	1.73	5.12	5.19	4.80	5.64	3.50	5.40	5.48	5.39
Europe	2.84	6.69	6.63	6.46	6.08	4.81	6.37	5.81	6.36
Δ(US/Europe)	-1.11	-1.57	-1.44	-1.66	-0.44	-1.31	-0.97	-0.33	-0.97

Table 2.5 – Upper tail dependence between the banking and non-bank sectors within the United States and Europe
All figures are estimated from the full sample of daily CDS bid quotes ranging from October 2004 to October 2009 applying the methodology outlined in Section 2.3. We present aggregate statistics of upper tail dependence coefficients between banks and firms from a non-bank sector $\boldsymbol{I}$ within the same region. Panels A and B provide figures associated with Hypothesis 4a stating that *systemic risk between the banking and any non-bank sector is lower in Europe than in the US*. The statistics presented in Panel A (Panel B1) are calculated according to Expression (2.5) (Expressions (2.7) and (2.8)); the count statistics in Panels B2 and B3 are determined according to Expression (2.9). Panels C, D1, and D2 present figures associated with Hypothesis 4b stating that *systemic risk between the banking and a non-bank sector is lower in Europe than in the US when evaluated relative to systemic risk between that and any other non-bank sector*. The rank statistics of Panel C are computed according to Expression (2.6b) and the rank count statistics presented in Panel D1 are calculated applying Expression (2.10b). Appendix-Tables 2.12, 2.13, 2.14, and 2.15 present detailed statistics supplementary to the figures given in Panels A, B, and C.

Table 2.5 – continued:
Panels A and B1 are organized as follows: Column one gives the region to which the statistics in the following columns refer. Columns two to ten report mean upper tail dependence coefficients between the regional banking and the respective non-bank sector given in the column header. Panels B2 and B3 read as follows: Columns two to ten of Panel B2 (B3) report the number of dates where the mean upper tail dependence coefficients between banks and firms from a non-bank sector $\boldsymbol{I}$ within the row-name region is (significantly) larger than in the alternative region, relative to the total number of dates. Panel C reports the rank of the mean upper tail dependence coefficients between banks and firms from non-bank sector $\boldsymbol{I}$ when benchmarked against the upper tail dependence coefficients between firms from non-bank sector $\boldsymbol{I}$ given in the header and firms from any other non-bank sector $\boldsymbol{J}$. Columns two to ten of Panels D1 and D2 are organized accordingly but refer to the dynamic ranks where a low rank indicates high systemic risk. Panel D1 presents the count statistics, whereas Panel D2 reports the mean dynamic ranks across time. Each panel's last row reports the deviations of the US figures from the European ones – either expressed in percentage (Δ%) or in absolute (Δ) terms. We assign asterisks if these deviations are statistically significant. (*** = 1%-level; ** = 5%-level; * = 10%-level)

Panel C reports the rank of the mean UTDC between the banking and any non-bank sector $\boldsymbol{I}^R$ in comparison to the mean UTDC between non-bank sector $\boldsymbol{I}^R$ and any other non-bank sector $\boldsymbol{J}^R$ in the corresponding regions. Recall that we assign rank 1 when systemic risk is highest and rank 9 when systemic risk is lowest. We observe that the mean UTDC between the non-bank and banking sectors is usually assigned rank 9. Therefore, systemic risk between a non-bank sector and the banking sector is lower than systemic risk between that sector and any other non-bank sector. In other words, banks and non-banks are on average less strongly related than any two non-banks.

Panel D1 dynamically evaluates systemic risk between the banking sector and a non-bank sector relative to systemic risk between that non-bank sector and any other non-bank sector. We observe that the ranks are mostly lower for the US than for Europe. Panel D2 displays the mean of ranks across time and confirms these results; the ranks for the US are slightly lower than for Europe. Jointly, Panel C to D2 allow us to reject Hypothesis 4b.

The mean ranks of Panel D2 are lower than the ones reported in Panel C. This is because the ranks in Panel C are calculated from $\widetilde{\mathrm{UTDC}}\left(\boldsymbol{I}^R, \boldsymbol{J}^R\right)$ (pooled across all dates; see Expression (2.5)), but the figures on the ranks in Panels D1 and D2 are determined from all $\overline{\mathrm{UTDC}}\left(t; \boldsymbol{I}^R, \boldsymbol{J}^R\right)$ calculated for all dates t (see Expression (2.7)). When measuring systemic risk, we focus on the level of connectedness among firms in adverse economic conditions. The figures in Panel C are strongly driven by estimates from the second half of our sample, representing the period of the recent financial crisis. This is because we have relatively more estimates available for the second half of the sample than for the first half. In contrast, the figures of Panels D1 and D2 weigh all $\overline{\mathrm{UTDC}}\left(t; \boldsymbol{I}^R, \boldsymbol{J}^R\right)$ equally across time. Thus, the figures in Panel D2 underestimate the ranks for dates where systemic risk is generally low and overestimate systemic risk between the banking and the non-bank sectors in both regions.

As discussed in the introduction, the default of a large bank may well affect other banks and real-sector firms differently from the default of a small bank. On the one hand, a large bank is likely to have stronger ties to other banks, and thus systemic risk within the banking sector should be higher for large banks. On the other hand, Altunbas et al. (2002) show that large banks provide fewer loans (relative to their asset size) to real-sector firms than small banks, which suggests lower systemic risk between large banks and the real sector. Therefore, we test whether large banks' relations to other banks or non-banks are different from those of small banks. We proceed as follows. We first collect end-of-quarter total asset values for all banks in our sample from 2004 to 2009. Second, we rank banks within the two regions US and Europe according to their asset size. Third, we choose the three largest and the three smallest banks in each region for each quarter, and pool the UTDC (i) by only considering the three largest banks, and (ii) by only considering the three smallest banks.[22] We then perform a t-test to analyze whether the dependence between large banks and a given sector differs from the dependence between small banks and a given sector. The results of the test are displayed in Table 2.6.

Table 2.6 shows two main results. First, systemic risk for large banks is larger than systemic risk for small banks (0.6195 vs. 0.5582 for the US, 0.5709 vs. 0.4631 for Europe). The differences are statistically significant at the 1%-level. As in Table 2.2, we find that systemic risk in the US is higher than in Europe. Second, systemic risk between large banks and any non-bank sector is always smaller than systemic risk between small banks and any non-bank sector, and 13 out of the 16 differences are statistically significant at the usual significance levels. Comparing Table 2.6 to Table 2.5, we find that systemic risk within a non-bank sector is still higher than systemic risk between small banks and the non-bank sector in 13 out of 16 cases.

The most important take-aways from our analysis of systemic risk between the banking and the non-bank sectors in the US and Europe are as follows: Even though systemic risk between banks and non-banks is higher in Europe than in the US, both are low when compared to systemic risk between two different non-bank sectors. This is even more pronounced when we consider large banks and suggests that the main beneficiaries of bailouts for large banks termed *too big to fail* are in fact other large banks. Real-sector firms, which are more dependent on smaller banks playing an important role in the provision of loans, benefit from such bailouts only to a limited extent.

[22] To avoid misclassifications, we only use UTDC which are estimated from CDS premia in a given quarter, since a bank that is among the three largest banks in a given quarter might not be part of this group in the next quarter.

Panel A – United States

	Bank	Basi	Comm	Cons	Energy	Fina	Indu	Tech	Util
Small Bank	0.5582	0.5064	0.4721	0.4890	0.4809	0.5090	0.4950	0.4821	0.5004
Large Bank	0.6195	0.4663	0.4466	0.4510	0.4372	0.4924	0.4539	0.4356	0.4691
Δ%(large/small)	10.98***	-7.92***	-5.40*	-7.77***	-9.09***	-3.26*	-8.30***	-9.65***	-6.25**

Panel B – Europe

	Bank	Basi	Comm	Cons	Energy	Fina	Indu	Tech	Util
Small Bank	0.4631	0.5429	0.5006	0.5100	0.5561	0.6046	0.5437	0.5484	0.5492
Large Bank	0.5709	0.4757	0.4763	0.4682	0.5031	0.5209	0.4697	0.4564	0.4980
Δ%(large/small)	23.28***	-12.38***	-4.85	-8.20***	-9.53	-13.84***	-13.61***	-16.78	-9.32***

Table 2.6 – **Upper tail dependence between small/large banks and non-banks within the United States and Europe**
All figures are estimated from the full sample of daily CDS bid quotes ranging from October 2004 to October 2009 applying the methodology outlined in Section 2.3. We present aggregate statistics of upper tail dependence coefficients between banks and firms from a non-bank sector $\boldsymbol{I}$ within the same region. Panels A and B provide figures associated with Hypothesis 5a stating that *systemic risk between large banks is smaller than systemic risk between small banks* and Hypothesis 5b stating that *systemic risk between large banks and a given non-bank sector is larger than systemic risk between small banks and the same non-bank sector*. The statistics presented in Panels A and B are calculated according to Expression (2.5). Panels A and B are organized as follows: column one gives the bank size; columns two to ten report mean upper tail dependence coefficients between regional banks (small or large) and the respective non-bank sector given in the column header. The panel's last row reports the deviations of the US figures from the European ones expressed in percentage (Δ%) terms. We assign asterisks if these deviations are statistically significant. (*** = 1%-level; ** = 5%-level; * = 10%-level)

2.5 Summary and conclusion

In this paper, we study systemic risk in the US and European banking sectors. Using a data set of CDS premia for 550 banks, other financial firms, and non-financial firms from October 2004 to October 2009, we compute pair-wise lower tail dependence applying a copula approach.

Our study makes two main contributions. First, we provide evidence that banks' portfolio exposures to common risk factors play a central role for systemic risk in the banking sector. We come to this central conclusion by first showing that relations between US and European banks are smaller than systemic risk within each geographic region. We then show that the onset of the Subprime Mortgage Crisis increases systemic risk in Europe much more strongly than in the US. Given the lower degree of transatlantic linkage, this finding could not arise if contagion were the primary channel of risk transmission. Second, we show that dependence between the banking sector and a wide range of real sectors is rather limited. In fact, dependence between any two real sectors is higher than dependence between the banking sector and either of these real sectors.

Our findings have the following main implications. First, we take our findings as an indication that the impact of common shocks to the banking sector is more important than the effect of direct contagion. Since bank supervisors limit concentration risk, the probability of a banking crisis originating from a bank's exposure to another bank or a particular real sector is rather limited. In contrast, banks on both sides of the Atlantic are exposed to common shocks as a result of an increasingly integrated international banking market. Though supervisors should pay attention to these connections, a supra-national regulator may be unnecessary and national supervision based on harmonized standards may suffice.

Second, the low dependence of real-sector firms on banks shows that the importance of the banking sector in providing capital to the real sector is limited. While this finding may partly depend on our sample, it still suggests that fears of a credit crunch resulting from the default of a large, international bank may be exaggerated. Instead of providing unlimited liquidity to the banking system as a whole, regulators should therefore (i) improve real-sector firms' access to the capital markets and (ii) continue to limit exposures between large international banks and those banks providing the largest share of loans to real-sector firms.

2.A Robustness issues

Panel A – Robustness of Table 2.2								
	#obs	mean	min	median	max	sdev	t-value	p-value
United States	43	0.6738	0.0304	0.7955	0.9576	0.2446		
Europe	155	0.5822	0.0629	0.6408	0.9385	0.2728		
Δ%(US/Europe)		15.73					-1.9902	0.0233

Panel B – Robustness of Table 2.3								
	#obs	mean	min	median	max	sdev	t-value	p-value
Transatlantic	175	0.6108	0.0624	0.7492	0.9114	0.2628		
Δ%(US/Trans)		10.31					-1.4262	0.0769
Δ%(Europe/Trans)		-4.69					-0.9702	0.1660

Panel C – Robustness of Table 2.5									
	Bank	Basi	Comm	Cons	Ener	Fina	Indu	Tech	Util
United States	0.6738	0.4939	0.4091	0.5194	0.5191	0.5041	0.5135	0.471	0.5147
Europe	0.5822	0.5279	0.4945	0.5226	0.6371	0.5645	0.5144	0.4706	0.5794
Δ%(US/Europe)	15.73**	-6.44*	-17.28***	-0.59	-18.52***	-10.7***	-0.17	0.08	-11.17***

Table 2.7 – Robustness with respect to length of times series
All figures are estimated from the full sample of daily CDS bid quotes applying the methodology outlined in Section 2.3. In contrast to the method of rolling windows of three months length across the sample, the above figures are estimated from the entire time series of CDS quotes available from Credit Market Analysis (CMA). Panel A presents aggregate statistics of the upper tail dependence coefficients for banks within the same region. The exhibited figures are associated with Hypothesis 1a stating that *systemic risk within the European banking sector is higher than within the US banking sector*. Panel B reports the upper tail dependence coefficients between US and European banks as well as the deviations of these figures from the ones within the individual regions. The displayed figures are associated with Hypothesis 2a stating that *systemic risk between the US and European banking sectors is higher than systemic risk within the individual regions' banking sectors*. Panel C presents aggregate statistics of upper tail dependence coefficients between banks and firms from a non-bank sector $\boldsymbol{I}$ within the same region. The exhibited figures are associated with Hypothesis 4a stating that *systemic risk between the banking and any non-bank sector is lower in Europe than in the US* Panels A to B are organized as follows: Column one gives the region to which the statistics in the following columns refer. Column two reports the number of estimates used to compute the statistics given in columns three to seven. The last two columns report the result of a t-test with the null hypothesis that the banks' mean upper tail dependence coefficients for the US and Europe are identical. Panel C is organized differently: Column one gives the region to which the statistics in the following columns refer. Columns two to ten report mean upper tail dependence coefficients between the regional banking and the respective non-bank sector given in the column header. The panel's last row reports the deviations of the US figures from the European ones expressed in percentage (Δ%) terms. We assign asterisks if these deviations are statistically significant. (*** = 1%-level; ** = 5%-level; * = 10%-level)

Panel A – Robustness of Table 2.2								
	#obs	mean	min	median	max	sdev	Wilcoxon W	p-value
United States	11,040	0.5872	0.0029	0.6362	0.9738	0.2109		
Europe	29,219	0.5375	0.0028	0.5729	0.9680	0.2329		
Δ%(US/Europe)				11.06			724,123,788	0.0000

Panel B – Robustness of Table 2.3								
	#obs	mean	min	median	max	sdev	Wilcoxon W	p-value
Transatlantic	35,635	0.5031	0.0029	0.5397	0.9418	0.2209		
Δ%(US/Trans)				17.88			484,235,522	0.0000
Δ%(Europe/Trans)				6.14			1,139,819,042	0.0000

Panel C – Robustness of Table 2.4								
	#obs	mean	min	median	max	sdev	Wilcoxon W	p-value
pre-crisis								
United States	6,246	0.5580	0.0031	0.6053	0.9195	0.2131		
Europe	11,823	0.4499	0.0028	0.4687	0.9196	0.2280		
Δ%(US/Europe)				29.14			189,108,812	0.0000
Transatlantic	17,046	0.4381	0.0029	0.4618	0.8971	0.2090		
Δ%(US/Trans)				31.07			141,954,634	0.0000
Δ%(Europe/Trans)				1.49			207,819,478	0.0000
crisis								
United States	4,794	0.6252	0.0029	0.6738	0.9738	0.2019		
Europe	17,396	0.5970	0.0028	0.6428	0.9680	0.2168		
Δ%(US/Europe)				4.82			178,715,204	0.0000
Transatlantic	18,589	0.5627	0.0030	0.6156	0.9418	0.2146		
Δ%(US/Trans)				9.45			105,094,508	0.0000
Δ%(Europe/Trans)				4.42			355,568,316	0.0000

Panel D – Robustness of Table 2.5									
	Bank	Basi	Comm	Cons	Ener	Fina	Indu	Tech	Util
United States	0.6362	0.4876	0.4908	0.4854	0.4930	0.5127	0.4885	0.4905	0.5076
Europe	0.5729	0.5068	0.5024	0.4971	0.5248	0.5473	0.5085	0.4726	0.5139
Δ%(US/Europe)	11.06***	-3.79***	-2.32***	-2.36***	-6.06***	-6.33***	-3.94***	3.78**	-1.22***

Table 2.8 – Robustness with respect to Wilcoxon test
All figures are estimated from the full sample of daily CDS bid quotes ranging from October 2004 to October 2009 applying the methodology outlined in Section 2.3. Instead of using a standard t-test for the difference tests, we use the non-parametric Wilcoxon W-statistic.

Table 2.8 – continued:
Panel A presents aggregate statistics of the upper tail dependence coefficients for banks within the same region. The exhibited figures are associated with Hypothesis 1a stating that *systemic risk within the European banking sector is higher than within the US banking sector.* Panel B reports the upper tail dependence coefficients between US and European banks as well as the deviations of these figures from the ones within the individual regions. The displayed figures are associated with Hypothesis 2a stating that *systemic risk between the US and European banking sectors is higher than systemic risk within the individual regions' banking sectors.* Panel C presents aggregate statistics of upper tail dependence coefficients for banks within the same region during the pre-crisis and crisis time regimes. The *pre-crisis series* contains upper tail dependence coefficients for all dates from October 2004 to June 2007; the *crisis series* consists of upper tail dependence coefficients for all dates from July 2007 to October 2009. The exhibited figures are associated with Hypothesis 3a stating that *in the course of the crisis, the increase in systemic risk is higher for the US banking sector than for the European banking sector.* Panel D presents aggregate statistics of upper tail dependence coefficients between banks and firms from a non-bank sector $\boldsymbol{I}$ within the same region. The exhibited figures are associated with Hypothesis 4a stating that *systemic risk between the banking and any non-bank sector is lower in Europe than in the US.* Panels A to C are organized as follows: Column one gives the region to which the statistics in the following columns refer. Column two reports the number of estimates used to compute the statistics given in columns three to seven. The last two columns report the result of a Wilcoxon test with the null hypothesis that the banks' median upper tail dependence coefficients for the US and Europe are identical. Panel D is organized differently: Column one gives the region to which the statistics in the following columns refer. Columns two to ten report median upper tail dependence coefficients between the regional banking and the respective non-bank sector given in the column header. The panel's last row reports the deviations of the US figures from the European ones expressed in percentage (Δ%) terms. We assign asterisks if these deviations are tested statistically significant according to the Wilcoxon test. (*** = 1%-level; ** = 5%-level; * = 10%-level)

2.B Supplementary tables

Supplement to Table 2.2, Panel C

Panel A – United States

Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Bank	1	11,040	0.5872	0.0029	0.6362	0.9738	0.2109	–	–
Ener	2	36,082	0.5638	0.0028	0.6105	0.9893	0.2335	-9.39	0.0000
Util	3	17,934	0.5407	0.0028	0.5785	0.9644	0.2353	-16.98	0.0000
Basi	4	32,827	0.5231	0.0028	0.5548	0.9556	0.2373	-25.21	0.0000
Indu	5	83,010	0.5089	0.0028	0.5385	0.9763	0.2362	-33.12	0.0000
Fina	6	62,272	0.5073	0.0028	0.5404	0.9905	0.2346	-33.45	0.0000
Cons	7	538,077	0.4921	0.0028	0.5186	0.9955	0.2300	-43.08	0.0000
Comm	8	11,388	0.4894	0.0032	0.5055	0.9940	0.2374	-32.56	0.0000
Tech	9	7,689	0.4877	0.0031	0.5160	0.9770	0.2365	-30.19	0.0000

Panel B – Europe

Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Fina	1	31,675	0.5871	0.0029	0.6376	0.9860	0.2322	-26.34	0.0000
Ener	2	1,225	0.5722	0.0054	0.6233	0.9439	0.2443	-5.11	0.0000
Util	3	39,824	0.5651	0.0030	0.6091	0.9719	0.2292	-15.54	0.0000
Indu	4	71,690	0.5585	0.0028	0.6039	0.9724	0.2310	-13.09	0.0000
Basi	5	23,103	0.5472	0.0031	0.5832	0.9731	0.2298	-4.79	0.0000
Bank	6	29,219	0.5375	0.0028	0.5729	0.9680	0.2329	–	–
Comm	7	62,514	0.5357	0.0028	0.5718	0.9672	0.2266	-1.11	0.1342
Cons	8	237,569	0.5346	0.0028	0.5692	0.9777	0.2267	-2.05	0.0202
Tech	9	178	0.4777	0.0031	0.4844	0.9192	0.2181	-3.41	0.0003

Table 2.9 – Intra-sectoral upper tail dependence coefficients by geographical region
The above upper tail dependence coefficients are estimated from the full series of daily CDS bid quotes ranging from October 2004 to October 2009. The statistics are calculated from all available upper tail dependence coefficients between firms *within* one sector and one region according to Expression (2.5) on page 17. (E.g., all upper tail dependence coefficients used to calculate the statistics for the basic materials sector (Basi) are between firms within the basic materials sector.) The *rank* is identified by the mean upper tail dependence coefficient applying Expression (2.6a); *#obs* is the number of estimates used to compute the statistics in columns four to eight. The last two columns report the results of a t-test with the null hypothesis that the banks' mean upper tail dependence coefficient is identical to the mean upper tail dependence coefficient of firms from the row-name sector.

Supplement to Table 2.3, Panel C

Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Ener	1	13,904	0.5218	0.0034	0.5674	0.9136	0.2256	-8.40	0.0000
Bank	2	35,635	0.5031	0.0029	0.5397	0.9418	0.2209	–	–
Fina	3	87,396	0.4980	0.0028	0.5282	0.9930	0.2245	-3.59	0.0002
Indu	4	151,566	0.4967	0.0028	0.5280	0.9327	0.2233	-4.85	0.0000
Basi	5	54,232	0.4960	0.0028	0.5255	0.9454	0.2242	-4.66	0.0000
Cons	6	694,292	0.4868	0.0028	0.5126	0.9967	0.2215	-13.55	0.0000
Comm	7	52,087	0.4794	0.0028	0.5014	0.9455	0.2229	-15.55	0.0000
Util	8	49,697	0.4783	0.0028	0.5033	0.9294	0.2199	-16.21	0.0000
Tech	9	3,346	0.4616	0.0039	0.4805	0.9036	0.2124	-10.43	0.0000

Table 2.10 – Upper tail dependence between Europe and the United States by sector
The above upper tail dependence coefficients are estimated from the full series of daily CDS bid quotes ranging from October 2004 to October 2009. The statistics are calculated from all available upper tail dependence coefficients between firms within the same sector I but from different regions according to Expression (2.5) on page 17. The *rank* is identified by the mean upper tail dependence coefficient applying Expression (2.6a); *#obs* is the number of estimates used to compute the statistics in columns four to eight. The last two columns report the results of a t-test with the null hypothesis that the mean inter-regional upper tail dependence coefficient for banks and the mean upper tail dependence coefficient for firms from a non-bank sector I are identical.

Supplement to Table 2.4, Panel C

United States: Pre-Crisis

Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Bank	1	6,246	0.5580	0.0031	0.6053	0.9195	0.2131	–	–
Util	2	8,007	0.5059	0.0028	0.5343	0.9397	0.2186	-14.26	0.0000
Fina	3	22,132	0.4782	0.0028	0.5040	0.9594	0.2233	-25.18	0.0000
Ener	4	10,139	0.4656	0.0029	0.4922	0.9321	0.2274	-25.85	0.0000
Comm	5	4,071	0.4523	0.0032	0.4601	0.9343	0.2217	-24.23	0.0000
Indu	6	33,483	0.4505	0.0028	0.4658	0.9623	0.2234	-35.14	0.0000
Tech	7	2,353	0.4494	0.0031	0.4657	0.8871	0.2295	-20.62	0.0000
Basi	8	9,626	0.4383	0.0031	0.4497	0.9243	0.2168	-34.19	0.0000
Cons	9	178,246	0.4204	0.0028	0.4292	0.9433	0.2163	-49.43	0.0000

United States: Crisis

Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Bank	1	4,794	0.6252	0.0029	0.6738	0.9738	0.2019	–	–
Ener	2	25,943	0.6022	0.0028	0.6544	0.9893	0.2245	-6.61	0.0000
Util	3	9,927	0.5687	0.0033	0.6209	0.9644	0.2444	-13.89	0.0000
Basi	4	23,201	0.5583	0.0028	0.6040	0.9556	0.2366	-18.27	0.0000
Indu	5	49,527	0.5483	0.0028	0.5921	0.9763	0.2365	-21.76	0.0000
Cons	6	359,831	0.5276	0.0028	0.5664	0.9955	0.2283	-29.46	0.0000
Fina	7	40,140	0.5233	0.0030	0.5633	0.9905	0.2392	-28.32	0.0000
Comm	8	7,317	0.5101	0.0032	0.5392	0.9940	0.2433	-27.20	0.0000
Tech	9	5,336	0.5046	0.0031	0.5356	0.9770	0.2376	-27.38	0.0000

Table 2.11 – continued on the next page

– continued –

Europe: Pre-Crisis									
Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Fina	1	11,151	0.5262	0.0029	0.5532	0.9441	0.2251	-25.50	0.0000
Util	2	19,101	0.5036	0.0039	0.5318	0.9492	0.2301	-19.99	0.0000
Basi	3	10,786	0.4911	0.0031	0.5132	0.9731	0.2233	-13.69	0.0000
Comm	4	28,484	0.4895	0.0029	0.5154	0.9631	0.2205	-16.24	0.0000
Cons	5	101,513	0.4636	0.0028	0.4802	0.9479	0.2200	-6.34	0.0000
Indu	6	31,355	0.4575	0.0028	0.4741	0.9227	0.2230	-3.10	0.0010
Bank	7	11,823	0.4499	0.0028	0.4687	0.9196	0.2280	–	–
Ener	8	597	0.4084	0.0054	0.4439	0.8118	0.2074	-4.36	0.0000
Tech	9	82	0.3877	0.0031	0.3822	0.7627	0.1983	-2.47	0.0068
Europe: Crisis									
Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Ener	1	628	0.7279	0.0123	0.7682	0.9439	0.1605	-14.99	0.0000
Indu	2	40,335	0.6370	0.0028	0.6928	0.9724	0.2051	-21.18	0.0000
Util	3	20,723	0.6218	0.0030	0.6722	0.9719	0.2132	-11.23	0.0000
Fina	4	20,524	0.6202	0.0031	0.6848	0.9860	0.2292	-10.10	0.0000
Bank	5	17,396	0.5970	0.0028	0.6428	0.9680	0.2168	–	–
Basi	6	12,317	0.5964	0.0048	0.6466	0.9542	0.2240	-0.22	0.4143
Cons	7	136,056	0.5876	0.0030	0.6332	0.9777	0.2169	-5.37	0.0000
Comm	8	34,030	0.5743	0.0028	0.6202	0.9672	0.2244	-10.95	0.0000
Tech	9	96	0.5546	0.0600	0.5620	0.9192	0.2049	-1.91	0.0281

Table 2.11 – Pre-crisis and crisis levels of intra-sectoral upper tail dependence coefficients by geographical region
The above upper tail dependence coefficients are estimated from the full series of daily CDS bid quotes ranging from October 2004 to October 2009. The statistics are calculated from all available upper tail dependence coefficients between firms *within* one sector and region according to Expression (2.5) on page 17. E.g., all upper tail dependence coefficients used to calculate the statistics for the basic materials sector (Basi) in the first panel are between US firms within the basic materials sector. The *rank* is identified by the mean upper tail dependence coefficient applying Expression (2.6a); $\#obs$ is the number of estimates used to compute the statistics in columns four to eight. The last two columns report the results of a t-test with the null hypothesis that the mean upper tail dependence coefficient for banks in the given region and during the given time regime is identical to the mean upper tail dependence coefficient for firms from the non-bank sector I in the same region and during the same time regime.

Supplement to Table 2.5, Panel A

Panel A – United States

Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Bank	1	11,040	0.5872	0.0029	0.6362	0.9738	0.2109	–	–
Fina	2	50,533	0.4853	0.0028	0.5127	0.9419	0.2180	-44.72	0.0000
Util	3	26,385	0.4762	0.0028	0.5076	0.9297	0.2179	-45.35	0.0000
Ener	4	34,441	0.4673	0.0028	0.4930	0.9261	0.2179	-50.68	0.0000
Basi	5	34,312	0.4670	0.0029	0.4876	0.9324	0.2229	-49.90	0.0000
Comm	6	20,575	0.4647	0.0029	0.4908	0.9509	0.2200	-47.84	0.0000
Indu	7	57,001	0.4642	0.0028	0.4885	0.9320	0.2161	-54.95	0.0000
Tech	8	16,866	0.4637	0.0028	0.4905	0.9185	0.2189	-46.75	0.0000
Cons	9	139,948	0.4631	0.0028	0.4854	0.9543	0.2169	-57.99	0.0000

Panel B – Europe

Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Bank	1	29,219	0.5375	0.0028	0.5729	0.9680	0.2329	–	–
Fina	2	60,251	0.5183	0.0028	0.5473	0.9702	0.2286	-11.68	0.0000
Ener	3	12,046	0.4999	0.0028	0.5248	0.9436	0.2358	-14.83	0.0000
Util	4	59,340	0.4913	0.0028	0.5139	0.9400	0.2320	-27.79	0.0000
Indu	5	83,233	0.4889	0.0028	0.5085	0.9504	0.2302	-30.91	0.0000
Basi	6	47,924	0.4879	0.0028	0.5068	0.9468	0.2295	-28.92	0.0000
Comm	7	77,473	0.4840	0.0028	0.5024	0.9601	0.2259	-34.20	0.0000
Cons	8	154,464	0.4811	0.0028	0.4971	0.9532	0.2269	-38.80	0.0000
Tech	9	5,760	0.4582	0.0028	0.4726	0.9243	0.2234	-23.78	0.0000

Table 2.12 – Inter-sectoral upper tail dependence coefficients by geographical region
The above upper tail dependence coefficients are estimated from the full series of daily CDS bid quotes ranging from October 2004 to October 2009. The statistics are calculated from all available upper tail dependence coefficients *between* banks and firms from any non-bank sector $\boldsymbol{I}$ within the same region according to Expression (2.5) on page 17. (E.g., all upper tail dependence coefficients used to calculate the statistics in row "Basi" are between firms of the basic materials sector (Basi) and firms of the banking sector (Bank).) The *rank* is identified by the inter-sectoral mean upper tail dependence coefficient applying Expression (2.6b); #*obs* is the number of estimates used to compute the statistics in columns four to eight. The last two columns report the results of a t-test with the null hypothesis that the banks' mean upper tail dependence coefficient and the mean upper tail dependence coefficient between banks and firms from any non-bank sector $\boldsymbol{I}$ are identical.

Supplement to Table 2.5, Panel B

Panel A – United States

Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Bank	1	256	0.5748	0.2729	0.5788	0.8721	0.1266	–	–
Fina	2	256	0.4709	0.2155	0.4621	0.7999	0.1085	-9.97	0.0000
Util	3	256	0.4547	0.1846	0.4364	0.8264	0.1155	-11.21	0.0000
Cons	4	256	0.4452	0.1562	0.4320	0.7296	0.0977	-12.97	0.0000
Indu	5	256	0.4435	0.1598	0.4225	0.7382	0.1099	-12.54	0.0000
Comm	6	256	0.4417	0.1727	0.4374	0.7086	0.1082	-12.79	0.0000
Tech	7	256	0.4395	0.0759	0.4411	0.6834	0.1127	-12.77	0.0000
Basi	8	256	0.4391	0.1449	0.4151	0.7488	0.1225	-12.33	0.0000
Ener	9	256	0.4323	0.1157	0.4231	0.7421	0.1251	-12.80	0.0000

Panel B – Europe

Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Bank	1	256	0.5107	0.2393	0.4983	0.8792	0.1449	–	–
Fina	2	256	0.4912	0.2332	0.4788	0.8276	0.1309	-1.60	0.0551
Comm	3	256	0.4515	0.1969	0.4272	0.7893	0.1287	-4.89	0.0000
Basi	4	256	0.4511	0.1894	0.4300	0.8494	0.1384	-4.76	0.0000
Cons	5	256	0.4511	0.2235	0.4233	0.8353	0.1258	-4.97	0.0000
Indu	6	256	0.4503	0.2189	0.4269	0.8118	0.1339	-4.90	0.0000
Util	7	256	0.4474	0.1736	0.4302	0.8155	0.1430	-4.97	0.0000
Ener	8	253	0.4473	0.0439	0.4188	0.8604	0.1683	-4.56	0.0000
Tech	9	255	0.4249	0.0285	0.4104	0.8045	0.1427	-6.74	0.0000

Table 2.13 – Inter-sectoral upper tail dependence coefficients by geographical region
The above upper tail dependence coefficients are estimated from the full series of daily CDS bid quotes ranging from October 2004 to October 2009. The statistics are calculated from all available upper tail dependence coefficients *between* banks and firms from any non-bank sector $\boldsymbol{I}$ within the same region according to Expression (2.8) on page 18. (E.g., all upper tail dependence coefficients used to calculate the statistics in row "Basi" are between firms of the basic materials sector (Basi) and firms of the banking sector (Bank).) The *rank* is identified by the inter-sectoral mean upper tail dependence coefficient applying Expression (2.6b); #*obs* is the number of estimates used to compute the statistics in columns four to eight. The last two columns report the results of a t-test with the null hypothesis that the banks' mean upper tail dependence coefficient and the mean upper tail dependence coefficient between banks and firms from any non-bank sector $\boldsymbol{I}$ are identical.

Supplement to Table 2.5, Panel C (United States)

Panel A – Banks

Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Bank	1	11,040	0.5872	0.0029	0.6362	0.9738	0.2109	–	–
Fina	2	50,533	0.4853	0.0028	0.5127	0.9419	0.2180	-44.72	0.0000
Util	3	26,385	0.4762	0.0028	0.5076	0.9297	0.2179	-45.35	0.0000
Ener	4	34,441	0.4673	0.0028	0.4930	0.9261	0.2179	-50.68	0.0000
Basi	5	34,312	0.4670	0.0029	0.4876	0.9324	0.2229	-49.90	0.0000
Comm	6	20,575	0.4647	0.0029	0.4908	0.9509	0.2200	-47.84	0.0000
Indu	7	57,001	0.4642	0.0028	0.4885	0.9320	0.2161	-54.95	0.0000
Tech	8	16,866	0.4637	0.0028	0.4905	0.9185	0.2189	-46.75	0.0000
Cons	9	139,948	0.4631	0.0028	0.4854	0.9543	0.2169	-57.99	0.0000

Panel B – Basic Materials

Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Basi	1	32,827	0.5231	0.0028	0.5548	0.9556	0.2373	-31.56	0.0000
Ener	2	68,177	0.5116	0.0029	0.5435	0.9854	0.2344	-29.18	0.0000
Indu	3	105,884	0.5042	0.0028	0.5331	0.9631	0.2350	-25.77	0.0000
Cons	4	271,713	0.4972	0.0028	0.5252	0.9968	0.2301	-22.94	0.0000
Comm	5	40,564	0.4932	0.0028	0.5154	0.9949	0.2346	-15.57	0.0000
Tech	6	33,114	0.4910	0.0028	0.5191	0.9479	0.2324	-13.67	0.0000
Util	7	48,183	0.4894	0.0028	0.5128	0.9429	0.2297	-13.95	0.0000
Fina	8	86,188	0.4746	0.0028	0.4943	0.9792	0.2319	-5.15	0.0000
Bank	9	34,312	0.4670	0.0029	0.4876	0.9324	0.2229	–	–

Panel C – Communication

Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Ener	1	41,220	0.4937	0.0028	0.5180	0.9412	0.2322	-14.88	0.0000
Basi	2	40,564	0.4932	0.0028	0.5154	0.9949	0.2346	-14.48	0.0000
Tech	3	20,439	0.4901	0.0029	0.5168	0.9475	0.2335	-11.33	0.0000
Comm	4	11,388	0.4894	0.0032	0.5055	0.9940	0.2374	-9.33	0.0000
Indu	5	63,428	0.4848	0.0029	0.5040	0.9860	0.2339	-10.84	0.0000
Cons	6	161,914	0.4824	0.0028	0.5033	0.9969	0.2313	-10.34	0.0000
Util	7	29,058	0.4785	0.0029	0.5007	0.9664	0.2278	-6.72	0.0000
Fina	8	50,925	0.4661	0.0029	0.4829	0.9757	0.2331	-0.73	0.2340
Bank	9	20,575	0.4647	0.0029	0.4908	0.9509	0.2200	–	–

Table 2.14 – continued on the next page

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Panel D – Consumer									
Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Basi	1	271,713	0.4972	0.0028	0.5252	0.9968	0.2301	-45.93	0.0000
Ener	2	274,135	0.4953	0.0028	0.5246	0.9956	0.2278	-43.73	0.0000
Cons	3	538,077	0.4921	0.0028	0.5186	0.9955	0.2300	-42.52	0.0000
Indu	4	422,455	0.4884	0.0028	0.5143	0.9920	0.2306	-36.14	0.0000
Comm	5	161,914	0.4824	0.0028	0.5033	0.9969	0.2313	-23.52	0.0000
Util	6	194,764	0.4792	0.0028	0.5066	0.9968	0.2233	-20.91	0.0000
Tech	7	133,009	0.4789	0.0028	0.5053	0.9775	0.2269	-18.70	0.0000
Fina	8	353,210	0.4739	0.0028	0.4963	0.9917	0.2273	-15.30	0.0000
Bank	9	139,948	0.4631	0.0028	0.4854	0.9543	0.2169	–	–

Panel E – Energy									
Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Ener	1	36,082	0.5638	0.0028	0.6105	0.9893	0.2335	-56.69	0.0000
Util	2	51,486	0.5259	0.0028	0.5639	0.9831	0.2324	-37.14	0.0000
Basi	3	68,177	0.5116	0.0029	0.5435	0.9854	0.2344	-29.24	0.0000
Indu	4	109,551	0.5075	0.0028	0.5395	0.9924	0.2306	-28.55	0.0000
Tech	5	34,749	0.4977	0.0029	0.5313	0.9476	0.2298	-17.83	0.0000
Cons	6	274,135	0.4953	0.0028	0.5246	0.9956	0.2278	-21.57	0.0000
Comm	7	41,220	0.4937	0.0028	0.5180	0.9412	0.2322	-16.02	0.0000
Fina	8	89,247	0.4910	0.0028	0.5182	0.9952	0.2336	-16.26	0.0000
Bank	9	34,441	0.4673	0.0028	0.4930	0.9261	0.2179	–	–

Panel F – Financial (Non-Bank)									
Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Fina	1	62,272	0.5073	0.0028	0.5404	0.9905	0.2346	-16.12	0.0000
Ener	2	89,247	0.4910	0.0028	0.5182	0.9952	0.2336	-4.43	0.0000
Bank	3	50,533	0.4853	0.0028	0.5127	0.9419	0.2180	–	–
Util	4	63,179	0.4829	0.0028	0.5072	0.9922	0.2319	-1.79	0.0368
Basi	5	86,188	0.4746	0.0028	0.4943	0.9792	0.2319	-8.47	0.0000
Cons	6	353,210	0.4739	0.0028	0.4963	0.9917	0.2273	-10.63	0.0000
Tech	7	41,610	0.4683	0.0028	0.4943	0.9478	0.2312	-11.47	0.0000
Indu	8	136,297	0.4672	0.0028	0.4878	0.9947	0.2305	-15.37	0.0000
Comm	9	50,925	0.4661	0.0029	0.4829	0.9757	0.2331	-13.56	0.0000

Table 2.14 – continued on the next page

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Panel G – Industrials

Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Indu	1	83,010	0.5089	0.0028	0.5385	0.9763	0.2362	-36.00	0.0000
Ener	2	109,551	0.5075	0.0028	0.5395	0.9924	0.2306	-37.13	0.0000
Basi	3	105,884	0.5042	0.0028	0.5331	0.9631	0.2350	-33.70	0.0000
Util	4	77,120	0.4959	0.0028	0.5270	0.9767	0.2275	-25.76	0.0000
Tech	5	52,927	0.4914	0.0028	0.5195	0.9601	0.2311	-20.20	0.0000
Cons	6	422,455	0.4884	0.0028	0.5143	0.9920	0.2306	-23.72	0.0000
Comm	7	63,428	0.4848	0.0029	0.5040	0.9860	0.2339	-15.84	0.0000
Fina	8	136,297	0.4672	0.0028	0.4878	0.9947	0.2305	-2.64	0.0041
Bank	9	57,001	0.4642	0.0028	0.4885	0.9320	0.2161	–	–

Panel H – Technology

Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Ener	1	34,749	0.4977	0.0029	0.5313	0.9476	0.2298	-16.00	0.0000
Indu	2	52,927	0.4914	0.0028	0.5195	0.9601	0.2311	-13.74	0.0000
Basi	3	33,114	0.4910	0.0028	0.5191	0.9479	0.2324	-12.66	0.0000
Comm	4	20,439	0.4901	0.0029	0.5168	0.9475	0.2335	-11.20	0.0000
Tech	5	7,689	0.4877	0.0031	0.5160	0.9770	0.2365	-7.77	0.0000
Util	6	23,981	0.4861	0.0028	0.5107	0.9663	0.2268	-9.96	0.0000
Cons	7	133,009	0.4789	0.0028	0.5053	0.9775	0.2269	-8.26	0.0000
Fina	8	41,610	0.4683	0.0028	0.4943	0.9478	0.2312	-2.23	0.0130
Bank	9	16,866	0.4637	0.0028	0.4905	0.9185	0.2189	–	–

Panel I – Utilities

Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Util	1	17,934	0.5407	0.0028	0.5785	0.9644	0.2353	-29.60	0.0000
Ener	2	51,486	0.5259	0.0028	0.5639	0.9831	0.2324	-28.86	0.0000
Indu	3	77,120	0.4959	0.0028	0.5270	0.9767	0.2275	-12.25	0.0000
Basi	4	48,183	0.4894	0.0028	0.5128	0.9429	0.2297	-7.64	0.0000
Tech	5	23,981	0.4861	0.0028	0.5107	0.9663	0.2268	-4.98	0.0000
Fina	6	63,179	0.4829	0.0028	0.5072	0.9922	0.2319	-4.03	0.0000
Cons	7	194,764	0.4792	0.0028	0.5066	0.9968	0.2233	-2.08	0.0188
Comm	8	29,058	0.4785	0.0029	0.5007	0.9664	0.2278	-1.22	0.1118
Bank	9	26,385	0.4762	0.0028	0.5076	0.9297	0.2179	–	–

Table 2.14 – Intra- and inter-sectoral upper tail dependence coefficients (United States)
The above upper tail dependence coefficients are estimated from the full series of daily CDS bid quotes ranging from October 2004 to October 2009.

Table 2.14 – continued:
The statistics are calculated from all available upper tail dependence coefficients *between* firms of one sector $\boldsymbol{I}$ and firms of any other sector $\boldsymbol{J}$ within the United States. E.g., all statistics reported in "Panel B – Basic Materials" are between US firms of the basic materials sector (Basi) and US firms of any other sector (e.g., banking sector or utilities sector). The intra-sectoral mean upper tail dependence coefficients are included for reference. The *rank* is identified by the inter-sectoral mean upper tail dependence coefficients according to Expression (2.6b); $\#obs$ is the number of estimates used to compute the statistics in columns four to eight. The last two columns report the results of a t-test with the null hypothesis that the mean upper tail dependence coefficient between firms from sector $\boldsymbol{I}$ and banks and the mean upper tail dependence coefficient between firms from sector $\boldsymbol{I}$ (panel name) and $\boldsymbol{J}$ (row name) are identical. E.g., in "Panel B – Basic Materials", the hypothesis that the mean upper tail dependence coefficient between banks and basic material firms of 0.4670 is identical to the mean upper tail dependence coefficient between basic material and energy firms of 0.5116 can be rejected with a t-statistic of -29.18.

Supplement to Table 2.5, Panel C (Europe)

Panel A – Banks

Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Bank	1	29,219	0.5375	0.0028	0.5729	0.9680	0.2329	–	–
Fina	2	60,251	0.5183	0.0028	0.5473	0.9702	0.2286	-11.68	0.0000
Ener	3	12,046	0.4999	0.0028	0.5248	0.9436	0.2358	-14.83	0.0000
Util	4	59,340	0.4913	0.0028	0.5139	0.9400	0.2320	-27.79	0.0000
Indu	5	83,233	0.4889	0.0028	0.5085	0.9504	0.2302	-30.91	0.0000
Basi	6	47,924	0.4879	0.0028	0.5068	0.9468	0.2295	-28.92	0.0000
Comm	7	77,473	0.4840	0.0028	0.5024	0.9601	0.2259	-34.20	0.0000
Cons	8	154,464	0.4811	0.0028	0.4971	0.9532	0.2269	-38.80	0.0000
Tech	9	5,760	0.4582	0.0028	0.4726	0.9243	0.2234	-23.78	0.0000

Panel B – Basic Matertials

Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Basi	1	23,103	0.5472	0.0031	0.5832	0.9731	0.2298	-32.25	0.0000
Indu	2	83,532	0.5430	0.0028	0.5807	0.9539	0.2293	-41.90	0.0000
Ener	3	11,975	0.5330	0.0028	0.5711	0.9323	0.2269	-19.26	0.0000
Cons	4	151,902	0.5326	0.0028	0.5671	0.9574	0.2277	-37.40	0.0000
Comm	5	78,482	0.5289	0.0028	0.5629	0.9542	0.2254	-31.17	0.0000
Fina	6	53,414	0.5261	0.0028	0.5570	0.9520	0.2299	-26.41	0.0000
Util	7	59,540	0.5194	0.0028	0.5508	0.9468	0.2287	-22.38	0.0000
Tech	8	5,732	0.5131	0.0035	0.5420	0.9297	0.2250	-7.87	0.0000
Bank	9	47,924	0.4879	0.0028	0.5068	0.9468	0.2295	–	–

Panel C – Communication

Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Comm	1	62,514	0.5357	0.0028	0.5718	0.9672	0.2266	-42.50	0.0000
Indu	2	136,018	0.5300	0.0028	0.5656	0.9519	0.2264	-45.25	0.0000
Basi	3	78,482	0.5289	0.0028	0.5629	0.9542	0.2254	-39.34	0.0000
Ener	4	19,058	0.5248	0.0031	0.5608	0.9427	0.2281	-22.32	0.0000
Cons	5	248,033	0.5245	0.0028	0.5563	0.9583	0.2238	-43.92	0.0000
Util	6	99,845	0.5217	0.0028	0.5550	0.9474	0.2265	-34.86	0.0000
Fina	7	85,982	0.5179	0.0028	0.5471	0.9502	0.2258	-30.31	0.0000
Tech	8	9,735	0.5043	0.0032	0.5245	0.9281	0.2243	-8.36	0.0000
Bank	9	77,473	0.4840	0.0028	0.5024	0.9601	0.2259	–	–

Table 2.15 – continued on the next page

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Panel D – Consumer									
Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Indu	1	263,081	0.5393	0.0028	0.5771	0.9663	0.2271	-79.96	0.0000
Cons	2	237,569	0.5346	0.0028	0.5692	0.9777	0.2267	-72.19	0.0000
Basi	3	151,902	0.5326	0.0028	0.5671	0.9574	0.2277	-62.77	0.0000
Comm	4	248,033	0.5245	0.0028	0.5563	0.9583	0.2238	-59.59	0.0000
Ener	5	37,130	0.5244	0.0028	0.5632	0.9471	0.2268	-33.02	0.0000
Fina	6	171,254	0.5188	0.0028	0.5469	0.9829	0.2247	-47.62	0.0000
Util	7	187,087	0.5155	0.0028	0.5466	0.9599	0.2282	-44.02	0.0000
Tech	8	18,444	0.4940	0.0029	0.5168	0.9345	0.2258	-7.31	0.0000
Bank	9	154,464	0.4811	0.0028	0.4971	0.9532	0.2269	–	–

Panel E – Energy									
Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Ener	1	1,225	0.5722	0.0054	0.6233	0.9439	0.2443	-10.19	0.0000
Fina	2	13,156	0.5522	0.0028	0.6033	0.9323	0.2281	-17.89	0.0000
Util	3	15,778	0.5498	0.0036	0.5937	0.9517	0.2277	-17.81	0.0000
Indu	4	20,872	0.5488	0.0029	0.5967	0.9412	0.2298	-18.39	0.0000
Basi	5	11,975	0.5330	0.0028	0.5711	0.9323	0.2269	-11.07	0.0000
Comm	6	19,058	0.5248	0.0031	0.5608	0.9427	0.2281	-9.25	0.0000
Cons	7	37,130	0.5244	0.0028	0.5632	0.9471	0.2268	-10.17	0.0000
Tech	8	1,392	0.5206	0.0045	0.5581	0.8994	0.2260	-3.11	0.0009
Bank	9	12,046	0.4999	0.0028	0.5248	0.9436	0.2358	–	–

Panel F – Financial (Non-Bank)									
Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Fina	1	31,675	0.5871	0.0029	0.6376	0.9860	0.2322	-43.14	0.0000
Ener	2	13,156	0.5522	0.0028	0.6033	0.9323	0.2281	-15.42	0.0000
Indu	3	93,351	0.5390	0.0028	0.5787	0.9482	0.2281	-17.36	0.0000
Basi	4	53,414	0.5261	0.0028	0.5570	0.9520	0.2299	-5.71	0.0000
Util	5	64,832	0.5248	0.0029	0.5583	0.9491	0.2300	-4.96	0.0000
Cons	6	171,254	0.5188	0.0028	0.5469	0.9829	0.2247	-0.44	0.3309
Bank	7	60,251	0.5183	0.0028	0.5473	0.9702	0.2286	–	–
Comm	8	85,982	0.5179	0.0028	0.5471	0.9502	0.2258	-0.36	0.3592
Tech	9	6,483	0.5057	0.0031	0.5241	0.9221	0.2279	-4.23	0.0000

Table 2.15 – continued on the next page

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Panel G – Industrials

Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Indu	1	71,690	0.5585	0.0028	0.6039	0.9724	0.2310	-59.21	0.0000
Ener	2	20,872	0.5488	0.0029	0.5967	0.9412	0.2298	-33.59	0.0000
Basi	3	83,532	0.5430	0.0028	0.5807	0.9539	0.2293	-48.06	0.0000
Cons	4	263,081	0.5393	0.0028	0.5771	0.9663	0.2271	-55.55	0.0000
Fina	5	93,351	0.5390	0.0028	0.5787	0.9482	0.2281	-45.88	0.0000
Comm	6	136,018	0.5300	0.0028	0.5656	0.9519	0.2264	-41.01	0.0000
Util	7	104,364	0.5262	0.0028	0.5614	0.9496	0.2284	-35.03	0.0000
Tech	8	10,187	0.5148	0.0050	0.5444	0.9345	0.2238	-10.74	0.0000
Bank	9	83,233	0.4889	0.0028	0.5085	0.9504	0.2302	–	–

Panel H – Technology

Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Ener	1	1,392	0.5206	0.0045	0.5581	0.8994	0.2260	-9.34	0.0000
Indu	2	10,187	0.5148	0.0050	0.5444	0.9345	0.2238	-15.36	0.0000
Basi	3	5,732	0.5131	0.0035	0.5420	0.9297	0.2250	-13.14	0.0000
Fina	4	6,483	0.5057	0.0031	0.5241	0.9221	0.2279	-11.62	0.0000
Comm	5	9,735	0.5043	0.0032	0.5245	0.9281	0.2243	-12.38	0.0000
Util	6	7,654	0.5002	0.0032	0.5233	0.9284	0.2210	-10.86	0.0000
Cons	7	18,444	0.4940	0.0029	0.5168	0.9345	0.2258	-10.54	0.0000
Tech	8	178	0.4777	0.0031	0.4844	0.9192	0.2181	-1.15	0.1249
Bank	9	5,760	0.4582	0.0028	0.4726	0.9243	0.2234	–	–

Panel I – Utilities

Sector	rank	#obs	mean	min	median	max	sdev	t-value	p-value
Util	1	39,824	0.5651	0.0030	0.6091	0.9719	0.2292	-49.30	0.0000
Ener	2	15,778	0.5498	0.0036	0.5937	0.9517	0.2277	-28.23	0.0000
Indu	3	104,364	0.5262	0.0028	0.5614	0.9496	0.2284	-29.55	0.0000
Fina	4	64,832	0.5248	0.0029	0.5583	0.9491	0.2300	-25.47	0.0000
Comm	5	99,845	0.5217	0.0028	0.5550	0.9474	0.2265	-25.67	0.0000
Basi	6	59,540	0.5194	0.0028	0.5508	0.9468	0.2287	-20.99	0.0000
Cons	7	187,087	0.5155	0.0028	0.5466	0.9599	0.2282	-22.40	0.0000
Tech	8	7,654	0.5002	0.0032	0.5233	0.9284	0.2210	-3.17	0.0008
Bank	9	59,340	0.4913	0.0028	0.5139	0.9400	0.2320	–	–

Table 2.15 – Intra- and inter-sectoral upper tail dependence coefficients (Europe)
The above upper tail dependence coefficients are estimated from the full series of daily CDS bid quotes ranging from October 2004 to October 2009.

Table 2.15 – continued:
The statistics are calculated from all available upper tail dependence coefficients *between* firms of one sector $\boldsymbol{I}$ and firms of any other sector $\boldsymbol{J}$ within Europe. E.g., all statistics reported in "Panel B – Basic Materials" are between European firms of the basic materials sector (Basi) and European firms of any other sector (e.g., banking sector or utilities sector). The intra-sectoral mean upper tail dependence coefficients are included for reference. The *rank* is identified by the inter-sectoral mean upper tail dependence coefficients according to Expression (2.6b); $\#obs$ is the number of estimates used to compute the statistics in columns four to eight. The last two columns report the results of a t-test with the null hypothesis that the mean upper tail dependence coefficient between firms from sector $\boldsymbol{I}$ and banks and the mean upper tail dependence coefficient between firms from sector $\boldsymbol{I}$ (panel name) and $\boldsymbol{J}$ (row name) are identical E.g., in "Panel B – Basic Materials", the hypothesis that the mean upper tail dependence coefficient between banks and basic material firms of 0.4879 is identical to the mean upper tail dependence coefficient between basic material and energy firms of 0.5330 can be rejected with a t-statistic of -19.26.

United States Banks	
American Express Co	
Bank of America Corp	
Bank One Corp	
Capital One Financial Corp	
CIT Group Inc	
Citigroup Inc	
Goldman Sachs Group Inc/The	
JPMorgan Chase & Co	
Lehman Brothers Holdings Inc	
Morgan Stanley	
Washington Mutual Inc	
Wells Fargo & Co	
European Banks	**Country**
Erste Bank der Oesterreichischen Sparkassen AG	Austria
Dexia SA	Belgium
Fortis Bank SA/NV	Belgium
Danske Bank A/S	Denmark
Credit Agricole SA	France
Societe Generale	France
Commerzbank AG	Germany
Deutsche Bank AG	Germany
IKB Deutsche Industriebank AG	Germany
Alpha Bank AE	Greece
Allied Irish Banks PLC	Ireland
Bank of Ireland	Ireland
UniCredit SpA	Italy
ING Groep NV	Netherlands
Banco Espirito Santo SA	Portugal
Banco Pastor SA	Spain
Banco Santander SA	Spain
Nordea Bank AB	Sweden
Skandinaviska Enskilda Banken AB	Sweden
Svenska Handelsbanken AB	Sweden
Credit Suisse Group	Switzerland
UBS AG	Switzerland
Standard Chartered PLC	United Kingdom

Table 2.16 – Description of banks
All United States' CDS in USD; all European CDS in EUR.

	Currency		Gross Notional Amount	# Contracts	% of Total	% of Total of 4, 5 & 9
1.	Australian Dollar	AUD	1,373,500,000	95	0.00	–
2.	Canadian Dollar	CAD	8,002,919,000	668	0.01	–
3.	Swiss Franc	CHF	946,419,000	146	0.00	–
4.	Euro	EUR	7,981,449,847,310	754,018	13.72	36.28
5.	British Sterling	GBP	12,342,004,534	2,152	0.02	0.06
6.	Hong Kong Dollar	HKD	589,800,000	23	0.00	–
7.	Japanese Yen	JPY	36,179,866,711,183	67,255	62.17	–
8.	Singapore Dollar	SGD	486,150,000	123	0.00	–
9.	US Dollar	USD	14,006,627,266,904	1,298,196	24.07	63.67
10.	Other	–	0	0	0.00	–
	TOTAL of 4, 5 & 9		22,000,419,118,748	2,054,366	–	100.00
	TOTAL		58,191,684,617,931	2,122,676	100.00	–

Table 2.17 – CDS notional volume by currency
The above table exhibits the outstanding CDS notional volume by currency as of May 31, 2013. Source: *DTCC, Trade Information Warehouse Data.*

2.C Time series diagnostics and goodness of fit

Sector	#obs	mean	min	$q = 0.25$	$q = 0.50$	$q = 0.75$	max	$\#p : p < 0.1$ (in %)	$\#p : p < 0.05$ (in %)	$\#p : p < 0.01$ (in %)
Panel A – Unit roots & stationarity: Augmented Dickey-Fuller test										
Bank	7,351	0.4551	0.0100	0.2134	0.4399	0.6803	0.9900	17.32	11.32	0.00
Basi	8,984	0.4327	0.0100	0.2023	0.4175	0.6363	0.9900	18.11	11.79	0.00
Comm	9,923	0.4249	0.0100	0.1744	0.4032	0.6373	0.9900	19.66	12.90	0.00
Cons	33,565	0.4280	0.0100	0.1858	0.4110	0.6373	0.9900	18.89	12.24	0.00
Ener	6,286	0.4265	0.0100	0.1810	0.4105	0.6307	0.9900	19.23	12.46	0.00
Fina	11,770	0.4161	0.0100	0.1604	0.3907	0.6244	0.9900	21.03	14.32	0.00
Indu	15,584	0.4269	0.0100	0.1804	0.4082	0.6353	0.9900	19.37	12.63	0.00
Tech	3,098	0.4363	0.0100	0.1865	0.4226	0.6492	0.9900	19.14	12.59	0.00
Util	9,067	0.4009	0.0100	0.1428	0.3741	0.6019	0.9900	21.61	14.24	0.00
Panel B – Heteroscedasticity: Breusch-Pagan test										
Bank	7,362	0.1686	0.0000	0.0002	0.0175	0.2445	1.0000	65.15	58.76	45.94
Basi	9,013	0.1667	0.0000	0.0001	0.0144	0.2333	1.0000	65.94	60.24	47.30
Comm	9,939	0.1572	0.0000	0.0001	0.0121	0.2031	1.0000	67.57	61.09	48.60
Cons	33,600	0.1668	0.0000	0.0001	0.0136	0.2308	1.0000	65.97	59.63	48.03
Ener	6,299	0.1667	0.0000	0.0001	0.0144	0.2315	1.0000	65.57	59.22	47.67
Fina	11,788	0.1577	0.0000	0.0001	0.0102	0.2020	1.0000	67.73	61.86	49.89
Indu	15,596	0.1644	0.0000	0.0001	0.0128	0.2241	1.0000	66.40	60.12	48.28
Tech	3,102	0.1563	0.0000	0.0001	0.0110	0.2069	0.9993	67.96	61.57	49.58
Util	9,077	0.1545	0.0000	0.0001	0.0095	0.1948	1.0000	68.34	62.30	50.41
Panel C – Auto-correlation: Durbin-Watson test										
Bank	7,351	0.0012	0.0000	0.0000	0.0000	0.0000	0.9604	99.73	99.71	99.54
Basi	8,984	0.0000	0.0000	0.0000	0.0000	0.0000	0.0066	100.00	100.00	100.00
Comm	9,923	0.0028	0.0000	0.0000	0.0000	0.0000	0.9986	99.65	99.64	99.62
Cons	33,565	0.0004	0.0000	0.0000	0.0000	0.0000	0.9804	99.91	99.88	99.81
Ener	6,286	0.0027	0.0000	0.0000	0.0000	0.0000	0.9868	99.62	99.51	99.44
Fina	11,770	0.0036	0.0000	0.0000	0.0000	0.0000	0.9990	99.35	99.25	99.17
Indu	15,584	0.0023	0.0000	0.0000	0.0000	0.0000	0.9819	99.63	99.60	99.57
Tech	3,098	0.0040	0.0000	0.0000	0.0000	0.0000	0.9762	99.23	99.13	98.93
Util	9,067	0.0001	0.0000	0.0000	0.0000	0.0000	0.2358	99.98	99.96	99.92
Panel D – Non-normality: Jarque-Bera test										
Bank	7,351	0.0832	0.0000	0.0004	0.0118	0.0710	0.9998	79.38	70.00	48.10
Basi	8,984	0.0809	0.0000	0.0009	0.0143	0.0722	0.9995	79.06	69.66	45.27
Comm	9,923	0.0831	0.0000	0.0008	0.0137	0.0785	0.9997	78.42	68.79	45.54
Cons	33,565	0.0805	0.0000	0.0007	0.0126	0.0704	0.9992	79.64	70.11	46.90
Ener	6,286	0.0688	0.0000	0.0007	0.0101	0.0550	0.9958	82.55	73.59	49.90
Fina	11,770	0.0714	0.0000	0.0002	0.0077	0.0535	0.9951	82.41	74.13	53.34
Indu	15,584	0.0743	0.0000	0.0004	0.0096	0.0604	0.9978	81.07	72.70	50.51
Tech	3,098	0.0686	0.0000	0.0002	0.0076	0.0507	0.9986	83.02	74.82	53.45
Util	9,067	0.0734	0.0000	0.0010	0.0114	0.0622	0.9980	81.21	71.87	48.15

Table 2.18 – Time series properties of CDS bid quotes: p-values
The above table exhibits p-values of various statistical tests on the time series properties of the three months time series of daily CDS premia used to estimate the extreme value distribution according to Equation (2.1). All CDS data are obtained via Bloomberg; the time series of observations ranges from October 2004 to October 2009. To minimize the impact of factors other than the underlying reference entity's default risk, we only consider bid quotes.

Table 2.18 – continued:
In total, we have 5-year CDS contracts on 550 firms in our sample, all of which are on senior unsecured debt. The table is organized as follows: *Panel A* exhibits the results of the Augmented Dickey-Fuller test with the null hypothesis that the time series are stationary, i.e., there is no unit root. *Panel B* presents the results of the Breusch-Pagan test with the null hypothesis that the time series are homoscedastic, i.e., there is no heteroscedasticity. *Panel C* gives the results of the Durbin-Watson test with the null hypothesis that the time series exhibit no auto-correlation. *Panel D* presents the results of the Jarque-Bera test with the null hypothesis that the time series follow the Gaussian distribution. Column one gives the sectoral abbreviations to which the statistics refer. (E.g., all statistics on p-values in row "Basi" refer to three-month series of daily CDS premia on firms of the basic materials sector.) Column two gives the number of series tested for each sector and thus the number of test results. Column three gives the mean p-value of the test results, columns four to eight the quantiles, and columns nine to eleven provide the percentage of test results significant at the 10%, 5%, and 1% confidence levels.

Sector	#obs	mean	min	$q = 0.25$	$q = 0.50$	$q = 0.75$	max	$\#p : p < 0.1$ (in %)	$\#p : p < 0.05$ (in %)	$\#p : p < 0.01$ (in %)
Parameter *a*										
Bank	6,850	9.83E-157	0.0000	3.52E-273	7.46E-252	4.65E-230	6.70E-153	100.00	100.00	100.00
Basi	8,541	8.08E-140	0.0000	1.01E-269	9.37E-252	8.12E-234	6.90E-136	100.00	100.00	100.00
Comm	9,367	3.52E-141	0.0000	9.14E-275	9.90E-256	1.14E-237	3.30E-137	100.00	100.00	100.00
Cons	31,460	6.81E-126	0.0000	6.43E-273	5.02E-254	5.14E-236	2.14E-121	100.00	100.00	100.00
Ener	5,690	6.44E-144	0.0000	1.68E-275	1.03E-252	8.79E-234	3.66E-140	100.00	100.00	100.00
Fina	10,720	1.07E-83	0.0000	1.62E-275	2.91E-252	1.83E-229	1.15E-79	100.00	100.00	100.00
Indu	14,415	4.62E-116	0.0000	1.57E-277	4.37E-256	8.37E-236	6.66E-112	100.00	100.00	100.00
Tech	2,845	8.89E-159	0.0000	1.35E-270	1.08E-251	6.30E-235	2.53E-155	100.00	100.00	100.00
Util	8,390	3.15E-163	0.0000	1.10E-274	7.31E-256	1.08E-236	2.30E-159	100.00	100.00	100.00
Parameter *b*										
Bank	6,850	2.46E-104	0.0000	1.05E-181	5.93E-178	4.24E-173	1.53E-100	100.00	100.00	100.00
Basi	8,541	1.36E-89	0.0000	1.54E-180	8.29E-177	2.01E-171	1.16E-85	100.00	100.00	100.00
Comm	9,367	2.26E-77	0.0000	1.09E-180	5.47E-177	2.05E-171	2.12E-73	100.00	100.00	100.00
Cons	31,460	8.58E-69	0.0000	8.84E-181	7.52E-177	1.89E-171	1.95E-64	100.00	100.00	100.00
Ener	5,690	8.62E-98	0.0000	1.17E-180	1.30E-176	9.97E-171	4.62E-94	100.00	100.00	100.00
Fina	10,720	9.45E-68	0.0000	6.80E-181	1.47E-176	3.50E-170	1.01E-63	100.00	100.00	100.00
Indu	14,415	3.21E-56	0.0000	1.16E-180	1.21E-176	8.84E-171	4.63E-52	100.00	100.00	100.00
Tech	2,845	8.93E-59	0.0000	1.82E-180	2.17E-176	2.47E-170	2.54E-55	100.00	100.00	100.00
Util	8,390	4.04E-86	0.0000	3.86E-180	3.17E-176	1.57E-170	3.39E-82	100.00	100.00	100.00
Parameter *c*										
Bank	6,850	4.64E-04	0.0000	5.84E-162	4.39E-139	2.10E-107	4.62E-01	99.87	99.74	99.69
Basi	8,541	6.15E-04	0.0000	1.56E-159	1.20E-136	3.69E-107	4.57E-01	99.82	99.77	99.65
Comm	9,367	7.74E-04	0.0000	1.80E-160	4.21E-138	3.09E-108	4.83E-01	99.74	99.66	99.55
Cons	31,460	6.78E-04	0.0000	5.82E-162	2.25E-139	1.32E-108	5.00E-01	99.79	99.72	99.59
Ener	5,690	5.85E-04	0.0000	5.70E-165	4.45E-142	5.29E-111	4.16E-01	99.81	99.77	99.58
Fina	10,720	6.64E-04	0.0000	5.45E-163	6.66E-142	4.00E-112	4.61E-01	99.78	99.72	99.66
Indu	14,415	6.17E-04	0.0000	2.68E-161	5.69E-140	2.26E-111	4.99E-01	99.81	99.76	99.62
Tech	2,845	1.08E-03	0.0000	1.29E-163	1.01E-140	3.89E-112	4.15E-01	99.65	99.61	99.47
Util	8,390	6.24E-04	0.0000	4.77E-162	9.49E-141	2.96E-113	4.70E-01	99.81	99.79	99.65

Table 2.19 – Goodness of fit of the extreme value distribution: *p*-values
The above table exhibits p-values for the goodness of fit of parameters estimated for the extreme value distribution according to Equation (2.1). The empirical distribution is estimated on the basis of three months time series of daily CDS premia. All CDS data are obtained via Bloomberg; the time series of observations ranges from October 2004 to October 2009. To minimize the impact of factors other than the underlying reference entity's default risk, we only consider bid quotes. In total, we have 5-year CDS contracts on 550 firms in our sample, all of which are on senior unsecured debt. The table is organized as follows: The statistics for the extreme value distribution parameters a, b, and c are displayed in the respective panels. Column one gives the sectoral abbreviations to which the statistics refer. (E.g., all statistics on p-values in row "Basi" refer to the respective parameter of the extreme value distribution function estimated on the basis of three-month series of daily CDS premia on firms of the basic materials sector.) Column two gives the number of estimates for the respective parameter in each sector. Column three gives the mean p-value of the test results, columns four to eight the quantiles, and columns nine to eleven provide the percentage of test results significant at the 10%, 5%, and 1% confidence levels.

Sector	#obs	mean	min	$q = 0.25$	$q = 0.50$	$q = 0.75$	max
Bank	6,850	-244.2785	-781.3849	-387.3297	-214.3838	-112.2635	695.9677
Basi	8,541	-307.5743	-782.6197	-397.1976	-299.0921	-213.4035	546.4824
Comm	9,367	-325.2135	-844.3461	-409.0496	-319.5345	-237.9545	569.8428
Cons	31,460	-313.3514	-833.7323	-408.3801	-314.0032	-221.9438	694.9567
Ener	5,690	-268.8659	-616.2666	-372.5147	-273.0252	-173.9852	630.2298
Fina	10,720	-299.0830	-772.8726	-430.8348	-286.7780	-165.4277	694.9546
Indu	14,415	-271.7299	-794.8183	-367.6081	-270.8365	-174.4742	624.9858
Tech	2,845	-298.6774	-692.4794	-379.9814	-305.8367	-209.6718	530.0584
Util	8,390	-255.9665	-588.4578	-343.0045	-241.7911	-170.8678	584.9753

Table 2.20 – Goodness of fit of the extreme value distribution: Log-likelihood values
The above table exhibits log-likelihood values for the overall goodness of fit of the extreme value distribution according to Equation (2.1). The empirical distribution is estimated on the basis of three months time series of daily CDS premia. All CDS data are obtained via Bloomberg; the time series of observations ranges from October 2004 to October 2009. To minimize the impact of factors other than the underlying reference entity's default risk, we only consider bid quotes. In total, we have 5-year CDS contracts on 550 firms in our sample, all of which are on senior unsecured debt. The table is organized as follows: Column one gives the sectoral abbreviations to which the statistics refer. (E.g., all statistics on log-likelihood values in row "Basi" refer to the extreme value distribution functions estimated on the basis of three-month series of daily CDS premia on firms of the basic materials sector.) Column two gives the number of estimates for each sector and thus the number of test results. Column three gives the mean t-value and columns four to eight the quantiles.

Sector	#obs	mean	min	$q = 0.25$	$q = 0.50$	$q = 0.75$	max	$\#p : p < 0.1$ (in %)	$\#p : p < 0.05$ (in %)	$\#p : p < 0.01$ (in %)
Panel A										
Bank	72,773	3.71E-09	0	9.57E-36	1.24E-32	5.95E-31	2.65E-04	100.00	100.00	100.00
Basi	106,873	1.77E-11	0	7.05E-37	4.06E-33	4.72E-31	2.67E-07	100.00	100.00	100.00
Comm	122,225	1.51E-12	0	8.94E-37	4.00E-33	4.19E-31	2.26E-08	100.00	100.00	100.00
Cons	1,429,092	2.37E-10	0	4.03E-37	2.53E-33	3.40E-31	2.07E-04	100.00	100.00	100.00
Ener	49,551	7.03E-12	0	5.91E-36	1.81E-32	1.18E-30	1.95E-07	100.00	100.00	100.00
Fina	175,429	1.49E-11	0	1.36E-36	6.79E-33	6.75E-31	3.60E-07	100.00	100.00	100.00
Indu	296,066	3.94E-12	0	1.40E-36	5.41E-33	5.29E-31	9.55E-08	100.00	100.00	100.00
Tech	10,840	2.83E-11	0	1.41E-37	2.56E-33	3.97E-31	4.74E-08	100.00	100.00	100.00
Util	104,625	5.79E-12	0	1.24E-36	4.59E-33	4.16E-31	1.09E-07	100.00	100.00	100.00
Panel B										
Basi	169,213	2.57E-11	0	6.75E-38	7.32E-34	1.35E-31	3.13E-06	100.00	100.00	100.00
Comm	178,823	3.25E-11	0	1.43E-37	1.13E-33	1.77E-31	2.80E-06	100.00	100.00	100.00
Cons	616,507	6.57E-09	0	4.60E-38	5.99E-34	1.26E-31	3.75E-03	100.00	100.00	100.00
Ener	111,265	3.65E-11	0	5.58E-38	8.06E-34	1.53E-31	2.48E-06	100.00	100.00	100.00
Fina	226,405	1.21E-10	0	1.63E-37	1.66E-33	2.54E-31	2.43E-05	100.00	100.00	100.00
Indu	281,660	7.64E-09	0	7.16E-38	7.95E-34	1.46E-31	2.15E-03	100.00	100.00	100.00
Tech	52,865	3.60E-10	0	2.55E-38	4.93E-34	1.08E-31	1.48E-05	100.00	100.00	100.00
Util	162,823	4.02E-11	0	1.04E-37	1.22E-33	1.74E-31	5.07E-06	100.00	100.00	100.00

Table 2.21 – Goodness of fit of the Gumbel copula: *p*-values
The above table exhibits p-values for the overall goodness of fit of the Gumbel copula estimated according to Equation (2.3). The table is organized as follows: *Panel A* presents statistics for the estimated dependence between firms within the row sector. *Panel B* gives statistics for the estimated dependence between banks and non-banks of the respective row sector. Column one gives the sectoral abbreviations to which the statistics refer. Column two gives the number of copula estimates for each sector. Column three gives the mean p-value and columns four to eight the quantiles; columns nine to eleven provide the percentage of estimates significant at the 10%, 5%, and 1% confidence levels.

Sector	#obs	mean	min	$q = 0.25$	$q = 0.50$	$q = 0.75$	max
Panel A							
Bank	75,848	38.5326	0.0002	11.0749	31.0464	57.9785	391.1673
Basi	109,981	37.2133	0.0003	9.6470	28.1590	56.6028	386.3012
Comm	125,584	35.8789	0.0003	9.1792	27.1670	54.5160	516.0504
Cons	1,466,606	33.8003	0.0001	8.5471	25.4728	51.6029	603.5360
Ener	51,019	44.0924	0.0003	13.3536	36.1820	66.7306	443.3317
Fina	180,770	37.7231	0.0003	9.8088	28.9874	56.7877	537.9778
Indu	305,360	36.9935	0.0002	9.5733	28.6346	56.9069	444.0302
Tech	11,157	31.7599	0.0003	6.9200	22.7949	47.8081	275.0179
Util	107,348	38.2842	0.0003	10.0526	29.4757	57.7031	333.4561
Panel B							
Basi	169,259	30.0935	0.0002	6.8261	21.7398	45.9172	305.0356
Comm	178,850	30.3605	0.0003	7.2023	22.4304	45.9904	206.4019
Cons	616,606	28.8278	0.0000	6.6625	20.7014	43.7453	571.8760
Ener	111,282	29.5686	0.0001	7.0215	21.8744	45.1411	564.4110
Fina	226,440	31.9646	0.0002	8.1854	24.1357	48.4145	433.7839
Indu	281,715	29.8335	0.0002	6.9737	21.7277	45.3161	469.6477
Tech	52,873	27.0841	0.0002	5.6226	19.0526	41.6873	232.1569
Util	162,849	31.4244	0.0002	7.3899	23.2796	48.0059	360.9857

Table 2.22 – Goodness of fit of the Gumbel copula: Log-likelihood values
The above table exhibits log-likelihood values for the overall goodness of fit of the Gumbel copula estimated according to Equation (2.3). The table is organized as follows: *Panel A* presents statistics for the estimated dependence between firms within the row sector. *Panel B* gives statistics for the estimated dependence between banks and non-banks of the respective row sector. Column one gives the sectoral abbreviations to which the statistics refer. Column two gives the number of copula estimates for each sector. Column three gives the mean log-likelihood value and columns four to eight the quantiles.

Sector	#obs	mean	min	$q = 0.25$	$q = 0.50$	$q = 0.75$	max	$\#p : p < 0.1$ (in %)	$\#p : p < 0.05$ (in %)	$\#p : p < 0.01$ (in %)
Panel A										
Bank	65	0.0003	3.23E-56	1.66E-44	5.02E-40	6.16E-19	0.0178	100.00	100.00	98.46
Basi	321	0.0013	8.23E-52	1.30E-32	3.48E-23	1.31E-14	0.3941	99.69	99.69	99.38
Comm	108	0.0020	3.21E-41	6.28E-31	3.70E-21	8.22E-15	0.0620	100.00	98.15	94.44
Cons	5591	0.0010	2.58E-49	1.59E-28	1.29E-18	1.40E-11	0.8764	99.82	99.61	98.91
Ener	325	0.0003	9.84E-49	1.04E-32	4.53E-21	6.89E-14	0.0642	100.00	99.69	99.38
Fina	738	0.0029	1.41E-53	1.36E-22	2.47E-13	2.30E-08	0.4204	99.05	98.64	97.56
Indu	678	0.0008	4.36E-50	1.55E-34	1.06E-26	1.12E-13	0.1532	99.71	99.26	98.97
Tech	92	0.0174	2.07E-48	1.80E-24	8.08E-12	4.53E-05	0.7995	95.65	94.57	92.39
Util	153	0.0003	2.30E-49	2.55E-33	2.60E-21	1.59E-13	0.0130	100.00	100.00	98.69
Panel B										
Basi	298	0.0004	2.14E-45	3.66E-33	2.15E-26	4.06E-14	0.0419	100.00	100.00	98.99
Comm	179	0.0019	9.44E-47	2.23E-33	9.02E-23	3.10E-12	0.0818	100.00	98.32	96.09
Cons	1192	0.0021	2.21E-49	6.75E-34	1.90E-23	3.02E-11	0.4563	99.33	99.16	98.15
Ener	297	0.0021	1.11E-44	6.04E-33	2.65E-23	1.28E-13	0.2989	99.33	99.33	97.64
Fina	434	0.0024	1.18E-47	9.65E-35	2.51E-18	5.42E-10	0.3867	99.31	99.08	98.39
Indu	429	0.0004	1.03E-44	1.13E-35	2.96E-29	5.27E-14	0.0594	100.00	99.53	99.30
Tech	150	0.0100	2.51E-45	2.79E-33	2.80E-19	9.35E-10	0.6700	98.00	96.67	94.67
Util	211	0.0002	1.36E-42	5.68E-34	3.52E-27	2.67E-11	0.0242	100.00	100.00	99.53
Panel C										
Bank	226	2.19E-03	4.53E-54	2.63E-40	1.65E-25	4.74E-18	4.78E-01	99.56	99.56	99.56
Basi	151	6.97E-06	1.39E-49	5.60E-41	5.17E-36	3.75E-20	4.47E-04	100.00	100.00	100.00
Comm	404	2.55E-05	1.70E-56	1.97E-40	6.28E-33	1.65E-17	9.47E-03	100.00	100.00	100.00
Cons	1639	4.91E-04	1.12E-51	3.17E-38	6.06E-31	1.04E-21	5.48E-01	99.88	99.82	99.69
Ener	6	1.73E-32	3.41E-49	6.73E-44	8.73E-42	2.77E-38	1.04E-31	100.00	100.00	100.00
Fina	272	4.94E-04	6.41E-53	1.17E-36	5.82E-21	4.51E-11	8.56E-02	100.00	99.63	99.26
Indu	434	6.34E-11	3.32E-49	4.31E-40	3.14E-33	4.32E-26	2.74E-08	100.00	100.00	100.00
Tech	1	1.96E-35	1.96E-35	1.96E-35	1.96E-35	1.96E-35	1.96E-35	100.00	100.00	100.00
Util	230	2.89E-06	2.05E-52	1.03E-43	1.27E-36	1.34E-27	5.67E-04	100.00	100.00	100.00
Panel D										
Basi	374	5.49E-04	2.09E-47	1.21E-35	2.00E-30	5.15E-16	5.42E-02	100.00	99.73	98.40
Comm	624	1.73E-03	2.65E-46	1.42E-35	1.37E-27	6.29E-15	8.72E-01	99.84	99.68	99.04
Cons	1256	1.51E-03	8.19E-49	5.44E-35	1.07E-27	1.81E-15	4.63E-01	99.60	99.52	98.65
Ener	88	1.70E-04	8.58E-42	4.30E-37	1.87E-31	7.80E-20	1.39E-02	100.00	100.00	98.86
Fina	521	8.61E-04	3.99E-50	8.60E-37	4.78E-21	3.17E-12	1.90E-01	99.62	99.62	98.66
Indu	652	1.19E-03	1.04E-46	3.12E-35	2.89E-28	7.86E-18	4.61E-01	99.69	99.69	98.77
Tech	43	7.92E-07	1.03E-40	6.55E-35	1.35E-31	1.06E-17	1.67E-05	100.00	100.00	100.00
Util	478	9.55E-04	3.53E-49	8.36E-36	2.13E-28	3.54E-16	1.91E-01	99.79	99.16	98.54
Panel E										
Bank	254	1.45E-03	1.04E-49	2.35E-40	3.46E-32	6.71E-18	3.58E-01	99.61	99.61	99.61
Basi	461	1.22E-03	1.05E-48	2.37E-34	1.43E-26	6.09E-16	5.32E-01	99.78	99.78	99.35
Comm	441	4.41E-03	3.70E-43	2.59E-32	4.40E-24	7.46E-17	7.28E-01	99.09	98.19	97.73
Cons	6139	8.24E-04	1.09E-51	4.61E-32	4.62E-23	2.43E-14	9.60E-01	99.82	99.69	99.28
Ener	104	5.26E-08	3.90E-44	5.42E-33	1.85E-28	1.50E-18	2.48E-06	100.00	100.00	100.00
Fina	928	8.90E-04	1.21E-47	2.20E-28	5.37E-17	1.19E-10	2.13E-01	99.68	99.35	99.35
Indu	1141	2.69E-04	1.92E-46	1.91E-34	5.39E-28	1.85E-17	1.90E-01	99.91	99.82	99.65
Tech	29	7.12E-04	7.20E-39	6.84E-33	5.22E-23	3.93E-09	1.79E-02	100.00	100.00	96.55
Util	410	2.04E-03	6.74E-45	1.46E-32	4.94E-26	8.93E-15	3.64E-01	99.51	99.02	97.56

Table 2.23 – Auto-correlation of upper tail dependence coefficients series: *p*-values
The above table exhibits p-values for the Durbin-Watson test, which we apply to the series of upper tail coefficients estimated from the full sample of daily CDS bid quotes ranging from October 2004 to October 2009 according to the methodology outlined in Section 2.3.

Table 2.23 – continued:
The table is organized as follows: *Panel A* presents statistics for the upper tail dependence series between US firms within the row sector; *Panel B* statistics for the upper tail dependence series between US banks and non-banks of the respective row sector. *Panel C* gives statistics for the upper tail dependence series between European firms within the row sector; *Panel D* statistics for the upper tail dependence series between European banks and non-banks of the respective row sector. *Panel E* exhibits statistics for the upper tail dependence series between European and US firms within the respective row sector. Column one gives the sectoral abbreviations to which the statistics refer. Column two gives the number of series tested. Column three gives the mean p-value for the Durbin-Watson test with the null hypothesis that the series of upper tail dependence coefficients do not exhibit any auto-correlation. Columns four to eight exhibit the quantiles; columns nine to eleven provide the percentage of test results significant at the 10%, 5%, and 1% confidence levels.

3 What can systemic risk measures predict?

3.1 Introduction

How should we measure systemic risk? In the aftermath of the Lehman bankruptcy that triggered an unprecedented international financial crisis, this question has become of vital interest to both regulators and researchers. According to the definition of the International Monetary Fund, systemic risk is the risk of excessive losses within all or parts of the financial system with potential negative spill-over effects to the real economy (FSB, IMF, BIS, 2009).

Recent research (e.g. Reinhart and Rogoff, 2009c) has shown that systemic financial crises often have substantial adverse effects on the real economy, such as drops in asset prices, output, and employment levels. Thus, the interconnectedness within the financial system and the important role that financial institutions play for the real economy stress the necessity of proper identification of systemic risk in the financial system.

Over the last years, a number of approaches to measure systemic risk and to identify systemically important financial institutions (SIFIs) have been proposed both by regulators and researchers. The Bank for International Settlements (2011b) identifies SIFIs by various balance and off-balance sheet characteristics, such as size, interconnectedness, and substitutability.[1] The revised Basel III rules stipulate tighter macro-prudential regulation and tackle SIFIs by imposing special requirements such as capital surcharges.

Academia has proposed a whole bunch of different approaches with a strand of literature based on asset prices applying the standard risk measures *Conditional Value at Risk* of Adrian and Brunnermeier (2011) and *Marginal Expected Shortfall* (Acharya et al., 2010), extreme value theory (De Jonghe, 2010; Zhou, 2010), principal component analysis (Billio et al., 2012; Kritzman et al., 2011), and default probabilities (Lehar, 2005; Huang et al., 2009; Segoviano and Goodhart, 2009; Huang et al., 2012; Gray and Jobst, 2010). Another strand of literature applies network analysis to investigate systemic risk arising from interbank relationships (Halaj and Kok Sorensen, 2013; Allen et al., 2010; Tarashev et al., 2010, e.g.). For a comprehensive survey on the literature on systemic risk measurement we refer to Bisias et al. (2012).

[1] This is in line with various studies finding that balance sheet characteristics such as size (Elsinger et al., 2006a), leverage (Acharya et al., 2010), and short-term wholesale funding (López-Espinosa et al., 2012) substantially drive the systemic importance of individual banks.

Despite the multitude of approaches, research on the measures' ability to capture the symptoms of systemic risk in the banking system is scarce. However, the assessment of a measure's adequacy as a tool for regulators is crucial. But how can the effectiveness of systemic risk measures be determined? Systemic risk measures should be able to pre-identify turmoil in the financial markets that potentially triggers downturns of the real economy. In addition, systemic risk measures should be leading indicators to other financial market-based stress variables in order to function properly as early warning indicators. While it is difficult to assess systemic risk measures at the bank level (because an individual institution's ranking with respect to its systemic importance is predominantly determined by the applied measure), an evaluation of systemic risk measures at the banking system level is more expedient.

This paper contributes to the literature on the assessment of systemic risk measures in several ways. We compare three prominent systemic risk measures such as to assess their adequacy as a monitoring tool for regulatory authorities. We investigate the dynamics and directionalities between the systemic risk measures at the banking system level and the macro-economy. Furthermore, we examine linkages between the systemic risk measures and balance sheet characteristics at both the bank and the banking system level.

In particular, we implement and compare the *Marginal Expected Shortfall* (MES) (Acharya et al., 2010), the related *SRISK* measure (Brownlees and Engle, 2012), and the *Conditional Value at Risk* (CoVaR) (Adrian and Brunnermeier, 2011) employing a common setup that is in line with Girardi and Ergün (2013) and Brownlees and Engle (2012). We model the stock return characteristics using a DCC GARCH specification and apply the latter to simulate the systemic risk measures.[2] Over the last years, these measures have had a high impact on research and regulation.[3] All three measures rely on stock price information and balance sheet data and thus can be implemented for all publicly listed banks.

We find that systemic risk measures possess substantial forecasting power for a variety of financial and macro-economic variables including interbank interest rates, real GDP, and economic sentiment. However, the systemic risk measures are not equally adequate for regulatory purposes. In general, the MES and SRISK measures outperform the CoVaR.

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[2] Note that our assessment framework is independent of the measures and measurement method and does not rely on any technical specifications. We implement the risk measures in a common setup to improve comparability and interpretability (see Section (3.3)).

[3] The measures are applied by the U.S. Treasury Department (Financial Stability Oversight Council, 2013) to monitor systemic risk in the banking system. Similarly, the European Systemic Risk Board uses CoVaR, among other indicators, to measure systemic risk in the European banking system (European Systemic Risk Board, 2013).

Moreover, we find that an individual bank's systemic importance is well explained by its balance sheet characteristics. However, at the banking system level, aggregate balance sheet characteristics cannot predict systemic risk.

We apply the measures to European banks between July 2005 and June 2013. The European banking system provides a unique setting for the evaluation of systemic risk measures, as European institutions are likely to be affected by both the Subprime Crisis including the subsequent International Financial Crisis of 2007–2009 and the current Euro Crisis. Thus, our sample of European banks allows for a broad analysis and ensures that systemic risk measures are not only evaluated by their performance during the Subprime Crisis.

In a first step, we analyze the measures at the bank level discussing the systemic importance ranking of institutions obtained for the Subprime Crisis and the Euro Crisis periods. We examine to what extent the bank level measures are driven by their balance sheet characteristics. In a second step, we perform a vector autoregression (VAR) analysis to study the measures' ability to act as leading indicators of systemic risk. The VAR analysis furthermore enables us to measure directionalities and causalities between the measures and a set of aggregate financial market, balance sheet and macro-economic variables.[4]

Lastly, our paper contributes to a growing body of literature on the MES, SRISK, and CoVaR measures which divides into three strands. The first strand implements MES, SRISK (Acharya and Steffen, 2012; Idier et al., 2013; Engle et al., 2012; Acharya et al., 2012), and CoVaR (López-Espinosa et al., 2012; Van Oordt and Zhou, 2011; Roengpitya and Rungcharoenkitkul, 2011; Gauthier et al., 2010) analyzing distress in the financial markets and identifying determinants of systemic importance. A second strand of literature extends those measures. Girardi and Ergün (2013) propose the use of multivariate GARCH estimates to measure CoVaR, Cao (2013) extends the CoVaR measure from one bank being in financial distress to a set of one or more banks being in distress, and Hong (2011) derives an analytical version of the CoVaR measure. A third strand of literature compares the measures. Jiang (2012) analyzes the tail dependence structure of MES and CoVaR, Benoit et al. (2013) rank US financial institutions according to MES, SRISK, and CoVaR and find that the risk measures can be proxied by market risk and liabilities, and Löffler and Raupach (2013) estimate the robustness of MES and CoVaR.

[4] In contrast to Rodriguez-Moreno and Peña (2013) who assess the performance of systemic risk measures at the banking system level applying an index of systemic events, our analysis does not necessitate the identification of specific systemic events that might be prone to selection biases.

The remainder of the paper is structured as follows: Section 3.2 describes the data used for our analysis and Section 3.3 introduces and defines the systemic risk measures. In Section 3.4 we provide an outline of the methodology and Section 3.5 presents and discusses our results; Section 3.6 summarizes and concludes.

3.2 Data description

Our empirical analysis focuses on the European banking system. We concentrate on the European Union excluding countries from Eastern Europe to ensure sufficiently homogeneous banking regulation across our sample. However, we include Switzerland given the country's individual banking sector's importance within the European banking system and its similar banking regulations.[5] Our sample covers the period from July 2005 to June 2013 including the International Financial Crisis from 2007 to 2009 and the subsequent European Sovereign Debt Crisis.

Our selection of banks is based on two major criteria: First, we select all banks included in the STOXX Europe TMI Banks Index at one point in time within our sample period.[6] According to the European Commission's proposal for a Single Supervisory Mechanism (SSM) for the European Banking Union, banks with total assets above €30bn are supervised directly by the ECB due to their potential systemic relevance (European Commission, 2013). Thus, we rank the institutions with respect to their size in total assets and select those where total assets are above €30bn in at least one of the quarters within the sample period. To our preselection of banks, we furthermore add the ING Groep N.V., the Bank of Cyprus as well as the Landesbank Berlin Holding AG. STOXX classifies the ING Groep as an insurance company. However, a substantial part of the ING Groep's revenues come from banking related activities. Moreover, we add the Bank of Cyprus in order to represent the Cyprian banking sector, which is not accounted for by the STOXX Europe TMI Banks Index. We include the Landesbank Berlin Holding AG in order to increase the German banking system's coverage in our sample.

[5] Our sample selection is in line with Trapp and Wewel (2013); all member states of the European Union and Switzerland implemented the Basel II Directives 2006/48/EC and 2006/49/EC and are introducing the new Basel III criteria.

[6] According to STOXX Limited (2013), the individual banks are admitted into the index based on their free float market capitalization and cover roughly 95% of the free float market capitalization of all banks headquartered in Western Europe. The index composition is updated on a quarterly basis. This leaves us with 126 banks. By selecting all banks that are included in the index within the sample period, we ensure that our sample selection adequately reflects the aggregate of traded stocks of banks in Western Europe.

Institution	Country	ISIN	Total Assets (in €m)	rank	Market/Book	rank	Leverage	rank
ABN AMRO Holding N.V.	Netherlands	NL0000301109	794,905	15	3.39	85	13.24	62
Ageas N.V.	Belgium	BE0974264930	420,419	23	1.36	52	23.17	29
Agricultural Bank of Greece S.A.	Greece	GRS414003004	25,216	82	14.39	86	13.63	61
Alliance & Leicester PLC	United Kingdom	GB0000386143	90,321	49	1.27	45	28.99	25
Allied Irish Banks PLC	Ireland	IE0000197834	148,411	38	1.51	61	10.61	73
Alpha Bank A.E.	Greece	GRS015013006	56,845	61	1.18	38	12.13	67
Banca Antonveneta S.p.A.	Italy	IT0003270102	44,553	68	2.59	83	6.17	84
Banca Carige S.p.A.	Italy	IT0003211601	33,588	72	1.09	29	10.97	71
Banca Civica S.A.	Spain	ES0148873005	74,048	56	0.30	5	83.08	3
Banca Lombarda	Italy	IT0000062197	40,222	69	2.04	81	7.25	82
Banca Monte dei Paschi di Siena S.p.A.	Italy	IT0001334587	196,445	33	0.82	17	27.30	27
Banca Nazionale del Lavoro S.p.A. (BNL)	Italy	IT0001254884	88,283	50	1.75	75	10.57	74
Banca Popolare dell'Emilia Romagna	Italy	IT0000066123	52,307	62	0.89	21	19.05	38
Banca Popolare di Milano	Italy	IT0000064482	45,742	67	0.72	12	17.95	40
Banca Popolare di Sondrio	Italy	IT0000784196	21,916	84	1.42	58	9.85	76
Banca Popolare Italiana S.C.A.R.L.	Italy	IT0000064300	46,138	65	1.79	77	7.13	83
Banche Popolari Unite S.C.A.R.L.	Italy	IT0003487029	109,530	44	0.73	13	17.18	46
Banco Bilbao Vizcaya Argentaria S.A.	Spain	ES0113211835	507,807	19	1.64	69	11.92	68
Banco Comercial Portugues S.A.	Portugal	PTBCP0AM0007	87,428	53	1.30	47	16.79	49
Banco de Sabadell S.A.	Spain	ES0113860A34	88,060	51	1.26	43	14.47	58
Banco Espanol de Credito S.A.	Spain	ES0113440038	104,562	46	1.38	53	16.81	48
Banco Espirito Santo S.A.	Portugal	PTBES0AM0007	70,588	57	0.98	25	16.00	53
Banco Pastor S.A.	Spain	ES0113790085	26,549	79	1.32	49	14.63	56
Banco Popolare Societa CooperativaAz.	Italy	IT0004231566	108,159	45	0.68	10	20.98	35
Banco Popular Espanol S.A.	Spain	ES0113790226	114,220	42	1.44	59	12.35	65
Banco Portugues de Investimento S.A.	Portugal	PTBPI0AM0004	39,802	71	1.70	72	17.75	43
Banco Santander S.A.	Spain	ES0113900J37	1,025,916	10	1.17	37	14.99	54
Bank Austria Creditanstalt AG	Austria	AT0000995006	206,010	32	1.46	60	11.09	70
Bank of Cyprus	Cyprus	CY0000100111	32,947	73	1.38	54	12.35	66
Bank of Greece	Greece	GRS004013009	84,172	55	0.50	6	86.95	2
Bank of Ireland	Ireland	IE0030606259	169,136	37	1.08	28	24.26	28
Bankia S.A.	Spain	ES0113307021	287,902	27	-0.44	1	76.05	4
Bankinter	Spain	ES0113679I37	50,617	63	1.56	66	16.25	51
Banque Cantonale Vaudoise	Switzerland	CH0015251710	25,552	80	1.74	73	9.76	77
Banque Nationale de Belgique S.A.	Belgium	BE0003008019	100,203	47	0.15	3	75.38	5
Barclays PLC	United Kingdom	GB0031348658	1,633,656	5	1.11	31	37.53	17
Basler Kantonalbank	Switzerland	CH0009236461	22,432	83	0.28	4	44.10	13
Bayerische Hypo- und Vereinsbank AG	Germany	DE0008022005	457,780	21	1.42	57	16.01	52
BNP Paribas S.A.	France	FR0000131104	1,743,205	1	0.95	24	30.68	20
Bradford & Bingley PLC	United Kingdom	GB0002228152	64,273	59	0.88	20	40.82	15
Caisse Regionale de Credit Agricole Mutuel de Paris et d'Ile de France SC	France	FR0000045528	29,870	76	0.58	7	44.59	11
Caixabank S.A.	Spain	ES0140609019	111,228	43	0.79	16	8.73	79
Capitalia S.p.A.	Italy	IT0003121495	138,590	39	1.74	74	8.67	80
Commercial Bank of Greece	Greece	GRS006013007	25,549	81	2.72	84	14.93	55
Commerzbank AG	Germany	DE000CBK1001	663,395	16	0.65	8	57.16	6
Crédit Agricole S.A.	France	FR0000045072	1,465,511	6	0.75	14	49.83	8
Credit Suisse Group AG	Switzerland	CH0012138530	805,461	13	1.54	65	20.68	37
Credito Emiliano S.p.A. CredemAz.	Italy	IT0003121677	27,395	78	1.22	40	14.53	57
Credito Valtellinese S.C.A.R.L. Az.	Italy	IT0000064516	21,571	85	0.66	9	22.27	31
Danske Bank	Denmark	DK0010274414	415,945	24	1.04	27	28.94	26
Depfa Bank	Germany	IE0072559994	223,521	30	1.86	79	44.48	12
Deutsche Bank AG	Germany	DE0005140008	1,722,101	2	0.94	23	47.39	9
Deutsche Postbank AG	Germany	DE0008001009	196,433	34	1.24	41	29.25	24
Dexia S.A.	Belgium	BE0003796134	523,914	18	0.93	22	44.99	10
Erste Group Bank AG	Austria	AT0000652011	194,229	35	1.34	50	17.76	42
Eurobank Ergasias S.A.	Greece	GRS323003004	67,235	58	1.24	42	12.63	63
GAM Holding AG	Switzerland	CH0102659627	13,786	86	1.68	71	3.21	86
HBOS PLC	United Kingdom	GB0030587504	805,950	12	1.76	76	30.57	21
HSBC Holdings	United Kingdom	GB0005405286	1,644,162	4	1.42	56	12.50	64
IKB Deutsche Industriebank AG	Germany	DE0008063306	40,094	70	0.86	18	38.87	16
ING Groep N.V.	Netherlands	NL0000303600	1,220,294	7	1.15	33	30.21	23
Intesa Sanpaolo S.p.A.	Italy	IT0000072626	542,920	17	0.87	19	192.58	1
Investec PLCShs	United Kingdom	GB00B17BBQ50	45,940	66	1.59	67	17.59	44
Irish Bank Resolution Corporation Ltd	Ireland	IE00B06H8J93	87,850	52	1.19	39	23.01	30
Julius Bär	Switzerland	CH0102484968	32597	74	1.65	70	6.04	85
Jyske Bank	Denmark	DK0010307958	28,094	77	1.40	55	13.68	60
KBC Groep N.V.	Belgium	BE0003565737	318,055	25	1.11	30	17.83	41
Landesbank Berlin Holding AG	Germany	DE0008023227	136,782	40	1.82	78	32.53	19
Lloyds Banking Group	United Kingdom	GB0008706128	798,099	14	1.53	64	21.70	33
Mediobanca - Banca di Credito Finanziario S.p.A.	Italy	IT0000062957	64,004	60	1.26	44	7.88	81
National Bank of Greece S.A.	Greece	GRS003003019	93,762	48	1.17	36	10.32	75
Natixis Banques Populaires	France	FR0000120685	425,956	22	0.69	11	41.18	14
Nordea Bank AB	Sweden	SE0000427361	485,820	20	1.35	51	18.14	39
Northern Rock PLC	United Kingdom	GB0001452795	123,666	41	0.11	2	56.88	7
Piraeus Bank S.A.	Greece	GRS014003008	46,352	64	1.16	34	14.37	59
Pohjola Bank PLC	Finland	FI0009003222	32,148	75	1.16	35	16.40	50
Raiffeisen Bank International AG	Austria	AT0000606306	86,980	54	1.52	63	10.96	72
Royal Bank of Scotland Group PLC	United Kingdom	GB00B7T77214	1,689,769	3	1.15	32	36.26	18
Sanpaolo IMI S.p.A. Az.	Italy	IT0001269361	279409	28	2.17	82	11.11	69
Skandinaviska Enskilda Banken AB	Sweden	SE0000148884	236,951	29	1.29	46	20.78	36
Société Générale S.A.	France	FR0000130809	1,054,032	9	1.04	26	30.53	22
Standard Chartered PLC	United Kingdom	GB0004082847	299,863	26	1.59	68	9.47	78
Svenska Handelsbanken AB	Sweden	SE0000193120	220,029	31	1.51	62	17.02	47
Swedbank AB	Sweden	SE0000242455	175,054	36	1.31	48	17.49	45
UBS AG	Switzerland	CH0024899483	1,212,246	8	1.99	80	21.82	32
UniCredit S.p.A.	Italy	IT0004781412	850,254	11	0.79	15	21.05	34

Table 3.1 – Bank characteristics and descriptives

The table exhibits figures averaged across the entire time series of quarterly balance sheet characteristics for each of the 86 sample banks. The time series of observations cover the period from July 2005 to June 2013. All data are obtained from Datastream.

Statistics	Total Assets (in €m)	Market/Book	Leverage
mean	337,939	1.40	25.87
sdev	462,771	1.52	25.24
min	13,786	-0.44	3.21
$q = 0.25$	46,191	0.93	12.39
$q = 0.50$	110,379	1.26	17.67
$q = 0.75$	424,572	1.54	30.45
max	1,743,205	14.39	192.58

Table 3.2 – Summary of bank balance sheet characteristics
The table gives a summary of Table 3.1. The time series of observations cover the period from July 2005 to June 2013. All data are obtained from Datastream.

We furthermore exclude penny stocks from our sample. We neglect banks if the price of their stock stays below a threshold of €1 for 20 consecutive trading days. Hence, our sample only contains banks with sound stock price information. To avoid survivorship bias, a preselected bank remains in our sample even if it is excluded from the TMI Index coverage. Thus, over time the number of sample banks diminishes as a result of bankruptcies. The resulting sample contains 86 banks from 16 countries including Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden, Switzerland, and the United Kingdom, with a minimum of 52 banks across the entire sample period.

Table 3.1 displays the names and balance sheet characteristics of the banks in our sample and Table 3.2 provides a summary of the latter. The institutions' mean total assets over the sample period range from €13.8bn (GAM Holding AG) to €1,743bn (BNP Paribas S.A.). The median-sized bank has around €110bn in total assets. The banks' mean market-to-book ratio of equity ranges from -0.44 (Bankia S.A.)[7] to 14.39 (Agricultural Bank of Greece S.A.) across the sample period with a sample median of 1.26 (see Table 3.2). Our sample banks are leveraged between 3.21 (GAM Holding AG) and 192.58 (Intesa Sanpaolo S.p.A.) with a median leverage of 17.59 (see Table 3.2) across the sample period.

We obtain daily stock prices and quarterly balance sheet data for our predefined selection of banks from Datastream. The balance sheet data employed in our calculation of risk measures and our later analyses includes (book valued) total assets, (book valued)

[7] After its IPO in July 2011, Bankia S.A. requested a bailout of €19bn in Mai 2012 and was partially nationalized by the Spanish government. As a consequence, the bank reported on average a negative balance for its book value of equity over the sample period.

shareholders' equity, the market values of equity, total net income, and the market-to-book ratio of equity. We calculate the total book values of debt as the difference between total assets and shareholders' equity. Moreover, we define leverage as the ratio of market valued total assets to market valued equity and calculate market valued total assets as the sum of total (book valued) debt and market valued equity.

For our later analyses we employ European financial market data as well as macro-economic data from the European Union. To measure the state of the European financial market, we obtain weekly series of the 12 month EURIBOR, the 12 month Euro OIS (overnight indexed swap) rate, and the VSTOXX Index from Datastream.[8]

In line with macro-economic forecasting literature, we measure the state of the European economy employing the following macro-economic variables: the monthly EU Industrial Production Index (excluding Construction) and the monthly EU Economic Sentiment Indicator; the EU House Price Index and real GDP on a quarterly basis; domestic credit to private sector (expressed in percentage of real GDP), nonperforming loans to total gross loans, and government debt to real GDP on an annual basis. The data on government debt are obtained from the European Central Bank, data on domestic credit to the private sector and nonperforming loans are obtained from the Worldbank's database, and all remaining data are from Datastream. All macro-economic variables refer to the EU27.

3.3 Systemic risk measures

In this section, we define the systemic risk measures implemented in this paper: (Multi)MES, SRISK, and (Multi)CoVaR.

3.3.1 Multi-period MES

The marginal expected shortfall (MES) proposed by Acharya et al. (2010) measures the expected one-period return (loss) of bank i's stock given that the banking system's overall return is in its tail:

$$\mathrm{MES}_t^i = -\mathbb{E}\left[r_{i,t+1} \left| r_{sys,t+1} \leq \mathrm{VaR}_{t,q}\left(r_{sys,t+1}\right)\right.\right]. \tag{3.1}$$

$r_{i,t+1}$ and $r_{sys,t+1}$ represent the one-period returns of bank i's stock and the banking system and $\mathrm{VaR}_{t,q}$ denotes the value at risk (VaR) of the banking system return $r_{sys,t+1}$

[8] The VSTOXX Index measures the volatility of the EURO STOXX 50. The calculation is based on EURO STOXX 50 option prices and thus the index reflects market implied volatility.

at confidence level q.[9] More intuitively, the MES can be interpreted as the average return of bank i's stock on the $q\%$ days in a year where the banking system's return is worst.

Acharya et al. (2012) and Brownlees and Engle (2012) introduce a multi-period extension of the one-period MES, which we henceforth refer to as *Multi-period Marginal Expected Shortfall* (MultiMES). It is defined as bank i's expected cumulative h-period stock return – i.e., over time interval $[t, t+h]$ – conditional on the banking system's cumulative h-period return falling below a pre-defined threshold C, indicating distress in the banking system:

$$\text{MultiMES}_t^{i,h}(C) = -\mathbb{E}\left[R_{i;[t,t+h]} \,\middle|\, R_{sys;[t,t+h]} \leq C\right] \tag{3.2}$$

with $R_{i;[t,t+h]}$ denoting bank i's cumulative stock return over h periods:

$$R_{i;[t,t+h]} = \exp\left(\sum_{\tau=1}^{h} r_{i,t+\tau}\right) - 1. \tag{3.3}$$

The h-period banking system return, $R_{sys;[t,t+h]}$, is defined analogously. Note that for the ease of interpretation we switch the sign of the risk measure. Thus, an increase in the measure indicates an increase in systemic risk.

3.3.2 SRISK

Based on the MES, Acharya et al. (2012) and Brownlees and Engle (2012) directly model a bank's expected (time-varying) undercapitalization in a financial crisis. The proposed systemic risk measure, SRISK, therefore incorporates financial market as well as balance sheet data. A bank's capital shortfall or its undercapitalization, respectively, is defined as the amount of capital that a bank would have to raise during a financial crisis in order to prevent bankruptcy. Hence, a bank's capital shortfall is calculated as follows:

$$\text{SRISK}_t^{i,h}(C,k) = \mathbb{E}\left[\text{capital shortfall}_{i;[t,t+h]} \,\middle|\, \text{crisis}\right]. \tag{3.4a}$$

Bank i's SRISK in period t is defined as its expected capital shortfall over the time interval $[t, t+h]$ given the event of a financial crisis or severe distress in the banking system. For

[9] We are using lagged time indexes (e.g. MES_t^i instead of MES_{t+1}^i) for our risk measures throughout the paper. By doing so, we indicate that the risk measures are forward looking and based on information available in t, i.e., on the information set $\mathcal{I}_t$.

the ease of interpretation, Equation (3.4a) can be expressed alternatively:

$$\mathrm{SRISK}_t^{i,h}\left(C,k\right)=\mathbb{E}\left[\left\{k\times(\text{debt}+\text{equity})-\text{equity}\right\}_{i;[t,t+h]}\middle|\,\text{crisis}\right]. \tag{3.4b}$$

In order to prevent bankruptcy, institution i's equity cushion needs to be larger than a fraction k of the (market valued) total assets. Within the Basel III framework, parameter k can be considered to represent the absolute Tier I capital ratio of 3% (which is consistent with the Basel III maximum Leverage Ratio of 33.3 that must be satisfied even during a crisis). Thus, k can be interpreted as a Basel Capital Adequacy Ratio equivalent on total assets instead of risk-weighted assets.[10] The market valued total assets can be determined using current debt balance sheet data and the market value of equity. The market value of equity within a future financial crisis can be expressed as a function of MultiMES:

$$\mathrm{SRISK}_t^{i,h}\left(C,k\right)=k\times\text{debt}_{i,t}-(1-k)\left(1-\mathrm{MultiMES}_t^{i,h}\left(C\right)\right)\times\text{equity}_{i,t}. \tag{3.4c}$$

The higher a bank's SRISK, the higher its capital shortfall during a crisis period. Contrary, a negative SRISK indicates that a bank's equity cushion is sufficiently large in order to avoid bankruptcy.

3.3.3 Multi-period CoVaR

The *Conditional Value at Risk* as proposed by Adrian and Brunnermeier (2011) allows for the calculation of an individual bank's contribution to systemic risk in the banking system measuring the value at risk return of the banking system conditional on institution i being at its own value at risk return, i.e., conditional on institution i being in financial distress. The one-period $\mathrm{CoVaR}_t^{sys|\mathcal{C}(r_{i,t+1})}\left(q\right)$ is defined as:

$$\mathbb{P}\left(r_{sys,t+1}\leq\mathrm{CoVaR}_t^{sys|\mathcal{C}(r_{i,t+1})}\left(q\right)\middle|\,\mathcal{C}\left(r_{i,t+1}\right)\right)=q, \tag{3.5}$$

where $\mathcal{C}\left(r_{i,t+1}\right)$ denotes the conditioning event concerning institution i with

$$\mathcal{C}\left(r_{i,t+1}\right)\in\begin{cases} r_{i,t+1}=\mathrm{VaR}_{t,q}\left(r_{i,t+1}\right)\\ r_{i,t+1}=\mathrm{median}_t\left(r_{i,t+1}\right)\end{cases}.$$

[10] See Bank for International Settlements (2004) and Bank for International Settlements (2011a) for a more detailed discussion of the Capital Adequacy Ratio and Leverage Ratio.

Hence, institution i's return is either at its value at risk (indicating financial distress) or at its median state. As for the MultiMES, parameter q indicates the confidence level.[11]

ΔCoVaR gives bank i's marginal contribution to overall systemic risk in the banking system. It is defined as the difference between the system's CoVaR conditional on bank i being in financial distress and the system's CoVaR conditional on bank i being in its median state. In contrast to the "top down" measures MultiMES and SRISK, the "bottom up" measure CoVaR explicitly captures the consequences of institution i's distress for the banking system.

Girardi and Ergün (2013) redefine institution i's "distress CoVaR" to institution i's return being *at* or *below* its value at risk and employ bivariate GARCH estimates for volatilities and correlations to account for a time-varying dependence structure between banks and the banking system. These changes enables the measure to better capture the tail events of distress.

In analogy to the MultiMES and SRISK measures, we define a *Multi-period Conditional Value at Risk* (that we henceforth refer to as MultiCoVaR). $\text{MultiCoVaR}_t^{sys|i\leq \text{VaR},h}$ is the banking system's h-period value at risk return, conditional on bank i's h-period (stock) return being lower or equal to bank i's h-period value at risk:

$$\mathbb{P}\left(R_{sys;[t,t+h]} \leq \text{MultiCoVaR}_t^{sys|i\leq \text{VaR},h}(q) \,\middle|\, R_{i;[t,t+h]} \leq \text{VaR}_{t,q}^{i,h}\right) = q \tag{3.6a}$$

with $\text{VaR}_{t,q}^{i,h}$ denoting bank i's h-period value at risk return. The median state CoVaR is given by conditioning on the one standard deviation band around institution i's median h-period return:

$$\mathbb{P}\left(R_{sys;[t,t+h]} \leq \text{MultiCoVaR}_t^{sys|i=\text{median},h}(q) \,\middle|\, \left|R_{i;[t,t+h]} - \nu_{i,t}^h\right| \leq \sigma_{i,t}^h\right) = q \tag{3.6b}$$

where $\sigma_{i,t}^h$ and $\nu_{i,t}^h$ indicate the standard deviation and the median return of institution i's h-period cumulative stock return. Thus, institution i's systemic risk contribution to overall systemic risk in the banking system is defined as:

$$\Delta\text{MultiCoVaR}_t^{i,h}(q) = -\left[\text{MultiCoVaR}_t^{sys|i\leq \text{VaR},h}(q) - \text{MultiCoVaR}_t^{sys|i=\text{median},h}(q)\right]. \tag{3.6c}$$

Note that again, we switch the sign of ΔMultiCoVaR in order to facilitate the comparison of the three different risk measures MultiMES, SRISK, and ΔMultiCoVaR. An increase

[11] Adrian and Brunnermeier (2011) calculate the CoVaR using quantile regressions. Moreover, they employ one week market valued total assets growth rates instead of daily stock returns.

in ΔMultiCoVaR thus indicates an increase in institution i's contribution to systemic risk in the banking system.

3.4 Methodology

We model the bivariate return dynamics of institution i $\{r_i\}_t$ and the banking system $\{r_{sys}\}_t$ applying a bivariate conditionally heteroscedastic process as employed by Brownlees and Engle (2012):

$$r_{sys,t} = \sigma_{sys,t}\epsilon_{sys,t} \tag{3.7a}$$

$$r_{i,t} = \sigma_{i,t}\left(\rho_{i,sys,t}\epsilon_{sys,t} + \sqrt{1-\rho^2_{i,sys,t}}\epsilon_{i,t}\right) \tag{3.7b}$$

where $\sigma_{j,t},\ j \in \{sys, i\}$ denotes the time-varying (conditional) volatilities and $\rho_{j,t}$ the time-varying (conditional) correlations; $r_{j,t} = \ln\left(P_{j,t}/P_{j,t-1}\right) - \mu_j$ denotes the detrended logarithmic returns, where $P_{j,t}$ represents either bank i's stock price or the banking system stock price index at time t and μ_j simply stands for the mean return over the full length of our sample period.

The banking system stock price index reflects the stock price movements within our sample and is calculated as the average total asset weighted stock price of our sample of banks.[12] The residuals ϵ_i and ϵ_{sys} are distributed according to the bivariate distribution $\mathcal{F}_i$ capturing the tail dependence of the return series and are assumed to be uncorrelated but not independent. Over time, however, the residuals are assumed to be independent and identically distributed with *zero* mean and *unit* variance.

The time-varying volatilities of institution i's ($\sigma_{i,t}$) and the banking system return ($\sigma_{sys,t}$) are estimated individually for every institution i applying a univariate GARCH(1,1) process[13] as proposed by Bollerslev (1986):

$$\sigma^2_{j,t} = \alpha_{0,j} + \alpha_{1,j} r^2_{j,t-1} + \beta_{1,j}\sigma^2_{j,t-1} \tag{3.8a}$$

$$\text{with} \qquad \xi_{j,t} = \frac{r_{j,t}}{\sigma_{j,t}}\ ; \quad j \in \{i, sys\}\,, \tag{3.8b}$$

[12] Our total-asset-weighted *banking system price index* has a correlation of 97.9% with the STOXX Europe 600 Banks and the TMI Banks Index.

[13] We apply various time series diagnostic tests to the individual banks' series of daily log stock returns. I.e., we test for stationarity, heteroscedasticity, auto-correlation, and non-normality. According to Appendix-Table 3.12, we cannot reject the null hypotheses that the time series are stationary for all series. Most series, however, exhibit heteroscedasticity, strong auto-correlation, and non-normality.

where the $\xi_{j,t}$ denote the (correlated) standardized residuals derived from the univariate GARCH(1,1) processes which we use to model the time-varying correlation coefficient $\rho_{i,sys,t}$. For the estimation of correlations, we apply the Dynamic Conditional Correlation (DCC) GARCH model of Engle (2002).

Rather than directly modeling the correlation between institution i's return and the banking system return, the DCC GARCH approach models the time-varying correlation of the standardized residuals $\xi_{j,t}$, whereas their covariance matrix serves as a proxy for the correlation matrix of returns $r_{i,t}$ and $r_{sys,t}$. The validity for this equivalence follows directly from the bivariate return process of Equation (3.7).[14]

In contrast to the one-period MES and CoVaR, the multi-period risk measures MultiMES and MultiCoVaR cannot be expressed in closed-form solution as a function of volatility, correlation, and tail dependence and thus have to be determined via simulation. Based on the simulated returns, we later calculate the pre-defined systemic risk measures for each institution i in our sample of banks. Thus, for each institution i we simulate returns carrying out the following five steps – as suggested by Brownlees and Engle (2012):

(i) To model the volatility and correlation dynamics of $\{r_{sys}, r_i\}_t$, we first estimate the parameter vectors of the univariate GARCH(1,1) and the DCC GARCH processes $(\alpha_{0,j}, \alpha_{1,j}, \beta_{1,j})$ and (α, β), respectively.[15]

(ii) Furthermore, the dynamics of $\{r_{sys}, r_i\}_t$ are assumed to be driven by the distribution $\mathcal{F}_i$ that we model using a t-copula and standard Gaussian marginal distributions.[16] The bivariate t-copula is fitted to the series of residuals $\{\epsilon_{sys}, \epsilon_i\}_t$ from the entire sample period.

(iii) In a third step, we simulate $S = 500,000$ paths of residuals with $h = 60$ days (a quarter of a year) length each. For every single path s, h independent pairs of

[14] See Appendix 3.A for a detailed exposition of the DCC GARCH model.

[15] All GARCH(1,1) and DCC GARCH parameters (see Appendix 3.A) are estimated maximizing the corresponding log likelihood functions under the assumption that the residuals be Gaussian. However, this does not imply that the estimated return series are normally distributed over time. In fact, in literature it is well documented that the unconditional return distribution of a GARCH process is heavy-tailed and exhibits excess kurtosis.

[16] Recall that we use Gaussian error terms to estimate the GARCH(1,1) and DCC GARCH parameters. To be consistent with our previous assumptions, we model the univariate residuals as standard Gaussian noise.

residuals are drawn from the parameterized distribution $\hat{F}_i$:

$$\left\{ \begin{array}{c} \epsilon^s_{sys,t+\tau} \\ \epsilon^s_{i,t+\tau} \end{array} \right\}_{\tau=1}^{h} \sim \hat{F}_i \quad \text{for} \quad s = 1, \ldots, S \tag{3.9}$$

(iv) In a fourth step, we employ the drawn residuals to calculate the daily bivariate returns for the simulated time interval $[t, t+h]$ by updating the volatilities $\{\sigma_{sys,t+\tau+1}, \sigma_{i,t+\tau+1}\}_{\tau=1}^{h-1}$ and correlations $\{\rho_{i,sys,t+\tau+1}\}_{\tau=1}^{h-1}$ on a daily basis.[17] This yields the following return series:

$$\left\{ \begin{array}{c} r^s_{sys,t+\tau} \\ r^s_{i,t+\tau} \end{array} \right\}_{\tau=1}^{h} \quad \text{for} \quad s = 1, \ldots, S \tag{3.10}$$

(v) In the last step, we determine the h-day cumulative returns of simulations $s = 1, \ldots, S$ at day t for institution i and the banking system (according to Equation (3.3)) from which we calculate the MultiMES and MultiCoVaR measures.

We perform the simulation procedures outlined in Steps 3–5 including the calculation of risk measures for each Wednesday within our sample period moving ahead one week in each step. We thus obtain a weekly series of MultiMES and MultiCoVaR values (for every week within the sample period). We calculate the h-day systemic risk measures from the simulated bivariate cumulative h-day returns as follows:

MultiMES

The h-day MultiMES is calculated using the average of institution i's cumulative h-day returns resulting from paths s for which the cumulative return of the banking system is below threshold C:

$$\text{MultiMES}_t^{i,h}(C) = -\frac{\sum_{s=1}^{S} R^s_{i;[t,t+h]} \mathbb{1}\left\{R^s_{sys;[t,t+h]} \leq C\right\}}{\sum_{s=1}^{S} \mathbb{1}\left\{R^s_{sys;[t,t+h]} \leq C\right\}}. \tag{3.11}$$

$\mathbb{1}$ denotes an indicator variable that takes the value *one* if the market return is below threshold level C and *zero* otherwise. We set $C = -25\%$.[18]

[17] The detailed procedure of how the daily correlations are updated is presented in Appendix 3.A.

[18] To calibrate the threshold level C, we observed the performance of the blue chip index STOXX EUROPE 50 during the most severe periods of the international financial crises and the Euro crisis. In both periods, the index dropped on average by around 25% within a three month window.

MultiCoVaR

ΔMultiCoVaR is calculated as the residual between bank i's "distress CoVaR" given by

$$\begin{aligned} \text{MultiCoVaR}_t^{sys|i\leq \text{VaR},h}(q) &= \text{VaR}_{t,q}\left(R^s_{sys;[t,t+h]}\right) \\ \text{with} \quad &\left\{R^s_{sys;[t,t+h]} : \; R^s_{i;[t,t+h]} \leq \text{VaR}_{t,q}\left(R^s_{i;[t,t+h]}\right)\right\} \end{aligned} \tag{3.12a}$$

and bank i's "median state CoVaR" given by

$$\begin{aligned} \text{MultiCoVaR}_t^{sys|i=\text{median},h}(q) &= \text{VaR}_{t,q}\left(R^s_{sys;[t,t+h]}\right) \\ \text{with} \quad &\left\{R^s_{sys;[t,t+h]} : \; \nu^{s,h}_{i,t} - \sigma^{s,h}_{i,t} \leq R^s_{i;[t,t+h]} \leq \nu^{s,h}_{i,t} + \sigma^{s,h}_{i,t}\right\}, \end{aligned} \tag{3.12b}$$

where $\nu^{s,h}_{i,t}$ is the simulated median h-day return of institution i and $\sigma^{s,h}_{i,t}$ the simulated standard deviation of institution i's h-day return. We set the confidence level $q = 5\%$ for both value at risk calculations.

3.5 Results

This section divides into two subsections. We commence with an analysis of the determinants of a single bank's systemic importance in the banking system in Section 3.5.1. Section 3.5.2 investigates the predictive power of systemic risk measures at the banking system level and analyzes dynamics and directionalities between systemic risk and the macro-economy.

3.5.1 Bank level

The Bank for International Settlements proposes the assessment of a bank's systemic importance by an indicator-based measurement approach (Bank for International Settlements, 2011b) that is directly related to a bank's balance sheet characteristics. Thus, in this section, we analyze to what extent the individual banks' MultiMES, SRISK, and ΔMultiCoVaR measures are determined by their respective balance sheet characteristics.

For a first overview on how the three measures evaluate our sample banks' individual level of systemic risk, we plot the individual banks' time series of systemic risk estimates for each of the three measures.

Panel A – MultiMES (in %)									
Institution	rank	# obs	mean	sdev	min	$q = 0.25$	median	$q = 0.75$	max
Ageas N.V.	1	53	49.11	17.10	24.25	36.59	47.01	61.52	89.40
Bank of Ireland	2	53	48.41	12.01	29.63	37.87	47.72	56.98	70.39
Royal Bank of Scotland Group PLC	3	53	47.56	7.12	38.29	43.79	45.97	49.94	74.02
Bradford & Bingley PLC	4	39	46.79	11.34	29.15	37.83	43.23	54.00	72.61
Allied Irish Banks PLC	5	53	44.15	9.54	29.79	35.92	41.10	52.91	64.10
HBOS PLC	6	53	44.12	10.60	29.84	35.88	39.98	50.17	74.00
Barclays PLC	7	53	43.79	5.19	33.76	40.01	43.43	47.43	55.52
Lloyds Banking Group	8	53	43.68	6.52	31.81	38.97	42.48	48.12	59.42
ING Groep N.V.	9	53	42.04	10.24	30.13	34.76	37.11	47.17	71.81
IKB Deutsche Industriebank AG	10	53	41.03	8.15	28.75	35.43	38.20	44.86	65.07
Société Générale S.A.	11	53	40.86	5.08	30.47	37.93	40.37	44.49	53.91
Alliance & Leicester PLC	12	53	39.50	11.81	17.79	34.63	40.04	44.98	73.90
Dexia S.A.	13	53	39.38	8.78	27.01	32.15	39.85	43.95	62.97
Landesbank Berlin Holding AG	14	53	38.64	9.40	26.96	31.41	37.54	44.65	63.17
Banca Popolare dell'Emilia Romagna	15	53	38.21	8.52	21.26	32.41	36.99	42.70	58.85
Crédit Agricole S.A.	16	53	37.13	4.61	25.58	34.60	35.92	40.12	46.13
Irish Bank Resolution Corporation Ltd	17	51	36.60	13.82	22.02	25.74	31.04	45.22	71.00
UniCredit S.p.A.	18	53	36.36	7.58	25.76	31.24	33.46	42.09	54.93
KBC Groep N.V.	19	53	36.04	8.62	25.43	29.55	33.17	43.73	56.49
BNP Paribas S.A.	20	53	35.60	4.37	30.31	32.66	34.61	37.49	52.46
Natixis Banques Populaires	21	53	35.10	5.43	26.62	30.73	34.46	38.27	47.29
UBS AG	22	53	34.00	5.29	26.85	30.29	32.75	36.90	48.51
Raiffeisen Bank International AG	23	53	33.35	6.74	24.74	28.82	30.74	36.01	51.66
National Bank of Greece S.A.	24	53	32.61	7.44	18.71	28.47	31.52	36.23	51.45
Erste Group Bank AG	25	53	32.38	6.35	24.49	27.68	29.88	34.57	45.76
Banco Popular Espanol S.A.	26	53	31.35	5.60	18.75	27.17	32.23	35.66	39.61
Deutsche Bank AG	27	53	30.95	7.89	24.26	25.61	27.12	33.24	49.74
Deutsche Postbank AG	28	53	30.90	6.89	20.41	26.07	29.16	34.43	51.08
Skandinaviska Enskilda Banken AB	29	53	30.66	5.59	23.64	26.74	28.79	34.01	47.88
Credit Suisse Group AG	30	53	30.26	6.72	21.32	25.51	28.38	33.26	48.30
Commerzbank AG	31	53	30.22	4.14	23.93	28.41	30.03	31.57	41.82
Standard Chartered PLC	32	53	30.18	4.55	23.39	27.61	29.11	32.16	43.14
Banco Santander S.A.	33	53	29.84	4.37	23.89	26.13	28.75	33.12	38.33
Swedbank AB	34	53	29.54	4.45	23.84	25.93	28.10	32.07	40.59
Investec PLCShs	35	53	29.05	3.41	21.59	26.40	28.66	31.45	36.48
Danske Bank	36	53	28.65	5.86	20.70	24.44	27.13	31.08	46.46
Banco Bilbao Vizcaya Argentaria S.A.	37	53	28.53	4.56	23.15	25.23	26.64	30.05	40.57
Nordea Bank AB	38	53	27.94	5.42	19.50	25.09	26.85	29.97	43.96
Piraeus Bank S.A.	39	53	27.85	4.14	20.66	24.59	27.05	30.58	36.19
Intesa Sanpaolo S.p.A.	40	53	27.63	6.02	20.87	24.35	25.30	28.58	47.07
Svenska Handelsbanken AB	41	53	27.57	5.45	19.25	24.41	26.92	29.35	39.98
Bankinter	42	53	27.19	3.30	21.86	25.26	26.86	29.17	38.17
Banco Popolare Societa CooperativaAz.	43	53	26.69	4.56	20.37	23.24	26.05	29.21	40.40
HSBC Holdings	44	53	26.33	4.93	17.02	23.11	25.08	28.82	38.97
Alpha Bank A.E.	45	53	25.53	5.76	16.70	20.79	25.33	29.34	38.51
Eurobank Ergasias S.A.	46	53	25.36	4.96	18.41	22.12	24.11	27.79	39.06
Banca Carige S.p.A.	47	53	25.33	3.92	18.50	22.44	24.38	27.57	34.15
Banco Portugues de Investimento S.A.	48	53	24.59	4.18	18.14	21.61	24.35	26.79	40.11
Pohjola Bank PLC	49	53	24.46	3.69	17.34	22.18	23.30	27.02	34.74
Banco Comercial Portugues S.A.	50	26	23.85	2.18	19.77	22.79	23.57	24.51	31.13
Agricultural Bank of Greece S.A.	51	53	23.69	4.25	18.57	20.39	23.00	25.04	35.45
Caixabank S.A.	52	53	23.65	3.21	18.69	21.07	23.25	24.98	33.33
Banco Espanol de Credito S.A.	53	53	23.38	2.75	17.83	21.58	23.00	24.43	32.58
GAM Holding AG	54	53	23.30	2.11	19.45	22.10	22.93	24.38	29.04
Banco Espirito Santo S.A.	55	53	23.22	4.60	16.15	19.96	22.35	25.87	38.59
Credito Emiliano S.p.A. CredemAz.	56	53	22.46	2.49	17.92	20.95	22.16	23.26	31.03
Mediobanca - Banca di Credito Finanziario S.p.A.	57	53	22.18	3.00	15.84	19.99	22.51	23.49	29.88
Jyske Bank	58	53	21.94	4.22	16.86	18.46	21.33	23.69	35.27
Banco de Sabadell S.A.	59	53	21.77	3.11	17.38	19.88	21.24	22.51	34.76
Banca Popolare di Milano	60	53	21.63	2.39	16.77	19.92	21.53	23.11	29.77
Commercial Bank of Greece	61	53	21.08	11.18	9.28	11.24	16.14	29.64	47.05
Bank of Cyprus	62	53	21.05	3.06	17.04	18.63	20.39	22.59	29.60
Banca Monte dei Paschi di Siena S.p.A.	63	53	19.97	2.13	17.04	18.79	19.35	20.75	28.66
Banche Popolari Unite S.C.A.R.L.	64	53	19.86	4.06	15.43	17.10	18.55	20.31	30.13
Credito Valtellinese S.C.A.R.L. Az.	65	53	18.20	2.50	13.87	16.82	17.99	19.03	26.02
Bank of Greece	66	53	17.80	3.49	15.01	15.80	16.87	17.80	33.13
Banco Pastor S.A.	67	53	16.93	1.70	14.01	15.65	17.20	17.98	21.04
Banca Popolare di Sondrio	68	53	16.19	5.16	10.84	13.20	15.11	17.53	41.54
Banque Cantonale Vaudoise	69	53	15.44	1.98	13.08	14.17	14.80	16.16	22.62
ABN AMRO Holding N.V.	70	17	13.62	1.57	11.07	13.16	13.66	14.63	16.46
Banque Nationale de Belgique S.A.	71	53	11.11	1.08	9.57	10.49	10.87	11.40	16.53
Bayerische Hypo- und Vereinsbank AG	72	37	10.54	1.21	8.64	9.76	10.30	10.96	14.11
Caisse Regionale de Credit Agricole Mutuel de Paris et d'Ile de France SC	73	53	10.27	0.81	8.86	9.72	10.06	10.68	12.32
Bank Austria Creditanstalt AG	74	19	7.94	0.27	7.45	7.80	7.96	8.04	8.55
Basler Kantonalbank	75	53	4.02	0.19	3.72	3.90	3.96	4.15	4.62

Table 3.3 – Statistics on weekly systemic risk estimates (Subprime Crisis 2008)

Panel B – SRISK (in €*bn*)									
Institution	rank	# obs	mean	sdev	min	$q = 0.25$	median	$q = 0.75$	max
Deutsche Bank AG	1	53	34.31	10.46	18.07	26.86	32.56	40.23	52.67
Barclays PLC	2	53	30.48	7.70	16.59	26.84	30.61	35.37	42.62
Royal Bank of Scotland Group PLC	3	53	28.97	22.66	2.70	16.08	18.53	58.67	71.22
Crédit Agricole S.A.	4	53	21.65	5.56	10.39	17.65	21.26	24.43	32.02
UBS AG	5	53	17.42	5.62	0.74	15.28	18.09	20.30	29.49
HBOS PLC	6	53	15.19	6.84	1.02	11.80	14.62	21.68	24.71
Intesa Sanpaolo S.p.A.	7	53	13.74	0.50	13.06	13.34	13.50	14.15	14.69
ING Groep N.V.	8	53	13.74	11.11	-1.10	5.19	10.13	24.28	33.84
BNP Paribas S.A.	9	53	13.04	8.49	-2.61	8.05	10.92	15.41	36.77
Ageas N.V.	10	53	12.40	8.76	-0.75	4.20	12.87	20.31	24.78
Société Générale S.A.	11	53	11.18	5.97	-2.08	7.50	10.60	14.65	22.09
Commerzbank AG	12	53	10.20	2.57	6.33	8.49	9.14	12.95	15.01
Dexia S.A.	13	53	8.86	4.96	1.95	4.09	10.03	14.25	16.22
Natixis Banques Populaires	14	53	8.84	3.20	2.18	6.46	9.00	11.58	12.82
Danske Bank	15	53	3.09	3.65	-2.96	0.36	2.38	5.01	9.86
Bank of Ireland	16	53	2.25	2.33	-0.80	-0.22	2.74	4.58	5.51
Alliance & Leicester PLC	17	53	1.82	0.55	0.34	1.50	1.98	2.23	2.56
Banque Nationale de Belgique S.A.	18	53	1.58	0.49	1.19	1.27	1.29	2.23	2.50
Bradford & Bingley PLC	19	39	1.46	0.49	0.53	1.10	1.62	1.90	2.10
Lloyds Banking Group	20	53	1.36	5.03	-8.52	-3.08	1.80	5.46	10.28
Landesbank Berlin Holding AG	21	53	1.24	1.15	-0.17	0.12	1.04	2.52	3.23
IKB Deutsche Industriebank AG	22	53	1.19	0.18	0.69	1.12	1.24	1.32	1.46
Skandinaviska Enskilda Banken AB	23	53	1.14	2.18	-1.66	-0.51	0.52	2.45	5.30
Deutsche Postbank AG	24	53	0.56	2.26	-2.31	-1.15	-0.11	3.40	4.79
Caisse Regionale de Credit Agricole Mutuel de Paris et d'Ile de France SC	25	53	0.28	0.10	0.13	0.20	0.24	0.37	0.47
Allied Irish Banks PLC	26	53	0.15	2.91	-3.97	-2.63	0.18	3.10	4.36
Credit Suisse Group AG	27	53	0.11	5.62	-10.63	-3.20	-1.66	2.74	12.54
Swedbank AB	28	53	0.10	2.01	-2.41	-1.71	-0.38	2.12	3.52
Bank of Greece	29	53	0.06	0.31	-0.23	-0.18	-0.08	0.36	0.67
Basler Kantonalbank	30	53	0.05	0.01	0.02	0.04	0.05	0.06	0.07
Investec PLCShs	31	53	0.01	0.38	-0.80	-0.24	-0.05	0.34	0.60
Irish Bank Resolution Corporation Ltd	32	51	-0.51	1.94	-3.40	-2.38	-0.80	0.91	2.68
Banco Portugues de Investimento S.A.	33	53	-0.53	0.51	-2.09	-0.91	-0.39	-0.17	0.19
Credito Valtellinese S.C.A.R.L. Az.	34	53	-0.54	0.10	-0.73	-0.60	-0.54	-0.47	-0.31
Banca Popolare dell'Emilia Romagna	35	53	-0.54	0.50	-1.60	-0.80	-0.45	-0.20	0.35
Pohjola Bank PLC	36	53	-0.60	0.19	-0.89	-0.77	-0.59	-0.45	-0.16
Credito Emiliano S.p.A. CredemAz.	37	53	-0.66	0.28	-1.14	-0.96	-0.56	-0.45	-0.21
Commercial Bank of Greece	38	53	-0.83	0.73	-1.63	-1.53	-0.81	-0.09	0.32
Jyske Bank	39	53	-0.85	0.53	-1.71	-1.22	-1.05	-0.63	0.19
Banca Popolare di Milano	40	53	-0.90	0.50	-1.67	-1.29	-0.95	-0.62	-0.04
Banco Pastor S.A.	41	53	-1.03	0.42	-1.96	-1.34	-1.22	-0.64	-0.36
Agricultural Bank of Greece S.A.	42	53	-1.05	0.52	-2.12	-1.32	-1.07	-0.73	-0.20
Banque Cantonale Vaudoise	43	53	-1.05	0.32	-1.74	-1.34	-0.96	-0.79	-0.53
Bankinter	44	53	-1.06	0.47	-2.06	-1.43	-1.10	-0.59	-0.25
Svenska Handelsbanken AB	45	53	-1.25	1.38	-4.50	-1.94	-1.48	-0.61	1.49
Banca Popolare di Sondrio	46	53	-1.58	0.37	-2.23	-1.88	-1.61	-1.28	-0.79
Banco Espirito Santo S.A.	47	53	-1.93	1.05	-4.37	-2.83	-1.57	-1.11	-0.18
Erste Group Bank AG	48	53	-1.93	2.73	-5.27	-3.65	-2.87	-1.33	3.38
Banca Carige S.p.A.	49	53	-1.96	0.51	-2.96	-2.29	-2.13	-1.70	-0.90
Banca Monte dei Paschi di Siena S.p.A.	50	53	-2.17	1.09	-5.11	-2.96	-2.10	-1.22	-0.33
Banco Espanol de Credito S.A.	51	53	-2.25	0.74	-3.75	-2.84	-2.20	-1.66	-1.12
Bank of Cyprus	52	53	-2.47	1.23	-4.79	-3.13	-2.85	-1.31	-0.13
Banco Popolare Societa CooperativaAz.	53	53	-2.64	1.90	-5.08	-3.83	-3.35	-1.51	1.43
Piraeus Bank S.A.	54	53	-2.86	1.54	-5.78	-3.99	-3.30	-1.76	-0.03
Banco de Sabadell S.A.	55	53	-3.19	0.64	-4.81	-3.73	-3.12	-2.67	-2.24
Banco Comercial Portugues S.A.	56	26	-3.46	0.72	-5.24	-3.89	-3.33	-2.90	-2.49
Alpha Bank A.E.	57	53	-3.75	1.88	-6.87	-5.09	-4.53	-2.85	-0.04
Eurobank Ergasias S.A.	58	53	-3.98	2.24	-8.26	-5.68	-4.40	-2.71	0.01
Banco Popular Espanol S.A.	59	53	-4.36	2.18	-8.49	-6.23	-3.74	-2.25	-1.33
Banche Popolari Unite S.C.A.R.L.	60	53	-4.51	1.61	-7.49	-5.64	-4.69	-4.16	-1.51
KBC Groep N.V.	61	53	-5.02	6.52	-14.09	-10.00	-7.45	-1.77	6.46
Mediobanca - Banca di Credito Finanziario S.p.A.	62	53	-5.15	1.16	-6.99	-6.31	-4.86	-4.27	-3.03
Raiffeisen Bank International AG	63	53	-5.34	3.34	-9.63	-7.64	-6.80	-2.49	0.51
Nordea Bank AB	64	53	-5.42	4.24	-11.84	-8.35	-6.91	-3.97	3.49
UniCredit S.p.A.	65	53	-5.93	13.67	-26.26	-15.83	-10.16	8.08	18.10
GAM Holding AG	66	53	-5.97	1.64	-8.54	-7.27	-6.35	-4.52	-2.89
National Bank of Greece S.A.	67	53	-7.31	3.63	-15.33	-9.35	-8.10	-5.96	-0.92
Caixabank S.A.	68	53	-8.69	2.15	-12.82	-10.31	-9.07	-7.47	-4.62
Standard Chartered PLC	69	53	-11.80	4.95	-18.31	-15.93	-12.94	-9.68	-1.71
Bank Austria Creditanstalt AG	70	19	-12.88	0.21	-13.29	-13.07	-12.80	-12.75	-12.49
Bayerische Hypo- und Vereinsbank AG	71	37	-16.23	1.29	-18.59	-17.12	-15.98	-15.11	-14.62
Banco Bilbao Vizcaya Argentaria S.A.	72	53	-18.39	7.77	-32.97	-24.77	-19.54	-15.17	-3.29
Banco Santander S.A.	73	53	-23.73	10.47	-39.49	-30.96	-26.74	-17.86	-0.95
ABN AMRO Holding N.V.	74	17	-31.73	2.22	-35.86	-32.60	-31.77	-30.87	-27.30
HSBC Holdings	75	53	-43.01	13.51	-60.29	-51.57	-47.76	-39.90	-5.37

Table 3.3 (continued) – Statistics on weekly systemic risk estimates (Subprime Crisis 2008)

Panel C – ΔMultiCoVaR (in %)									
Institution	rank	# obs	mean	sdev	min	$q = 0.25$	median	$q = 0.75$	max
Natixis Banques Populaires	1	53	32.35	3.29	23.04	30.84	33.50	34.78	37.23
Crédit Agricole S.A.	2	53	29.61	4.46	19.89	28.83	30.10	32.35	37.11
Banca Monte dei Paschi di Siena S.p.A.	3	53	28.44	5.99	15.76	25.47	29.89	33.66	36.00
Banche Popolari Unite S.C.A.R.L.	4	53	28.03	5.93	15.34	25.45	28.74	33.18	37.34
Skandinaviska Enskilda Banken AB	5	53	27.88	4.37	17.87	24.72	28.94	31.40	34.71
Irish Bank Resolution Corporation Ltd	6	51	27.31	3.62	18.88	25.20	28.11	30.38	31.98
Commerzbank AG	7	53	27.30	4.12	17.40	25.86	27.77	30.64	33.63
Nordea Bank AB	8	53	27.17	5.15	16.25	24.26	27.44	31.41	35.24
UniCredit S.p.A.	9	53	27.03	4.01	17.92	25.56	27.89	29.85	34.44
Mediobanca - Banca di Credito Finanziario S.p.A.	10	53	26.96	5.44	15.87	23.23	26.05	30.31	36.52
Banco Bilbao Vizcaya Argentaria S.A.	11	53	26.95	4.08	17.09	25.87	27.56	29.94	33.69
Banca Popolare di Milano	12	53	26.89	5.86	15.54	23.13	26.59	31.39	37.56
Banco Santander S.A.	13	53	26.86	3.72	17.60	25.76	27.98	29.08	33.07
Banco Popolare Societa CooperativaAz.	14	53	26.82	4.92	15.33	24.42	27.47	30.39	34.72
Société Générale S.A.	15	53	26.79	3.85	19.00	23.72	27.54	30.19	32.41
Deutsche Bank AG	16	53	26.77	4.26	17.18	25.32	27.15	29.64	33.96
Banco de Sabadell S.A.	17	53	26.71	4.79	15.52	24.33	27.65	30.16	33.26
Investec PLCShs	18	53	26.43	4.35	16.43	23.88	26.62	29.80	35.09
Barclays PLC	19	53	26.37	4.58	16.26	23.50	27.46	30.44	31.64
Allied Irish Banks PLC	20	53	25.92	4.87	15.01	22.09	26.59	29.99	32.38
BNP Paribas S.A.	21	53	25.84	3.63	17.49	24.39	27.05	27.74	31.93
Lloyds Banking Group	22	53	25.83	5.56	15.49	21.67	25.66	31.67	33.65
Credit Suisse Group AG	23	53	25.80	4.46	15.77	23.84	26.81	28.81	33.81
HSBC Holdings	24	53	25.78	4.23	15.74	24.10	26.99	28.99	32.47
Intesa Sanpaolo S.p.A.	25	53	25.54	5.01	14.57	23.95	26.20	28.57	35.78
Swedbank AB	26	53	24.99	4.16	15.79	23.33	26.21	28.32	31.58
ING Groep N.V.	27	53	24.96	4.41	15.86	21.75	24.64	29.09	31.17
Raiffeisen Bank International AG	28	53	24.95	3.88	16.00	22.74	25.96	27.88	31.23
Ageas N.V.	29	53	24.89	4.14	14.94	22.23	25.59	28.31	30.67
Bankinter	30	53	24.49	4.39	14.46	22.21	25.59	28.02	31.00
HBOS PLC	31	53	24.38	3.50	15.54	23.07	25.44	27.02	28.08
Banco Popular Espanol S.A.	32	53	24.27	4.12	15.13	21.95	25.06	27.30	30.20
GAM Holding AG	33	53	24.03	5.59	12.65	20.33	23.86	28.74	34.72
KBC Groep N.V.	34	53	23.95	4.23	14.56	21.69	24.38	27.73	29.72
Dexia S.A.	35	53	23.90	3.69	15.75	22.37	24.46	27.38	29.22
Svenska Handelsbanken AB	36	53	23.48	4.30	14.73	21.24	24.91	26.70	30.42
Erste Group Bank AG	37	53	23.39	4.18	14.54	21.11	24.12	26.20	31.00
UBS AG	38	53	23.03	3.24	15.11	21.89	23.83	25.52	26.62
Credito Valtellinese S.C.A.R.L. Az.	39	53	23.01	5.09	13.60	19.15	23.34	26.04	32.22
Royal Bank of Scotland Group PLC	40	53	22.85	4.43	13.75	20.24	23.57	26.65	29.15
Credito Emiliano S.p.A. CredemAz.	41	53	22.85	4.76	13.41	20.14	23.19	26.87	30.21
Standard Chartered PLC	42	53	22.53	4.40	13.50	19.87	23.47	25.63	29.02
Banca Carige S.p.A.	43	53	22.14	4.23	12.06	19.15	23.53	25.56	28.11
Jyske Bank	44	53	21.75	4.24	12.95	18.59	22.97	24.97	28.29
Danske Bank	45	53	21.50	4.07	13.08	19.11	21.99	24.72	27.17
Banco Espanol de Credito S.A.	46	53	21.39	3.91	12.48	19.71	21.97	24.68	26.18
Pohjola Bank PLC	47	53	21.04	5.33	11.81	17.47	21.17	26.30	30.40
Bank of Ireland	48	53	20.93	4.18	11.68	19.06	21.39	23.94	27.02
Banco Portugues de Investimento S.A.	49	53	20.55	5.27	9.78	16.44	20.93	25.38	28.19
Caixabank S.A.	50	53	20.48	3.94	12.78	18.36	20.54	23.62	28.11
Alliance & Leicester PLC	51	53	20.28	4.38	11.36	17.47	20.57	24.28	26.86
National Bank of Greece S.A.	52	53	19.85	4.25	11.11	17.16	19.94	23.74	25.49
Banco Espirito Santo S.A.	53	53	19.83	4.35	12.01	16.89	19.60	23.21	27.45
Alpha Bank A.E.	54	53	19.31	4.39	10.87	16.26	19.32	22.96	26.71
Piraeus Bank S.A.	55	53	18.88	4.39	9.39	16.39	18.59	23.66	25.04
Banco Pastor S.A.	56	53	18.84	4.14	10.63	16.09	19.02	22.38	24.62
Eurobank Ergasias S.A.	57	53	18.83	4.81	9.48	15.31	18.74	23.97	27.31
Deutsche Postbank AG	58	53	18.06	4.03	8.57	15.82	18.07	21.52	24.59
IKB Deutsche Industriebank AG	59	53	16.99	4.40	9.59	13.55	16.81	21.00	24.54
Bradford & Bingley PLC	60	39	16.99	3.92	11.14	14.21	16.41	19.63	26.88
Agricultural Bank of Greece S.A.	61	53	16.94	4.70	8.91	12.92	16.72	21.75	24.43
Banca Popolare di Sondrio	62	53	16.92	4.19	7.63	14.21	17.24	21.29	23.56
Bank of Cyprus	63	53	15.18	3.32	8.72	12.69	15.59	18.05	20.97
Banca Popolare dell'Emilia Romagna	64	53	14.64	4.33	7.69	11.13	13.67	18.88	22.41
Bank of Greece	65	53	12.90	3.23	7.13	11.00	13.00	15.50	18.71
Banque Cantonale Vaudoise	66	53	12.57	3.46	6.48	10.64	13.11	14.95	17.77
Bayerische Hypo- und Vereinsbank AG	67	37	12.41	3.08	7.42	9.94	12.02	13.72	20.09
Commercial Bank of Greece	68	53	11.75	3.30	6.56	9.07	11.42	13.90	17.72
Banque Nationale de Belgique S.A.	69	53	11.09	2.48	5.74	9.53	11.72	13.13	14.46
ABN AMRO Holding N.V.	70	17	11.04	2.89	5.16	9.97	11.23	12.11	16.84
Landesbank Berlin Holding AG	71	51	9.50	2.46	5.05	7.82	9.45	11.14	13.85
Caisse Regionale de Credit Agricole Mutuel de Paris et d'Ile de France SC	72	53	8.23	2.10	4.33	6.85	8.10	9.69	12.45
Banco Comercial Portugues S.A.	73	26	7.55	1.39	5.80	6.64	7.15	7.95	10.85
Bank Austria Creditanstalt AG	74	19	1.38	0.35	0.83	1.10	1.42	1.62	2.02
Basler Kantonalbank	75	53	-4.77	2.40	-10.10	-6.00	-4.38	-2.90	-0.89

Table 3.3 (continued) – Statistics on weekly systemic risk estimates (Subprime Crisis 2008)

Panel A – MultiMES (in %)									
Institution	rank	# obs	mean	sdev	min	$q = 0.25$	median	$q = 0.75$	max
Banca Popolare dell'Emilia Romagna	1	52	56.51	9.72	34.30	50.12	56.21	63.93	72.37
Société Générale S.A.	2	52	46.13	8.12	30.75	40.28	44.35	52.59	62.97
Ageas N.V.	3	52	45.76	6.29	32.00	41.60	46.59	50.21	60.20
ING Groep N.V.	4	52	44.23	6.67	31.22	39.17	44.28	49.90	57.12
UniCredit S.p.A.	5	52	44.15	5.21	36.85	40.07	43.56	47.38	55.95
BNP Paribas S.A.	6	52	40.98	5.15	32.56	37.39	38.53	45.88	53.46
Dexia S.A.	7	44	40.89	7.95	27.96	35.24	39.03	44.93	60.40
KBC Groep N.V.	8	52	40.57	6.16	31.31	36.04	39.47	44.68	57.24
Eurobank Ergasias S.A.	9	52	39.15	6.43	28.83	34.49	37.64	42.48	53.11
Royal Bank of Scotland Group PLC	10	52	39.02	4.75	31.92	36.40	38.25	41.94	53.56
Agricultural Bank of Greece S.A.	11	31	38.83	8.76	26.77	32.56	36.65	43.15	58.62
National Bank of Greece S.A.	12	52	38.37	7.78	27.59	32.44	36.99	43.17	55.26
Piraeus Bank S.A.	13	52	37.59	6.38	28.54	32.73	36.19	41.47	53.04
Barclays PLC	14	52	37.31	6.68	27.55	31.69	36.83	43.22	48.78
Crédit Agricole S.A.	15	52	37.03	5.00	30.72	32.85	35.01	42.12	48.40
Landesbank Berlin Holding AG	16	52	36.33	8.56	26.21	31.14	33.39	38.92	71.44
Alpha Bank A.E.	17	35	34.89	4.48	27.01	31.64	34.02	36.98	49.31
Intesa Sanpaolo S.p.A.	18	52	34.68	3.83	28.39	31.80	34.48	36.90	43.93
Banco Bilbao Vizcaya Argentaria S.A.	19	52	34.33	4.16	28.55	31.46	33.75	35.56	48.59
Banco Santander S.A.	20	52	33.13	4.43	23.61	29.18	33.52	36.04	45.52
Commerzbank AG	21	52	31.95	2.24	28.05	30.34	31.93	33.24	38.10
Commercial Bank of Greece	22	21	31.85	7.68	25.80	27.80	29.76	33.22	62.73
Deutsche Bank AG	23	52	31.33	5.15	24.57	27.23	29.28	35.83	42.42
Banco Espirito Santo S.A.	24	52	31.12	6.02	22.31	26.74	29.84	33.33	48.21
Raiffeisen Bank International AG	25	52	31.06	3.85	26.58	28.24	29.66	32.33	40.50
Banco Popolare Societa CooperativaAz.	26	52	30.07	3.04	24.92	27.86	29.75	31.90	37.71
Natixis Banques Populaires	27	52	29.43	4.45	24.93	25.66	26.93	33.46	38.91
Banche Popolari Unite S.C.A.R.L.	28	52	29.41	3.88	22.07	26.35	29.41	31.46	38.49
Banco Popular Espanol S.A.	29	52	29.22	4.27	21.68	25.79	28.40	31.00	39.25
Bankinter	30	52	28.87	4.33	20.62	25.39	29.11	31.05	41.35
Erste Group Bank AG	31	52	28.75	5.62	21.75	24.55	26.32	34.32	41.16
UBS AG	32	52	27.73	2.93	21.29	25.45	28.12	30.04	32.64
Banca Popolare di Sondrio	33	52	27.68	5.55	16.91	24.08	26.57	32.07	42.50
Swedbank AB	34	52	27.34	2.26	23.42	25.88	26.91	28.24	32.97
Danske Bank	35	52	27.32	5.07	19.76	23.08	25.97	32.38	36.53
Mediobanca - Banca di Credito Finanziario S.p.A.	36	52	27.08	3.36	20.08	25.76	27.16	28.18	34.45
Skandinaviska Enskilda Banken AB	37	52	27.06	2.46	22.70	25.35	26.92	28.42	32.97
Credito Emiliano S.p.A. CredemAz.	38	52	26.91	2.85	21.09	25.07	26.38	28.33	34.42
Banco Portugues de Investimento S.A.	39	33	26.50	2.89	21.46	24.95	26.13	28.40	33.59
Banca Carige S.p.A.	40	52	26.48	3.40	20.67	24.11	26.00	28.85	33.56
Nordea Bank AB	41	52	25.92	3.72	20.04	23.16	24.68	28.68	34.32
Credit Suisse Group AG	42	52	25.84	3.55	17.97	23.51	25.85	27.92	32.60
Standard Chartered PLC	43	52	25.25	2.87	20.07	23.13	25.01	27.71	30.02
Pohjola Bank PLC	44	52	25.13	1.80	22.16	23.95	24.91	25.72	29.56
Banco Espanol de Credito S.A.	45	52	24.97	3.99	18.01	22.15	25.43	27.59	34.33
Banca Popolare di Milano	46	12	24.79	0.58	23.71	24.47	24.70	25.36	25.55
Banca Civica S.A.	47	23	24.06	1.43	22.22	23.07	23.79	24.97	27.82
Banco de Sabadell S.A.	48	52	23.90	4.64	16.37	21.57	23.39	25.58	36.28
Bank of Cyprus	49	48	23.16	2.54	18.89	20.99	22.67	24.90	30.95
Svenska Handelsbanken AB	50	52	23.03	3.06	18.00	20.86	22.47	24.96	29.88
Caixabank S.A.	51	52	22.95	3.07	19.80	21.02	22.06	23.41	36.82
Credito Valtellinese S.C.A.R.L. Az.	52	52	22.04	3.14	17.13	19.22	22.38	24.35	29.67
GAM Holding AG	53	52	21.78	1.38	19.37	20.86	21.59	22.53	26.97
Jyske Bank	54	52	21.56	3.44	16.15	18.98	20.79	23.94	30.80
HSBC Holdings	55	52	21.15	4.39	11.51	19.10	21.46	23.59	29.37
Investec PLCShs	56	52	20.77	1.41	17.88	19.83	20.94	21.79	23.90
Bank of Greece	57	52	20.74	4.28	15.20	18.14	19.49	21.47	37.23
Deutsche Postbank AG	58	52	19.77	2.39	15.64	18.31	19.34	21.22	27.04
Julius Bär	59	52	19.07	2.38	15.59	16.66	19.14	20.91	23.31
Banco Pastor S.A.	60	52	17.74	1.92	14.76	16.17	18.12	18.86	25.93
Banque Cantonale Vaudoise	61	52	13.71	1.12	11.69	12.95	13.55	14.18	16.75
Banque Nationale de Belgique S.A.	62	52	10.84	0.39	10.10	10.56	10.82	11.08	11.72
Caisse Regionale de Credit Agricole Mutuel de Paris et d'Ile de France SC	63	52	10.14	0.70	9.14	9.68	10.26	10.42	13.24
Basler Kantonalbank	64	52	4.46	0.93	3.74	4.23	4.34	4.55	10.85

Table 3.4 – Statistics on weekly MultiMES estimates (Euro Crisis 2011)

Panel B – SRISK (in €*bn*)									
Institution	rank	# obs	mean	sdev	min	$q = 0.25$	median	$q = 0.75$	max
Royal Bank of Scotland Group PLC	1	52	38.58	2.45	34.72	36.96	37.73	39.43	44.97
Crédit Agricole S.A.	2	52	36.33	4.07	29.73	32.90	35.59	40.06	43.92
Deutsche Bank AG	3	52	32.06	8.24	17.57	27.40	31.02	39.65	44.17
BNP Paribas S.A.	4	52	31.35	8.83	16.71	25.05	28.68	38.88	51.89
Barclays PLC	5	52	30.52	8.61	15.12	26.58	32.05	36.50	42.58
ING Groep N.V.	6	52	20.85	4.59	12.36	17.52	19.56	25.39	27.67
Société Générale S.A.	7	52	18.65	6.56	9.25	12.69	15.10	25.93	27.87
Commerzbank AG	8	52	18.29	2.14	14.92	16.56	18.22	19.63	22.83
Intesa Sanpaolo S.p.A.	9	52	17.22	0.63	16.35	16.62	17.22	17.57	18.24
Dexia S.A.	10	44	15.11	0.85	13.60	14.29	15.11	15.97	16.23
UniCredit S.p.A.	11	52	12.57	5.41	4.15	7.51	12.11	17.77	20.40
Natixis Banques Populaires	12	52	7.72	2.09	3.83	6.37	8.38	9.16	11.11
KBC Groep N.V.	13	52	4.76	1.42	2.91	3.54	4.29	5.87	7.73
Danske Bank	14	52	4.55	1.93	1.68	2.70	4.67	6.01	7.85
Deutsche Postbank AG	15	52	3.09	0.40	2.10	2.79	3.27	3.39	3.57
Bank of Greece	16	52	2.89	0.55	2.45	2.52	2.61	3.03	3.86
Banco Popolare Societa CooperativaAz.	17	52	1.77	0.66	0.45	1.25	1.97	2.31	2.65
Landesbank Berlin Holding AG	18	52	1.69	0.37	1.21	1.40	1.58	1.90	2.85
Eurobank Ergasias S.A.	19	52	1.61	0.53	0.84	1.15	1.48	2.19	2.38
Banque Nationale de Belgique S.A.	20	52	1.51	0.26	1.07	1.44	1.55	1.68	1.98
Credit Suisse Group AG	21	52	1.45	6.00	-7.60	-2.81	-0.39	8.13	10.20
Banche Popolari Unite S.C.A.R.L.	22	52	1.19	0.76	-0.25	0.80	1.16	1.88	2.17
Banca Civica S.A.	23	13	1.17	0.02	1.11	1.16	1.17	1.18	1.20
Piraeus Bank S.A.	24	52	0.96	0.40	0.28	0.61	0.87	1.33	1.51
Banco Espanol de Credito S.A.	25	52	0.92	0.39	0.27	0.58	0.99	1.21	1.60
Banca Popolare dell'Emilia Romagna	26	52	0.81	0.24	0.29	0.62	0.82	1.01	1.18
National Bank of Greece S.A.	27	52	0.78	1.34	-1.64	-0.63	0.74	2.14	2.63
Alpha Bank A.E.	28	35	0.64	0.31	0.15	0.31	0.70	0.90	1.30
Banco Portugues de Investimento S.A.	29	33	0.61	0.11	0.44	0.51	0.61	0.69	0.77
Agricultural Bank of Greece S.A.	30	31	0.51	0.19	-0.01	0.50	0.54	0.62	0.75
Banco Espirito Santo S.A.	31	52	0.46	0.55	-0.28	-0.04	0.39	0.81	1.50
Caisse Regionale de Credit Agricole Mutuel de Paris et d'Ile de France SC	32	52	0.43	0.06	0.32	0.38	0.41	0.50	0.53
Ageas N.V.	33	52	0.40	0.68	-0.78	-0.24	0.30	1.02	1.35
Banca Popolare di Milano	34	12	0.34	0.04	0.28	0.31	0.33	0.36	0.42
Commercial Bank of Greece	35	21	0.30	0.07	0.22	0.23	0.26	0.35	0.49
Banco Pastor S.A.	36	52	0.21	0.06	0.05	0.16	0.23	0.26	0.29
Credito Valtellinese S.C.A.R.L. Az.	37	52	0.20	0.09	0.07	0.12	0.20	0.26	0.37
Bankinter	38	52	0.12	0.12	-0.11	0.02	0.14	0.21	0.33
Basler Kantonalbank	39	52	0.11	0.06	-0.01	0.04	0.11	0.17	0.22
Banco Popular Espanol S.A.	40	52	0.03	0.43	-0.67	-0.32	-0.01	0.43	0.81
Credito Emiliano S.p.A. CredemAz.	41	52	-0.09	0.22	-0.45	-0.29	-0.16	0.11	0.19
Bank of Cyprus	42	48	-0.11	0.56	-1.18	-0.54	-0.19	0.39	0.87
UBS AG	43	52	-0.21	5.99	-11.70	-4.40	-1.74	5.14	10.37
Banco de Sabadell S.A.	44	52	-0.40	0.28	-0.90	-0.58	-0.43	-0.23	0.23
Jyske Bank	45	52	-0.42	0.34	-0.89	-0.75	-0.40	-0.09	0.12
Pohjola Bank PLC	46	52	-0.53	0.19	-0.80	-0.71	-0.51	-0.39	-0.16
Investec PLCShs	47	52	-0.56	0.32	-1.23	-0.80	-0.62	-0.24	0.09
Banca Popolare di Sondrio	48	52	-0.56	0.15	-0.80	-0.67	-0.57	-0.47	-0.22
Banca Carige S.p.A.	49	52	-0.73	0.24	-1.22	-0.91	-0.74	-0.54	-0.30
Skandinaviska Enskilda Banken AB	50	52	-1.32	1.92	-4.03	-3.24	-1.50	0.44	1.71
Raiffeisen Bank International AG	51	52	-1.67	1.93	-3.87	-3.20	-2.54	-0.12	1.92
GAM Holding AG	52	52	-1.68	0.36	-2.19	-2.05	-1.75	-1.31	-1.14
Erste Group Bank AG	53	52	-1.70	2.83	-5.05	-3.86	-3.48	1.26	3.49
Swedbank AB	54	52	-1.76	1.06	-3.19	-2.67	-1.90	-1.16	0.61
Mediobanca - Banca di Credito Finanziario S.p.A.	55	52	-1.94	0.66	-2.77	-2.47	-2.02	-1.62	-0.32
Banque Cantonale Vaudoise	56	52	-2.08	0.18	-2.50	-2.17	-2.11	-1.95	-1.65
Svenska Handelsbanken AB	57	52	-3.03	1.40	-5.75	-3.88	-3.12	-1.95	-0.54
Julius Bär	58	52	-3.79	0.43	-4.85	-4.00	-3.75	-3.49	-3.03
Nordea Bank AB	59	52	-4.45	4.39	-12.40	-7.68	-5.26	-0.04	1.83
Banco Santander S.A.	60	52	-5.76	5.57	-15.98	-10.86	-6.41	-0.27	4.03
Banco Bilbao Vizcaya Argentaria S.A.	61	52	-6.12	2.21	-9.63	-8.07	-6.16	-4.52	-1.16
Caixabank S.A.	62	52	-10.20	1.35	-12.32	-11.63	-10.10	-9.11	-7.69
Standard Chartered PLC	63	52	-19.91	3.09	-27.05	-22.12	-19.19	-17.68	-13.22
HSBC Holdings	64	52	-41.43	13.44	-71.20	-48.58	-42.44	-28.69	-22.40

Table 3.4 (continued) – Statistics on weekly systemic risk estimates (Euro Crisis 2011)

Panel C – ΔMultiCoVaR (in %)									
Institution	rank	# obs	mean	sdev	min	$q = 0.25$	median	$q = 0.75$	max
Natixis Banques Populaires	1	52	30.84	3.45	24.14	28.01	30.90	33.77	37.25
Crédit Agricole S.A.	2	52	25.97	5.21	17.96	20.48	25.68	30.84	34.07
Skandinaviska Enskilda Banken AB	3	52	24.72	5.93	16.77	19.24	23.14	30.57	34.64
Investec PLCShs	4	52	23.87	6.49	16.27	17.91	21.61	29.95	37.26
Société Générale S.A.	5	52	23.32	3.95	17.29	19.90	22.74	26.34	32.04
Commerzbank AG	6	52	23.10	5.74	14.32	17.62	22.21	29.04	31.61
Banche Popolari Unite S.C.A.R.L.	7	52	23.05	6.72	11.94	17.77	21.91	29.19	34.68
Deutsche Bank AG	8	52	22.94	5.31	15.09	17.85	21.57	28.42	30.84
Banco Popolare Societa CooperativaAz.	9	52	22.89	5.24	14.89	17.97	22.11	27.46	32.37
Banco Santander S.A.	10	52	22.85	5.32	15.03	17.91	21.00	27.90	31.84
Nordea Bank AB	11	52	22.68	6.48	14.12	16.59	20.64	29.20	34.26
Barclays PLC	12	52	22.55	5.32	13.54	17.75	20.79	27.72	32.13
Banco Bilbao Vizcaya Argentaria S.A.	13	52	22.51	5.76	15.03	17.05	19.91	28.76	31.12
Mediobanca - Banca di Credito Finanziario S.p.A.	14	52	22.11	4.24	16.20	18.57	20.93	25.07	32.46
UniCredit S.p.A.	15	52	21.96	4.02	15.99	18.22	20.82	25.73	29.57
Banco de Sabadell S.A.	16	52	21.91	6.33	13.40	16.06	20.21	27.71	33.44
Credit Suisse Group AG	17	52	21.55	6.49	13.33	15.74	19.36	28.27	32.87
Raiffeisen Bank International AG	18	52	21.44	4.58	15.05	17.08	20.45	25.59	29.16
BNP Paribas S.A.	19	52	21.35	3.91	15.54	17.59	21.04	24.40	28.30
Swedbank AB	20	52	21.32	5.59	13.82	15.88	19.74	27.03	29.78
Banco Popular Espanol S.A.	21	52	21.17	6.06	13.02	15.47	19.34	27.40	32.33
Intesa Sanpaolo S.p.A.	22	52	21.16	5.51	13.59	16.01	19.90	26.51	30.75
Ageas N.V.	23	52	21.15	5.22	13.87	16.22	19.50	26.41	30.79
HSBC Holdings	24	52	20.98	6.49	12.93	15.10	17.83	27.87	33.00
ING Groep N.V.	25	52	20.95	4.96	13.77	16.55	19.40	25.52	30.60
Bankinter	26	52	20.93	5.97	13.40	15.11	18.96	26.68	32.52
Pohjola Bank PLC	27	52	20.42	6.73	11.73	14.47	17.62	26.91	33.18
UBS AG	28	52	20.32	5.30	12.97	15.24	19.00	25.67	29.37
KBC Groep N.V.	29	52	20.00	4.79	13.99	15.96	18.15	24.38	29.32
Erste Group Bank AG	30	52	19.94	5.57	12.37	14.57	18.09	24.80	30.19
Svenska Handelsbanken AB	31	52	19.94	5.60	12.06	14.68	18.27	25.49	29.35
Banca Popolare di Sondrio	32	52	19.68	4.09	13.14	15.77	18.88	23.32	26.98
Credito Valtellinese S.C.A.R.L. Az.	33	52	19.52	5.58	11.23	14.38	18.26	25.10	30.19
Dexia S.A.	34	44	19.35	4.57	13.11	15.57	17.08	23.25	28.67
Royal Bank of Scotland Group PLC	35	52	19.06	4.79	12.67	14.74	17.32	23.83	28.26
Credito Emiliano S.p.A. CredemAz.	36	52	18.66	4.84	12.20	14.18	17.40	23.26	28.53
Standard Chartered PLC	37	52	18.64	4.99	12.55	14.14	16.94	23.93	28.17
Banca Popolare di Milano	38	12	18.37	1.65	16.42	17.06	18.58	19.27	22.17
Banca Carige S.p.A.	39	52	18.18	4.31	9.23	15.03	17.33	21.60	26.30
Caixabank S.A.	40	52	17.69	5.11	9.72	13.60	15.79	22.48	27.69
GAM Holding AG	41	52	17.43	7.61	7.47	10.71	13.18	25.01	32.24
Jyske Bank	42	52	17.22	5.45	9.83	12.16	16.24	22.16	26.55
Banco Espanol de Credito S.A.	43	52	17.05	4.75	10.17	12.44	16.00	21.90	25.31
Banco Portugues de Investimento S.A.	44	33	16.98	3.22	12.08	14.83	16.26	18.03	24.72
Danske Bank	45	52	16.42	5.12	9.64	11.75	14.59	20.61	27.11
Julius Bär	46	52	15.93	5.54	9.97	10.97	12.58	21.64	26.13
Banco Espirito Santo S.A.	47	52	15.86	4.74	9.31	11.51	14.56	19.37	25.53
Banco Pastor S.A.	48	52	15.28	4.11	9.87	11.42	13.98	18.95	23.75
Banca Popolare dell'Emilia Romagna	49	52	14.77	4.51	7.60	10.78	14.57	18.80	23.38
Banca Civica S.A.	50	23	13.58	1.24	11.66	12.86	13.56	14.29	16.52
Deutsche Postbank AG	51	52	13.34	4.35	8.37	9.42	11.95	17.20	21.51
National Bank of Greece S.A.	52	52	13.25	3.46	8.17	9.58	12.80	15.86	19.13
Alpha Bank A.E.	53	35	12.60	2.50	9.65	10.79	11.41	14.20	18.86
Bank of Cyprus	54	48	12.08	3.30	8.24	9.14	10.95	15.01	20.40
Eurobank Ergasias S.A.	55	52	11.93	3.11	7.63	9.08	11.25	14.25	17.98
Piraeus Bank S.A.	56	52	11.63	4.04	5.62	7.57	11.85	15.49	18.85
Bank of Greece	57	52	10.03	2.87	6.21	7.32	9.46	12.95	16.12
Banque Cantonale Vaudoise	58	52	9.90	4.38	5.12	6.26	7.16	14.46	18.62
Banque Nationale de Belgique S.A.	59	52	8.56	3.24	4.73	5.61	7.35	11.64	15.39
Agricultural Bank of Greece S.A.	60	31	7.84	1.27	5.26	6.94	7.69	8.41	10.54
Landesbank Berlin Holding AG	61	51	7.11	2.68	3.84	4.68	5.94	9.73	13.57
Commercial Bank of Greece	62	21	6.63	0.72	5.08	6.16	6.75	7.04	8.07
Caisse Regionale de Credit Agricole Mutuel de Paris et d'Ile de France SC	63	52	6.54	2.05	3.99	4.73	5.74	8.49	11.17
Basler Kantonalbank	64	52	-2.17	1.63	-6.22	-2.60	-2.06	-1.12	1.26

Table 3.4 (continued) – Statistics on weekly systemic risk estimates (Euro Crisis 2011)

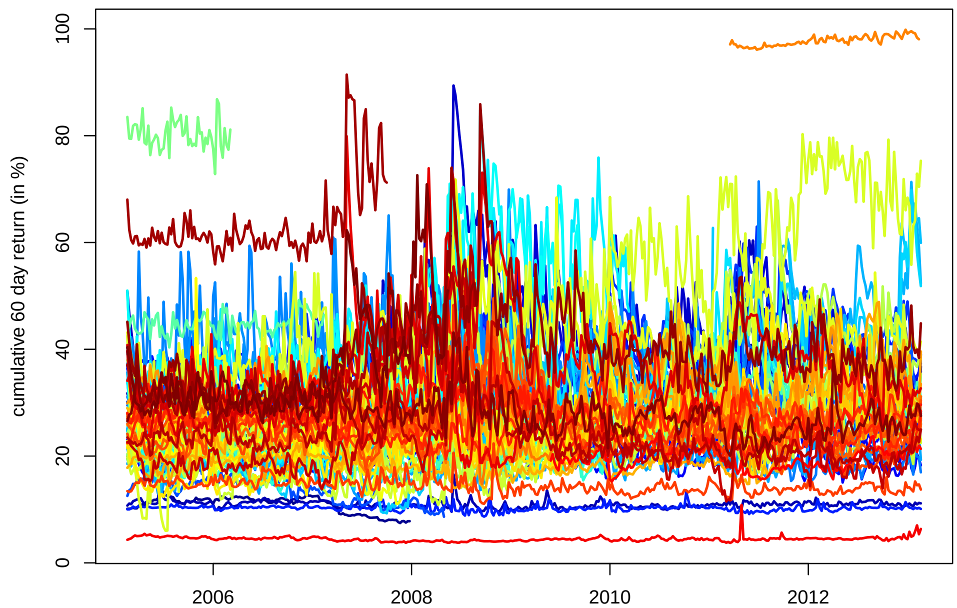

Figure 3.1 – Time evolution of MultiMES
The figure presents time series of weekly MultiMES values for all 86 sample banks expressed in percentage terms. The time series of observations cover the period from July 2005 to June 2013. All stock price and balance sheet data are obtained from Datastream.

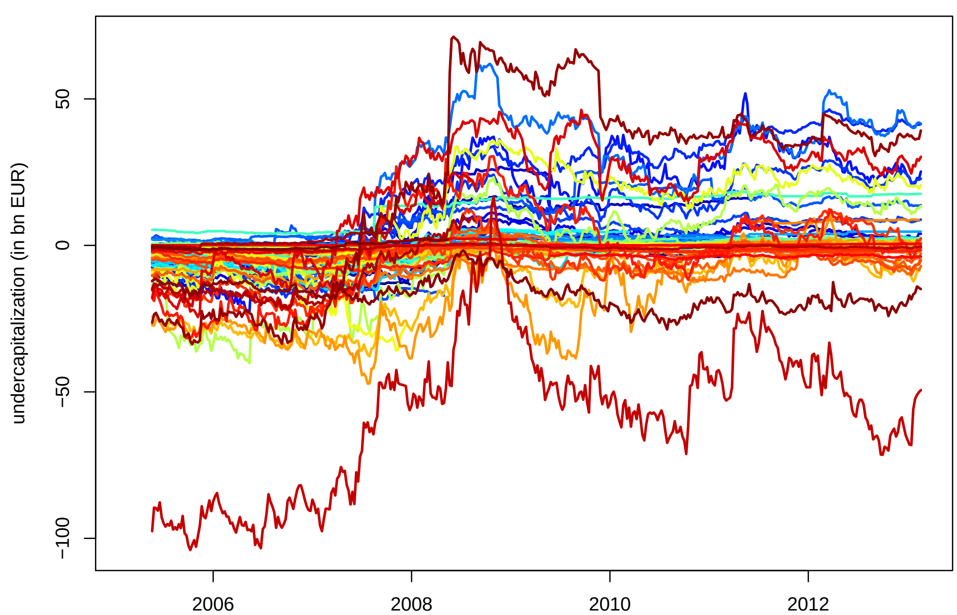

Figure 3.2 – Time evolution of SRISK
The figure presents time series of weekly SRISK values for all 86 sample banks expressed in €bn terms. The time series of observations cover the period from July 2005 to June 2013. All stock price and balance sheet data are obtained from Datastream.

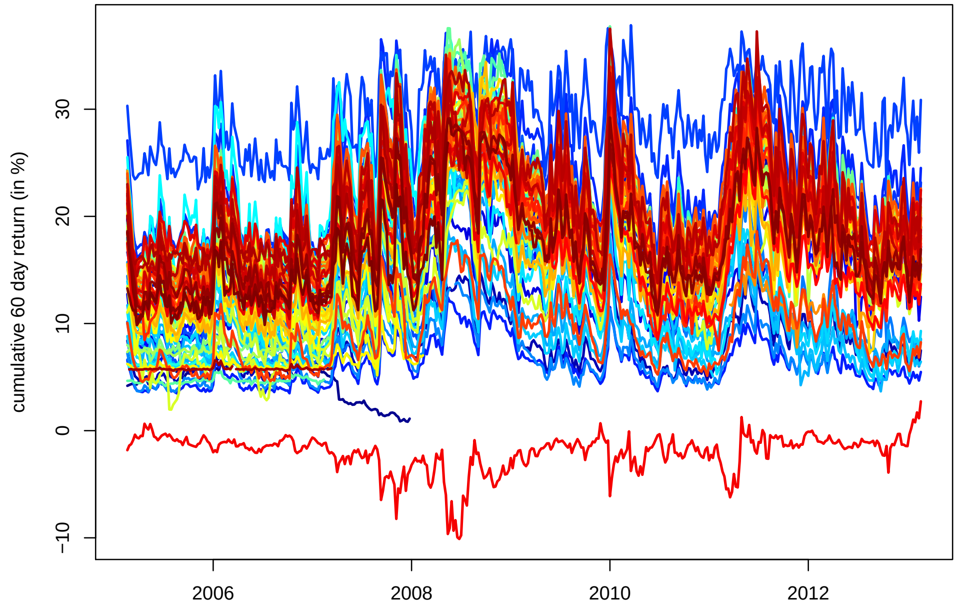

Figure 3.3 – Time evolution of ΔMultiCoVaR
The figure presents time series of weekly ΔMultiCoVaR values for all 86 sample banks expressed in percentage terms. The time series of observations cover the period from July 2005 to June 2013. All stock price and balance sheet data are obtained from Datastream.

Figure 3.1 exhibits the weekly time series of MultiMES, Figure 3.2 the weekly time series of SRISK, and Figure 3.3 the weekly time series of ΔMultiCoVaR, which are calculated as described in Section 3.4. The ΔMultiCoVaR series exhibit higher cross-sectional correlations than the MultiMES and SRISK series. However, all three systemic risk figures reveal two substantial peaks occurring in the time around the years 2008 and 2011. Thus, we draw two subsamples from the weekly time series of MultiMES, SRISK, and ΔMultiCoVaR. The first subsample contains all weekly values for the three sets of systemic risk measures within the year 2008. As the year 2008 marks the peak of turmoil in the financial markets caused by the bankruptcies of the two large investment banks Bear Stearns and Lehman Brothers, we henceforth refer to this subsample as the "Subprime Crisis". The second subsample contains all corresponding values within the year 2011 and we accordingly refer to this subsample as the "Euro Crisis".

Tables 3.3 and 3.4 exhibit descriptive statistics of the systemic risk estimates for our sample banks within the Subprime Crisis and the Euro Crisis time intervals. Both tables are designed in the same fashion. Panel A exhibits our estimates for MultiMES, Panel B the estimates for SRISK, and Panel C the estimates for ΔMultiCoVaR. We rank the banks according to their mean estimates. It is easily observed that the systemic risk measures rank institutions differently. However, when taking a closer look, it is evident that the systemic risk estimates for the banks are driven by their respective balance sheet characteristics.

In the following analysis, we consider the following balance sheet characteristics: leverage (calculated as the ratio of market valued total assets – i.e., the sum of the book value of total debt and market valued equity – and market valued equity) to proxy for balance sheet stability, market-to-book ratio (calculated as the ratio of market valued equity and book value of equity) to measure financial distress, profitability (calculated as ratio of net income and the book value of total assets) to evaluate a banks' business outlook, and total assets to assess potential default consequences. Taking the ten largest banks (by total assets), we observe that all six systemic importance rankings predominantly reflect the amount of an institution's total assets. Throughout all rankings of Tables 3.3 and 3.4, the vast majority of the ten largest banks is found in the upper tier. As expected, this effect is strongest for the SRISK measure as the latter incorporates balance sheet characteristics by construction.

Leverage also seems to have a substantial impact on an institution's systemic importance. As for total assets, the ten most leveraged banks are predominantly found on the systemically important ranks. This relationship is most clear-cut for the SRISK measure. For MultiMES and ΔMultiCoVaR, the same relationship seems to prevail, though less strongly. We also analyzed the rankings with respect to the ten most profitable banks and the banks with the lowest market-to-book ratio. However, no specific patterns can be observed, so – if at all existent – we would expect this relationship to be weak.

To explore if there exists any systematic relationship between the systemic risk estimates and the previously mentioned balance sheet characteristics, we perform the following simple least squares regression:

$$SysRisk_t^{bank} = \alpha + \beta\, SysRisk_{t-1}^{bank} + \gamma\, BalanceSheetCharacteristics_{t-1}^{bank} + \epsilon_t \tag{3.13}$$

where $SysRisk_t^{bank}$ represents any of the three risk measures ΔMultiCoVaR, MultiMES or SRISK at the institutional level and $BalanceSheetCharacteristics_{t-1}^{bank}$ is a vector consisting of the four lagged balance sheet characteristics leverage (lev), market-to-book ratio (mb), profitability (pf), and the logarithm of total assets (ta) as its elements. Parameters α, β, and $\gamma \equiv (\gamma_{lev}, \gamma_{mb}, \gamma_{pf}, \gamma_{ta})$ denote the regression coefficients and ϵ_t is Gaussian White Noise. We control for the lagged systemic risk measure to correct for endogenous risk persistence. The regression is performed on the basis of monthly time series. Thus, for the weekly series of systemic risk, we calculate monthly averages and we linearly interpolate the quarterly balance sheet data.

Table 3.5 presents the regression results for Equation (3.13) and is organized as follows: Panel A exhibits the results for the MultiMES measure, Panel B the results for the SRISK measure, and Panel C the results for the ΔMultiCoVaR measure. In all three regressions, the risk measures are highly autocorrelated. Thus, systemic risk at the bank level is stable over time, implying that a bank that was systemically important in the previous month will also be systemically important in this month. The result is most persistent for the SRISK measure.

The influence of log assets is consistently positive and significant at the 1% confidence level. The larger a bank, the higher its systemic risk estimate. This result is in line with our qualitative analysis of the rankings of Tables 3.3 and 3.4. For the ΔMultiCoVaR and MultiMES measures, leverage is significant as well, though this is not the case for the SRISK measure. However, the sign of the regression coefficients is ambiguous. Whereas a higher leverage increases MultiMES, it decreases ΔMultiCoVaR. This finding lasts in different regression setups.[19]

As predicted by our prior descriptive analysis, the market-to-book ratio as well as profitability do not have additional predictive power for all three systemic risk measures and thus seem to be already captured by the (simultaneously calculated) lagged systemic risk measures. The same relation holds for the SRISK measure and leverage. As a result, the exogenous variation in systemic risk in the cross-section is mainly driven by size and leverage.

In summary, our analysis shows that besides the lagged systemic risk measures, total assets and leverage are the most important drivers of systemic risk. The systemic importance of banks with high leverage and large total assets disproportionally increases during periods of financial turmoil. The results imply that regulators can effectively reduce systemic risk at the institutional level by imposing restrictions on bank size and leverage and thus justify new regulatory measures such as the introduction of a leverage ratio on total assets and capital surcharges to SIFI's Tier 1 capital in the range between 1% to 3.5% (European Parliament and the Council of the European Union, 2013).

[19] We also perform the same regression without controlling for endogenous risk persistence. As a result, all balance sheet characteristics are significant at the 5% level and thus have explanatory power for future systemic risk levels. Surprisingly, leverage has a negative influence on ΔMultiCoVaR, which is counterintuitive. Furthermore, MultiMES is positively related to the market-to-book ratio. On average, the risk measures are positively related to size and leverage and negatively related to profitability and the market-to-book ratio.

Panel A – MultiMES (in %)				
Lagged variables	coefficient	sdev	t-value	p-value
Intercept	-0.1661	0.3815	-0.4353	0.6633
MultiMES	0.9453	0.0043	219.1939	0.0000
Leverage	0.0011	0.0007	1.6046	0.1086
Market-to-Book	0.0231	0.0159	1.4555	0.1456
Profitability	-0.0039	0.0090	-0.4363	0.6626
Log Assets	0.1409	0.0337	4.1754	0.0000
	mean sum sq	R^2	F-value	p-value
Summary Stats	3.5193	0.9012	11,584.6800	0.0000
Panel B – SRISK (in *bn* EUR)				
Lagged variables	coefficient	sdev	t-value	p-value
Intercept	-1.0539	0.2145	-4.9143	0.0000
SRISK	0.9877	0.0019	516.9528	0.0000
Leverage	0.0001	0.0004	0.2586	0.7959
Market-to-Book	0.0076	0.0087	0.8663	0.3864
Profitability	0.0067	0.0049	1.3630	0.1729
Log Assets	0.0938	0.0178	5.2566	0.0000
	mean sum sq	R^2	F-value	p-value
Summary Stats	1.9344	0.9801	60,362.4500	0.0000
Panel C – ΔMultiCoVaR (in %)				
Lagged variables	coefficient	sdev	t-value	p-value
Intercept	-0.6398	0.2714	-2.3574	0.0184
MultiCoVaR	0.9222	0.0049	186.9164	0.0000
Leverage	-0.0014	0.0005	-2.8449	0.0045
Market-to-Book	0.0019	0.0112	0.1651	0.8689
Profitability	0.0054	0.0063	0.8494	0.3957
Log Assets	0.1689	0.0246	6.8625	0.0000
	mean sum sq	R^2	F-value	p-value
Summary Stats	2.4850	0.8742	8,773.7340	0.0000

Table 3.5 – Determinants of systemic risk at the bank level

Table 3.5 – continued:
All figures are estimated from monthly averaged time series of systemic risk measures at the bank level and monthly (linearly interpolated) time series of bank level balance sheet characteristics covering the period from July 2005 to June 2013. We estimate the equation $SysRisk_t^{bank} = \alpha + \beta\ SysRisk_{t-1}^{bank} + \gamma\ BalanceSheetCharacteristics_{t-1}^{bank} + \epsilon_t$, where $SysRisk_t^{bank}$ represents any of the three risk measures MultiCoVaR, MultiMES or SRISK at the bank level and $BalanceSheetCharacteristics_{t-1}^{bank}$ is a vector consisting of the four lagged balance sheet characteristics leverage (lev), market-to-book ratio (mb), profitability (pf), and the logarithm of total assets (ta) as its elements. Parameters α, β, and $\gamma \equiv (\gamma_{lev}, \gamma_{mb}, \gamma_{pf}, \gamma_{ta})$ denote the regression coefficients and ϵ_t is Gaussian White Noise. The table is organized as follows. Panel A presents the results for the regression with $SysRisk$ = MultiMES, Panel B the results for $SysRisk$ = SRISK, and Panel C the results for $SysRisk$ = ΔMultiCoVaR. The names of the lagged explanatory variables to which the regression coefficients refer are given in the respective rows. We provide the coefficients' estimates, standard errors, t- and p-values as well as various summary statistics in the columns. For a detailed description of the regression variables, we refer to Table 3.6.

3.5.2 Banking system level

Having analyzed the determinants of systemic risk at the institutional level, we now turn to the implications of systemic risk at the banking system level. Systemic banking crisis often have substantial adverse effects on the real economy, such as drops in asset prices, output, and employment (Reinhart and Rogoff, 2009c). Thus, if useful, systemic risk measures should not only reflect current distress in the financial system but also have predictive power for financial market and macro-economic variables. In this section, we investigate the two-sided relationship between systemic risk measures and financial market variables, macro-economic variables, and balance sheet characteristics at the aggregate banking system level.

Table 3.6 provides a summary of the variables used in our subsequent analyses. To capture movements at the financial markets, we employ the 12 month EURIBOR-OIS spread (which we henceforth simply refer to as EURIBOR-OIS spread) and the VSTOXX Index. The EURIBOR-OIS spread is the residual between the 12 month EURIBOR and the 12 month Euro OIS (overnight indexed swap) rate and captures liquidity and default risk within the European banking system. The data are on a weekly frequency.

In addition to our analyses at the bank level, we explore the two-sided relationship between systemic risk measures and balance sheet characteristics employing the same variables as in Section 3.5.1 but at the banking system level. I.e., for each of the balance sheet characteristics, we compute weekly time series for the aggregate of all banks included in our sample. Instead of log assets, however, we include the annual ratio of nonperforming loans to total gross loans in our analyses.

Label	**Description**	**Sampling Frequency**	**Data Source**
Financial Market Variables			
EURIBOR-OIS Spread	EURIBOR 12 month rate – EURO 12 month OIS rate (in %)	weekly	Datastream
Volatility	VSTOXX index (in %)	weekly	Datastream
Balance Sheet Variables			
Leverage	market valued total assets / market valued equity, where market valued total assets = book valued total debt + market valued equity	quarterly	Datastream
Market-to-Book	market valued equity / book valued equity	quarterly	Datastream
Profitability	net income / book valued total assets (in %)	quarterly	Datastream
Nonperforming Loans	nonperforming loans / total gross loans (EU27, in %)	annual	Worldbank
Macro-economic Variables			
Sentiment	Economic Sentiment Indicator (by the European Commission)	monthly	Datastream
Production	Industrial Production Index excluding construction (EU27)	monthly	Datastream
House Prices	EU House Price Index (EU evolving)	quarterly	Datastream
Credit Private	domestic credit to the private sector (EU27, in % of GDP)	annual	Worldbank
Government Debt	government debt (EU27, in % of GDP)	annual	ECB
Real GDP	real quarterly gross domestic product (EU27, in *bn* EUR)	quarterly	Datastream

Table 3.6 – Description of variables employed in the VAR models

We measure linkages between systemic risk levels and the macro-economy employing the following variables: the Economic Sentiment Indicator of the European Commission and the EU Industrial Production Index (excluding construction), both published on a monthly basis, the EU House Price Index and real GDP, both published on a quarterly basis, domestic credit to the private sector and government debt, both expressed in percentage terms of real GDP and on an annual basis. All macro-economic variables refer to the EU27.

To measure directionalities between the systemic risk measures and these variables, we apply a vector autoregressive (VAR) model. According to the Schwarz criterion, the data suggests a one lag structure. We thus employ a VAR system of the following type:

$$\Delta y_t = a + B\Delta y_{t-1} + \epsilon_t \tag{3.14}$$

with $y_t \equiv (SysRisk_t^{sys}, x_t{}')'$, where $SysRisk_t^{sys}$ represents any of the three systemic risk measures ΔMultiCoVaR, MultiMES or SRISK at the banking system level and x_t either is the vector of financial market, balance sheet or macro-economic variables. Parameter vector a denotes the intercepts, B is the coefficient matrix of lagged regression variables y_{t-1}, and ϵ_t is a vector of standard Gaussian error terms. The Δs indicate that we are running the regression in first differences to ensure that we do not violate the stationarity requirements.[20] Running the regression of Equation (3.14) requires that we harmonize data with respect to their sampling frequency. We harmonize data on a monthly frequency and achieve this by linearly interpolating all variables sampled on a frequency of lower than a month. For variables with a higher frequency, we calculate monthly averages.

Figures 3.4–3.7 exhibit the time series of the variables used for the regression of Equation (3.14). Figure 3.4 exhibits the time series of cross-sectional averages of the monthly averaged bank level systemic risk estimates. As observed in Section 3.5.1, the cross-section of ΔMultiCoVaR measures is more strongly correlated than the other measures' cross-sections and thus, the aggregate ΔMultiCoVaR series exhibits higher volatility. Nevertheless, all three figures exhibit peaks during the Subprime and the Euro Crises. Figure 3.5 presents the monthly, linearly interpolated time series of aggregate balance sheet characteristics, Figure 3.6 the monthly averaged time series of financial market variables, and Figure 3.7 the monthly, linearly interpolated time series of macro-economic variables.

[20] We perform several time series diagnostics. We test the differenced series $\Delta y_t = y_t - y_{t-1}$ for stationarity, heteroscedasticity, auto-correlation, and non-normality. According to Appendix-Table 3.11 we cannot reject the null hypotheses that the time series are stationary (Panel A) for all series and for most series we cannot reject the homoscedasticity null hypothesis (Panel B). The vast majority of the series exhibits strong auto-correlation (Panel C) and non-normality (Panel D).

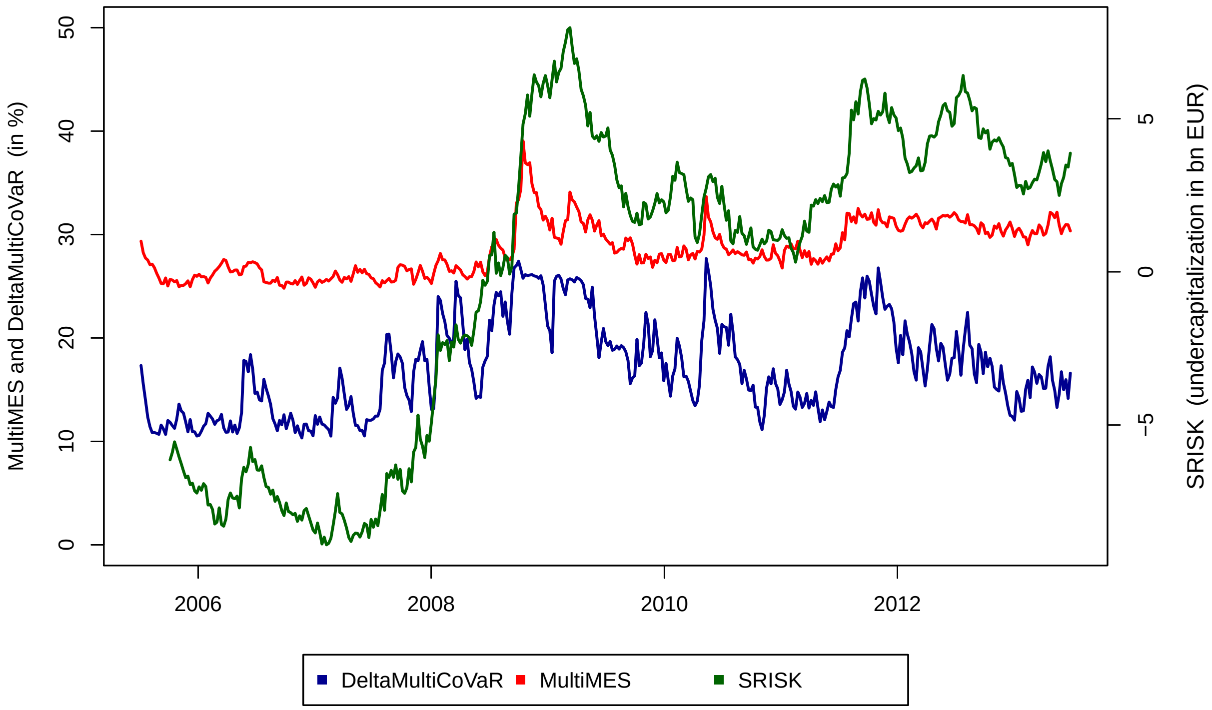

Figure 3.4 – Time evolution of risk measures
The figure presents averages across the time series of weekly systemic risk measures for all 86 sample banks. The time series of observations cover the period from July 2005 to June 2013. All stock price and balance sheet data are obtained from Datastream.

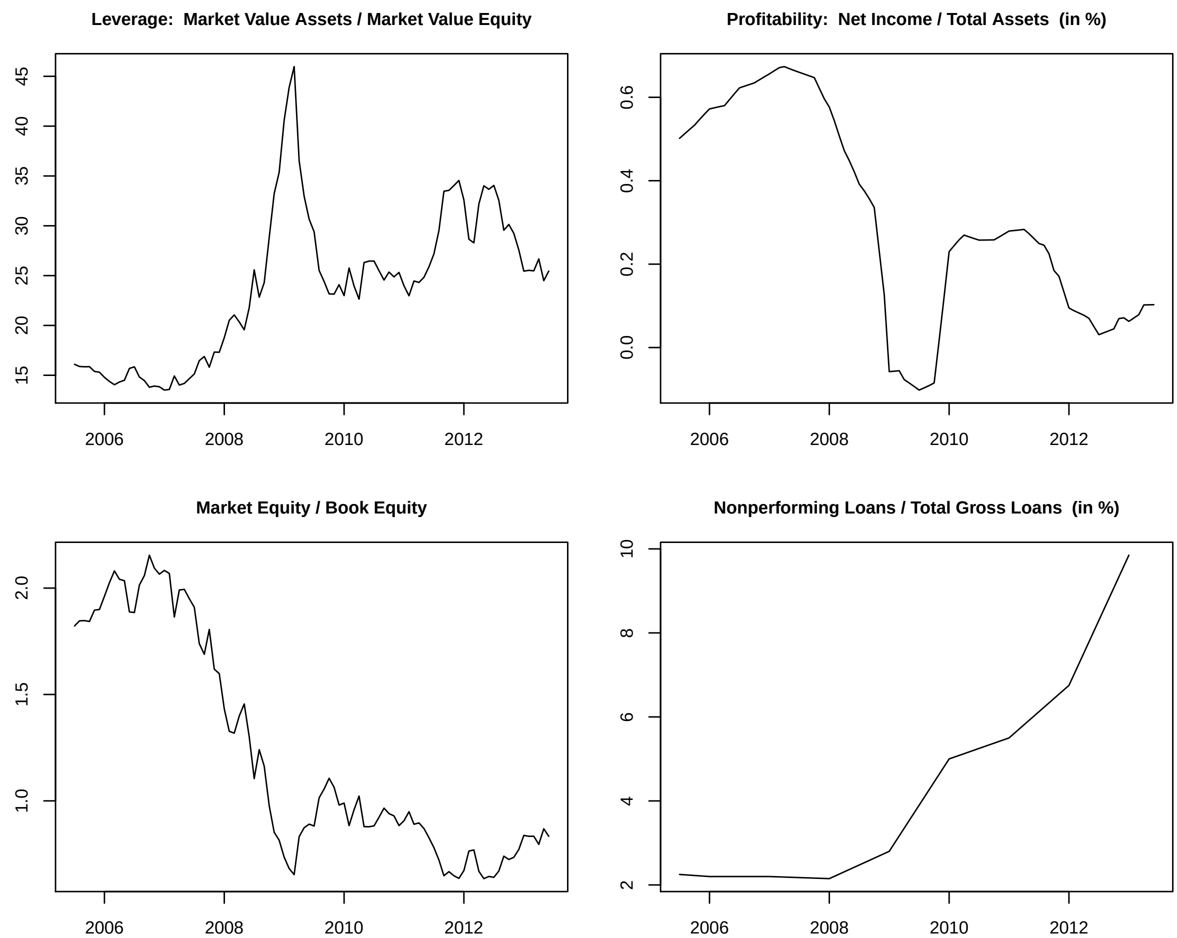

Figure 3.5 – Time evolution of bank balance sheet variables
The figure presents monthly, linearly interpolated time series of characteristic bank balance sheet variables averaged across all 86 sample banks. The time series of observations cover the period from July 2005 to June 2013. Market values, book values, and total assets are obtained from Datastream; data on nonperforming loans is obtained from the Worldbank's database.

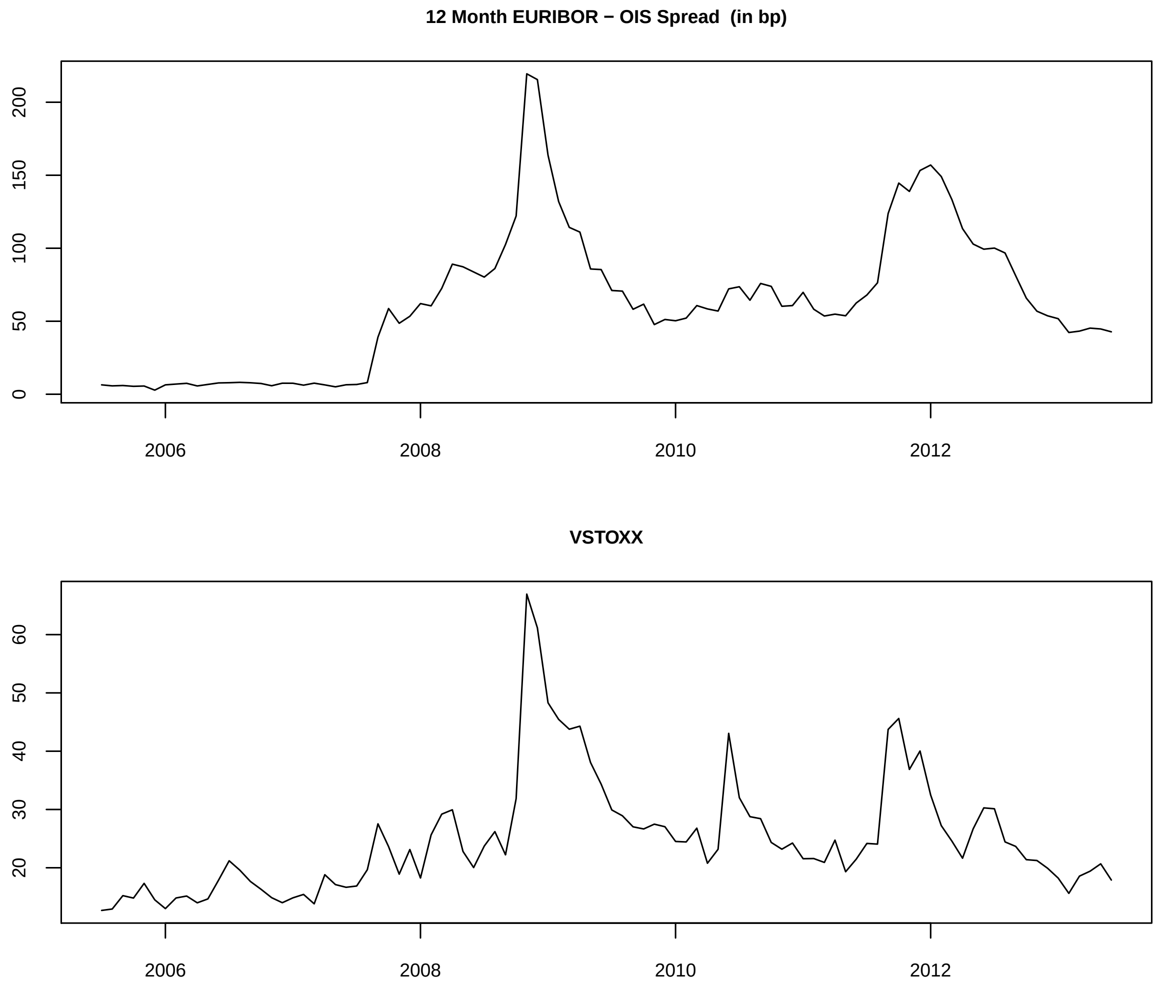

Figure 3.6 – Time evolution of financial market variables
The figure presents monthly time series of the VSTOXX index and the 12 month EURIBOR-OIS spread calculated as the difference between the 12 month EURIBOR and the Euro 12 month overnight index swap (OIS) rate. The time series of observations cover the period from July 2005 to June 2013. All data are obtained from Datastream.

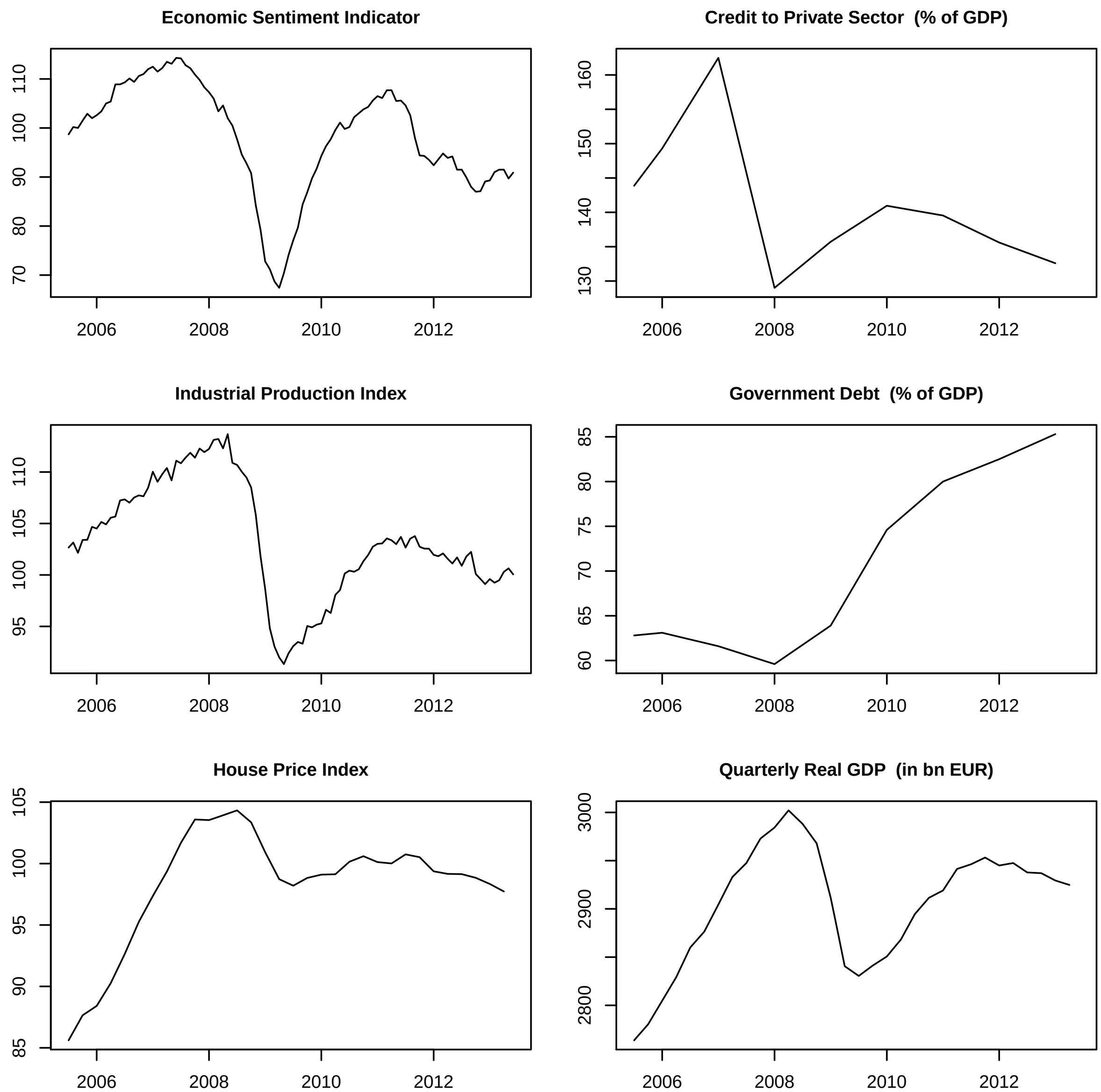

Figure 3.7 – Time evolution of macro-economic variables
The figure presents monthly (linearly interpolated) time series of macro-economic data from the EU27. The time series of observations cover the period from July 2005 to June 2013. Data on government debt is obtained from the European Central Bank, data on credit to the private sector is obtained from the Worldbank's database, and all remaining data is from Datastream.

	FINANCIAL MARKET			BALANCE SHEET					MACRO-ECONOMY						
	Systemic Risk	EURIBOR-OIS Spread	Volatility	Systemic Risk	Leverage	Market-to-Book	Profitability	Nonperforming Loans	Systemic Risk	Sentiment	Production	House Prices	Credit Private	Government Debt	Real GDP
Panel A – MultiMES (in %)															
MultiMES	0.040	0.084 ***	3.521 ***	-0.012	-0.055	-0.004	-0.006 **	0.000	0.008	-0.448 ***	0.063	-0.052 ***	0.026	-0.004	-0.835 ***
EURIBOR-OIS Spread	1.537	0.175	-0.958												
Volatility	-0.083 ***	0.004	-0.035												
Leverage				0.014	0.384 **	-0.004	0.000	-0.002							
Market-to-Book				0.460	3.135	-0.041	0.011	-0.025							
Profitability				5.110	-4.571	0.060	0.685 ***	-0.438 ***							
Nonperforming Loans				-1.010	-2.912	0.108	0.018	0.982 ***							
Sentiment									0.068	0.400 ***	0.261 ***	0.029 **	0.021	-0.005	0.493 **
Production									-0.054	0.213	-0.260 **	0.027	-0.047	0.001	1.329 ***
House Prices									-0.288	1.256 *	0.121	0.804 ***	-0.341	-0.040	1.885
Credit Private									-0.028	-0.060	-0.136 *	0.009	0.885 ***	-0.007	-0.205
Government Debt									-0.463	2.192 ***	0.416	-0.173 **	-0.130	0.911 ***	-1.140
Real GDP									-0.001	0.008	0.076 ***	-0.004	0.007	-0.002	0.600 ***
R^2	0.091	0.521	0.486	0.024	0.139	0.031	0.473	0.935	0.011	0.531	0.570	0.891	0.796	0.924	0.870
p-value (F-statistic)	0.035	0.000	0.000	0.842	0.027	0.748	0.000	0.000	0.996	0.000	0.000	0.000	0.000	0.000	0.000
Panel B – SRISK (in *bn* EUR)															
SRISK	0.298 ***	0.094 ***	5.336 ***	0.265	0.881 *	-0.040 **	-0.018 ***	-0.004	0.222 *	-1.112 ***	-0.055	-0.034	0.134 *	0.007	-1.024 **
EURIBOR-OIS Spread	1.051	0.135	-2.775												
Volatility	-0.044 **	0.002	-0.146												
Leverage				0.091	0.269	0.000	0.002	-0.001							
Market-to-Book				2.295	8.610 *	-0.271	-0.074	-0.047							
Profitability				0.205	-5.227	0.024	0.635 ***	-0.436 ***							
Nonperforming Loans				-0.880	-3.216	0.127	0.021	0.983 ***							
Sentiment									-0.040	0.279 ***	0.266 ***	0.028 **	0.034	-0.004	0.383
Production									-0.148	0.269	-0.224 **	0.035 *	-0.053	0.000	1.349 ***
House Prices									0.010	0.912	0.123	0.813 ***	-0.359	-0.042	1.536
Credit Private									-0.081	-0.129	-0.136 *	0.012	0.885 ***	-0.007	-0.255
Government Debt									-0.032	1.925 **	0.319	-0.196 **	-0.085	0.915 ***	-1.333
Real GDP									0.020	0.011	0.070 ***	-0.005	0.009	-0.002	0.606 ***
R^2	0.108	0.339	0.489	0.104	0.180	0.089	0.492	0.933	0.127	0.642	0.582	0.881	0.800	0.924	0.862
p-value (F-statistic)	0.018	0.000	0.000	0.113	0.007	0.181	0.000	0.000	0.142	0.000	0.000	0.000	0.000	0.000	0.000
Panel C – ΔMultiCoVaR (in %)															
ΔMultiCoVaR	0.054	0.022 ***	1.524 ***	-0.012	-0.034	0.001	0.002	0.000	0.001	-0.209 ***	0.040	-0.005	-0.004	0.000	0.072
EURIBOR-OIS Spread	0.817	0.213	2.320												
Volatility	-0.077	0.003	-0.108												
Leverage				0.057	0.378 **	-0.004	0.000	-0.002							
Market-to-Book				-0.118	2.752	-0.012	0.058	-0.028							
Profitability				-0.628	-4.832	0.020	0.620 ***	-0.436 ***							
Nonperforming Loans				-2.839	-2.961	0.107	0.017	0.982 ***							
Sentiment									-0.112	0.359 ***	0.269 ***	0.028 **	0.020	-0.005	0.514 **
Production									0.218	0.202	-0.259 **	0.024	-0.044	0.001	1.259 ***
House Prices									1.520	1.351 *	0.103	0.807 ***	-0.340	-0.040	1.862
Credit Private									-0.182	-0.064	-0.134 *	0.011	0.883 ***	-0.007	-0.160
Government Debt									-0.170	2.325 ***	0.393	-0.166 *	-0.131	0.912 ***	-1.080
Real GDP									-0.081	0.015	0.075 ***	-0.003	0.007	-0.002	0.603 ***
R^2	0.028	0.221	0.329	0.018	0.139	0.029	0.445	0.935	0.052	0.517	0.571	0.870	0.795	0.924	0.853
p-value (F-statistic)	0.468	0.000	0.000	0.914	0.027	0.776	0.000	0.000	0.723	0.000	0.000	0.000	0.000	0.000	0.000

Table 3.7 – VAR results (full sample) – Part I

Table 3.7 – continued:
All figures are estimated from monthly averaged time series of systemic risk measures at the banking system level and monthly (linearly interpolated) time series of financial market, aggregate balance sheet, and macro-economic variables covering the period from July 2005 to June 2013. We estimate the VAR system $\Delta y_t = a + B\Delta y_{t-1} + \epsilon_t$ with $y_t \equiv (SysRisk_t^{sys}, x_t)'$, where $SysRisk_t^{sys}$ represents any of the three systemic risk measures MultiCoVaR, MultiMES or SRISK at the banking system level and x_t is the vector of financial market, balance sheet or macro-economic variables. Parameter vector a denotes the intercepts, B is the coefficient matrix of the lagged regression variables y_{t-1}, and ϵ_t is a vector of standard Gaussian error terms. The Δs indicate that we are running the regression in first differences. The table is organized as follows. Panel A presents the results for the VAR systems with $SysRisk$ = MultiMES, Panel B the results for $SysRisk$ = SRISK, and Panel C the results for $SysRisk$ = ΔMultiCoVaR. The names of the lagged explanatory variables to which the regression coefficients refer are given in the respective rows and the dependent variables' names are given in the respective column headers. For a detailed description of the regression variables, we refer to Table 3.6. For ease of exposition, we suppress the intercepts' values. The regression coefficients are assigned asterisks if they are statistically significant. (*** = 1%-confidence level; ** = 5%-confidence level; * = 10%-confidence level)

Table 3.7 exhibits the results obtained for our estimated VAR systems on financial market, balance sheet, and macro-economic variables and is organized as follows: Panel A contains the results for the MultiMES, Panel B the results for the SRISK, and Panel C the results for the ΔMultiCoVaR regressions. Each column represents an estimated regression equation with the lagged explanatory variables given in the rows.

The regression of lagged financial market data on the systemic risk measures reveals that volatility possesses significant explanatory power for the MultiMES and SRISK measures. On the one hand, the negative coefficients indicate that an increase in volatility should result in lower levels of systemic risk. On the other hand, the systemic risk measures load significantly positive on volatility. This mechanism can be explained as follows: Systemic risk measures are capable of capturing distress before it is transmitted to the stock market. After distress (as measured by the systemic risk measures) is transmitted and realized as volatility at the financial market, the level of systemic risk declines. Interestingly, all three risk measures possess explanatory power for the EURIBOR-OIS spread, which itself may be considered as a proxy for systemic risk in the banking system. However, the opposite effect does not prevail, again suggesting that our systemic risk measures indicate financial distress earlier than the interest rate spreads.[21]

In Section 3.5.1 we analyzed the influence of balance sheet characteristics on systemic

[21] This result is in line with Rodriguez-Moreno and Peña (2013) who find that systemic risk measures based on principal components analysis and CDS spreads outperform LIBOR spread measures at the banking system level. We also performed one regression in which we applied the 3 month EURIBOR-OIS spread instead of its 12 month counterpart and another regression in which we include both spreads. However, the obtained results do not vary substantially.

risk measures at the bank level and found that total assets and leverage possess substantial additional predictive power. Turning towards aggregate balance sheet characteristics at the banking system level, we find that these do not possess significant additional predictive power for either of the three systemic risk measures. Thus, at the banking system level, balance sheet characteristics are not useful as leading indicators for the level of systemic risk carried in the financial system.

Nevertheless, the MultiMES and SRISK measures possess substantial predictive power for profitability at the banking system level. The negative coefficient indicates that a spike in systemic risk results in a decrease in profitability. Moreover, SRISK adds predictive power to banking system level balance sheet characteristics such as the market-to-book ratio of equity and leverage. The negative coefficient for leverage indicates that systemic events are linked to periods of significant losses resulting in a reduction of the banks' equity cushion. Thus, average leverage in the banking system increases.

In the right hand part of Table 3.7, we analyze interdependencies between macro-economic variables and systemic risk measures. Distress in the banking system may adversely affect the real economy, e.g., through a credit crunch as banks act as important suppliers of credit. Thus, systemic risk measures should – to some extent – anticipate output drops in the real economy and add further explanatory power to macro-economic forecasts.

Indeed, our results in Table 3.7 show that systemic risk measures possess significant predictive power for a range of macro-economic variables. Most importantly, the MultiMES and SRISK measures are able to forecast significant drops in real GDP. E.g., a monthly one percentage point increase in MultiMES explains a drop in monthly GDP of around €$0.8bn$, which converts to a drop of around €$10bn$ a year. ΔMultiCoVaR is less adequate for the prediction of future GDP. In fact, the estimated relationship is positive, though the coefficient is insignificant. All three systemic risk measures possess significant predictive power for economic sentiment. An increase in the systemic risk measures forecasts a drop in the European Commission's economic sentiment indicator.

Moreover, MultiMES loads significantly negative on house prices. Thus, an increase in MultiMES predicts future drops in house prices. This finding might be attributed to the specific house price dynamics during the Subprime Crisis where housing prices acted as a main driver of systemic risk (Longstaff, 2010).

	FINANCIAL MARKET			BALANCE SHEET				MACRO-ECONOMY					
	Systemic Risk	EURIBOR-OIS Spread	Volatility	Leverage	Market-to-Book	Profitability	Nonperforming Loans	Sentiment	Production	House Prices	Credit Private	Government Debt	Real GDP
Panel A – MultiMES (in %)													
MultiMES	-0.034	0.078***	2.873***	-0.035	-0.004	-0.005**	0.000	-0.279**	0.100	-0.048***	0.017	0.000	-0.709***
EURIBOR-OIS Spread	1.301	0.074	0.186	1.296	-0.050	-0.060**	-0.018	-1.966	0.348	-0.292*	0.560	-0.163*	-0.554
Volatility	-0.085**	0.004	-0.106	-0.053	0.002	0.000	-0.001	-0.016	-0.017	0.007*	-0.015	0.000	0.045
Leverage	0.064	0.002	0.410	0.296	-0.004	0.001	-0.001	-0.480***	-0.183**	-0.034**	-0.037	0.002	-1.256***
Market-to-Book	1.097	-0.133	-20.361**	1.982	-0.099	0.015	-0.010	-4.489	-2.654	-0.490	-1.537	-0.130	-19.628***
Profitability	13.940**	0.436	-2.115	0.348	-0.325	0.433***	-0.430***	1.862	1.996	0.421	-0.589	-1.636***	21.424*
Nonperforming Loans	-2.147	-0.316*	-0.632	-1.458	0.115	0.036	0.967***	-0.342	0.428	-0.385	-0.169	-0.034	-6.693
Sentiment	-0.060	-0.005	0.258	-0.190	0.006	-0.001	0.001	0.115	0.175**	0.020	0.026	0.002	0.120
Production	-0.032	0.019	1.067*	-0.360	0.014	0.004	0.001	0.042	-0.341***	0.015	-0.063	0.008	0.781**
House Prices	-0.596	-0.057	0.378	-0.581	0.003	0.024*	-0.020	1.193*	0.148	0.749***	-0.295	-0.002	0.799
Credit Private	-0.016	-0.001	0.379	-0.001	0.015*	0.000	0.000	0.021	-0.088	0.013	0.906***	-0.008	0.069
Government Debt	-0.564	0.019	-1.116	-0.174	-0.005	0.029**	-0.013	2.350***	0.375	-0.178**	-0.073	0.982***	-1.639
Real GDP	-0.016	0.004	-0.076	0.087	-0.001	0.001	0.001	0.061	0.089***	-0.002	0.007	0.000	0.648***
R^2	0.165	0.602	0.623	0.194	0.135	0.601	0.943	0.650	0.616	0.904	0.803	0.947	0.909
p-value (F-statistic)	0.339	0.000	0.000	0.183	0.557	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel B – SRISK (in *bn* EUR)													
SRISK	0.325	0.141***	6.362***	1.133**	-0.046**	-0.010*	-0.001	-1.269***	0.073	0.006	0.268**	0.013	-0.523
EURIBOR-OIS Spread	0.813	0.015	-2.680	0.503	-0.020	-0.055**	-0.017	-1.192	0.372	-0.313*	0.406	-0.169*	-0.522
Volatility	-0.048**	0.004	-0.149	-0.057	0.003	0.000	-0.001	-0.010	-0.018	0.007*	-0.017	0.000	0.051
Leverage	0.099	-0.004	0.011	0.126	0.002	0.002	0.000	-0.339**	-0.165**	-0.041**	-0.071	0.001	-1.303***
Market-to-Book	2.943	0.419	6.120	8.048	-0.337	-0.027	-0.016	-10.330***	-2.287	-0.311	-0.152	-0.059	-20.500***
Profitability	2.542	0.891	10.449	-3.757	-0.218	0.407***	-0.426***	2.519	2.835	-0.167	-1.361	-1.691***	14.697
Nonperforming Loans	-0.325	-0.293	1.029	-1.256	0.112	0.035	0.969***	-0.472	0.365	-0.427*	-0.021	-0.022	-6.746
Sentiment	-0.072	-0.006	0.191	-0.231	0.007	-0.001	0.001	0.148	0.192***	0.021	0.015	0.001	0.101
Production	-0.106	0.016	0.840	-0.476*	0.017	0.004	0.001	0.140	-0.308***	0.019	-0.086	0.007	0.737*
House Prices	0.033	-0.036	1.187	-0.273	-0.011	0.022	-0.021	0.865	0.154	0.778***	-0.271	-0.003	0.791
Credit Private	-0.100	0.001	0.385	0.009	0.014*	0.000	0.000	-0.001	-0.085	0.017	0.899***	-0.009	0.058
Government Debt	0.084	0.037	0.207	0.406	-0.024	0.028*	-0.013	1.899**	0.292	-0.162*	0.060	0.989***	-1.440
Real GDP	0.015	0.004	0.001	0.122*	-0.002	0.001	0.001	0.036	0.081***	-0.002	0.017	0.000	0.663***
R^2	0.205	0.478	0.571	0.251	0.194	0.591	0.941	0.704	0.620	0.897	0.810	0.947	0.900
p-value (F-statistic)	0.167	0.000	0.000	0.050	0.214	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel C – ΔMultiCoVaR (in %)													
ΔMultiCoVaR	-0.005	0.012	0.995***	-0.012	0.000	0.001	0.000	-0.132*	0.078*	0.000	-0.024	-0.004	0.332**
EURIBOR-OIS Spread	0.047	0.133	3.433	1.256	-0.053	-0.060**	-0.018	-2.352	0.548	-0.312*	0.521	-0.172*	-0.211
Volatility	-0.088	0.004	-0.167	-0.052	0.002	0.000	-0.001	-0.008	-0.021	0.007*	-0.014	0.000	0.031
Leverage	0.178	0.015	0.877*	0.290	-0.005	0.000	-0.001	-0.524***	-0.168**	-0.042***	-0.033	0.002	-1.382***
Market-to-Book	2.270	-0.134	-11.013	1.867	-0.097	0.046	-0.011	-6.006*	-1.588	-0.356	-1.985	-0.205	-12.099*
Profitability	4.488	1.323**	29.141	-0.038	-0.367	0.371***	-0.427***	-1.069	2.954	-0.149	-0.313	-1.624***	12.014
Nonperforming Loans	-1.968	-0.310	-0.192	-1.463	0.115	0.036	0.967***	-0.396	0.458	-0.386	-0.176	-0.035	-6.609
Sentiment	-0.198	-0.002	0.398	-0.192	0.006	-0.001	0.001	0.101	0.181***	0.018	0.026	0.002	0.090
Production	0.321	0.027	1.278*	-0.363	0.013	0.003	0.001	0.025	-0.338***	0.010	-0.059	0.008	0.675*
House Prices	1.455	-0.079	-0.676	-0.568	0.004	0.025*	-0.020	1.309*	0.094	0.760***	-0.290	0.000	0.830
Credit Private	-0.200	-0.002	0.297	0.000	0.015*	0.000	0.000	0.032	-0.094	0.013	0.908***	-0.008	0.043
Government Debt	0.140	-0.029	-2.913	-0.152	-0.003	0.032**	-0.013	2.527***	0.310	-0.149	-0.082	0.983***	-1.228
Real GDP	-0.086	0.001	-0.179	0.088	0.000	0.001	0.001	0.070*	0.085***	0.000	0.007	0.000	0.675***
R^2	0.103	0.350	0.458	0.194	0.133	0.580	0.943	0.643	0.624	0.890	0.804	0.947	0.906
p-value (F-statistic)	0.790	0.001	0.000	0.184	0.575	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 3.8 – VAR results (full sample) – Part II

Table 3.8 – continued:
All figures are estimated from monthly averaged time series of systemic risk measures at the banking system level and monthly (linearly interpolated) time series of financial market, aggregate balance sheet, and macro-economic variables covering the period from July 2005 to June 2013. We estimate the VAR system $\Delta y_t = a + B\Delta y_{t-1} + \epsilon_t$ with $y_t \equiv (SysRisk_t^{sys}, x_t)'$, where $SysRisk_t^{sys}$ represents any of the three systemic risk measures MultiCoVaR, MultiMES or SRISK at the banking system level and x_t is the vector comprising all financial market, balance sheet, and macro-economic variables. Parameter vector a denotes the intercepts, B is the coefficient matrix of the lagged regression variables y_{t-1}, and ϵ_t is a vector of standard Gaussian error terms. The Δs indicate that we are running the regression in first differences. The table is organized as follows. Panel A presents the results for the VAR systems with $SysRisk$ = MultiMES, Panel B the results for $SysRisk$ = SRISK, and Panel C the results for $SysRisk$ = ΔMultiCoVaR. The names of the lagged explanatory variables to which the regression coefficients refer are given in the respective rows and the dependent variables' names are given in the respective column headers. For a detailed description of the regression variables, we refer to Table 3.6. For ease of exposition, we suppress the intercepts' values. The regression coefficients are assigned asterisks if they are statistically significant. (*** = 1%-confidence level; ** = 5%-confidence level; * = 10%-confidence level)

The previous analysis was dedicated to the real effects of systemic risk. In the following, we analyze whether macro-economic variables potentially drive systemic risk. We would expect output-related macro-economic variables, such as real GDP and production, to be less capable of forecasting systemic risk because drops in GDP usually occur after systemic risk materializes as a consequence of distress in the banking system. However, an increase in sovereign debt (expressed as a percentage of GDP) is likely to result in a higher risk of sovereign default, which could then be reflected in the banks' systemic risk estimates. Our results show that SRISK and ΔMultiCoVaR – despite being insignificant – indeed do capture this effect. Though in general the signs of the macro-economic variables' regression coefficients are as expected, none of them possesses significant explanatory power for systemic risk, which is in line with our initial expectation that systemic risk is a latent leading variable.[22]

As a robustness check, we perform a regression in which we include all financial market, balance sheet, and macro-economic variables. Our results do not change substantially. An increase in profitability now possesses significant forecasting power for systemic risk. This result is intuitive because higher profitability usually points towards higher leverage and higher risk. The degree to which the systemic risk measures are able to forecast systemic risk also changes slightly. The coefficient for real GDP becomes insignificant in the SRISK regression (Panel B) and even significantly positive in the ΔMultiCoVaR re-

[22] As an exercise, we perform regressions including unemployment and inflation in our set of macro-economic variables. However, both variables' regression coefficients are insignificant in both directions.

gression (Panel C). Moreover, the ΔMultiCoVaR measure loads positively on production. Overall, our results suggest that the ΔMultiCoVaR measure is less valuable for macroeconomic forecasts and thus, regulatory authorities should be aware of the sometimes dubious regression coefficients' signs.

To analyze if our previous results hold for both crisis periods individually, we perform the regression of Equation (3.14) for the first half (July 2005 – June 2009) and the second half of our sample (July 2009 – June 2013) separately. We henceforth refer to the first half of the sample as the "Subprime Crisis sample" and to the second half of the sample as the "Euro Crisis sample".

Table 3.9 exhibits the results for the Subprime Crisis sample. In general, our results of Table 3.7 are confirmed and even stronger. The significance of an increase of MultiMES on house prices increases beyond the 1%-level and the SRISK measure now loads significantly on house prices at the 5%-level. Our results furthermore shed light on the evolution of the construction boom and the subsequent burst of the housing price bubble in southern European countries that coincided with the US Subprime crisis. The VAR framework captures the dynamics between house prices and systemic risk in the banking system well. As indicated by the regressions in column 13 (house prices), increases in the risk measures predict subsequent drops in house prices (that are significant for the MultiMES and SRISK measures). This drop is then followed by a further increase in systemic risk. The results also indicate that for the Subprime Crisis sample, the EURIBOR-OIS spread acts as a significant leading indicator for the SRISK measure. This is intuitive since turmoil in the financial markets was highest when the interbank lending market dried up. Thus, a liquidity risk proxy such as the EURIBOR-OIS spread is well suited to predict systemic risk during a liquidity crunch. For other crisis scenarios, however, the implemented risk measures are likely to indicate financial distress earlier than interest rate spreads (see, e.g., Tables 3.7 and 3.10).

Table 3.10 exhibits the results for the Euro Crisis sample. Most importantly, the systemic risk measures lose their predictive power for house prices. This is intuitive because at the start of the Euro Crisis, the burst of the housing price bubble had already materialized at the financial market. Compared to Tables 3.7–3.9, the overall significance of the coefficients is much weaker. Increases in systemic risk measures no longer predict drops in real GDP. However, the MultiMES and ΔMultiCoVaR measures reflect that increases in GDP result in a decrease in systemic risk. All systemic risk measures continue to possess predictive power for economic sentiment. I.e., an increase in systemic risk leads to a decrease in economic sentiment.

	FINANCIAL MARKET			BALANCE SHEET					MACRO-ECONOMY						
	Systemic Risk	EURIBOR-OIS Spread	Volatility	Systemic Risk	Leverage	Market-to-Book	Profitability	Nonperforming Loans	Systemic Risk	Sentiment	Production	House Prices	Credit Private	Government Debt	Real GDP
Panel A – MultiMES (in %)															
MultiMES	0.065	0.096 ***	3.518 ***	-0.113	-0.012	-0.010	-0.004	0.001	0.020	-0.484 ***	-0.011	-0.065 ***	0.046	-0.003	-1.321 ***
EURIBOR-OIS Spread	2.225	0.084	-1.410												
Volatility	-0.123 **	0.005	0.019												
Leverage				0.083	0.137	0.006	0.000	0.000							
Market-to-Book				-0.247	0.087	0.021	0.023	0.006							
Profitability				12.123	-26.726 **	0.838	0.576 ***	-0.424 ***							
Nonperforming Loans				3.567	-15.699 **	0.426	-0.061	0.933 ***							
Sentiment									0.204	0.327	0.326 ***	0.037 *	0.072	-0.003	0.586
Production									-0.139	0.471	-0.301 **	0.032	-0.074	0.002	1.849 ***
House Prices									-0.901	1.825	0.215	0.762 ***	-0.787	-0.120	2.375
Credit Private									-0.049	-0.080	-0.175 *	0.004	0.894 ***	-0.003	-0.242
Government Debt									-0.246	2.773	1.354	-0.129	-0.533	0.797 ***	-1.146
Real GDP									0.022	-0.014	0.095 ***	-0.002	0.013	-0.002	0.506 ***
R^2	0.130	0.628	0.586	0.055	0.315	0.077	0.387	0.934	0.050	0.504	0.678	0.919	0.801	0.916	0.904
p-value (F-statistic)	0.115	0.000	0.000	0.801	0.008	0.653	0.001	0.000	0.956	0.000	0.000	0.000	0.000	0.000	0.000
Panel B – SRISK (in *bn* EUR)															
SRISK	0.305 **	0.099 ***	5.511 ***	0.422	1.068 *	-0.057 *	-0.024 ***	-0.001	0.199	-1.057 ***	-0.095	-0.069 **	0.226	0.010	-1.759 **
EURIBOR-OIS Spread	2.861 **	-0.032	-6.764												
Volatility	-0.090 **	0.007	0.065												
Leverage				0.055	0.027	0.008	0.001	0.000							
Market-to-Book				2.998	6.503	-0.302	-0.112	-0.006							
Profitability				-3.100	-27.373 ***	0.630	0.489 ***	-0.399 ***							
Nonperforming Loans				-2.550	-16.799 ***	0.417	-0.072	0.945 ***							
Sentiment									-0.043	0.228	0.343 ***	0.036	0.100	-0.002	0.431
Production									-0.170	0.466 *	-0.248 *	0.034	-0.077	0.000	1.659 **
House Prices									-0.579	0.908	0.115	0.729 ***	-0.702	-0.122	0.998
Credit Private									-0.074	-0.100	-0.171 *	0.010	0.894 ***	-0.003	-0.227
Government Debt									-0.363	1.210	1.136	-0.286	-0.353	0.797 ***	-4.356
Real GDP									0.038	-0.016	0.086 **	-0.006	0.013	-0.002	0.497 ***
R^2	0.232	0.317	0.534	0.152	0.370	0.152	0.465	0.932	0.182	0.564	0.708	0.916	0.809	0.917	0.890
p-value (F-statistic)	0.015	0.002	0.000	0.274	0.003	0.274	0.000	0.000	0.379	0.000	0.000	0.000	0.000	0.000	0.000
Panel C – ΔMultiCoVaR (in %)															
ΔMultiCoVaR	0.176	0.027 **	1.449 ***	-0.043	-0.080	0.003	0.002	-0.001	0.090	-0.143	0.076	-0.013	-0.022	-0.005	0.121
EURIBOR-OIS Spread	3.148	0.214	6.488												
Volatility	-0.176 *	0.003	-0.156												
Leverage				0.128	0.128	0.003	-0.001	0.000							
Market-to-Book				-2.538	-1.246	0.100	0.075	-0.008							
Profitability				1.833	-25.683 **	0.570	0.440 ***	-0.386 ***							
Nonperforming Loans				-6.661	-15.349 **	0.333	-0.108	0.946 ***							
Sentiment									-0.208	0.338	0.333 ***	0.039 *	0.068	-0.003	0.661
Production									-0.241	0.355	-0.319 **	0.015	-0.056	0.002	1.433 **
House Prices									1.627	1.796	0.270	0.762 ***	-0.809	-0.124	2.652
Credit Private									-0.075	-0.057	-0.162 *	0.008	0.886 ***	-0.004	-0.103
Government Debt									-1.891	2.241	1.267	-0.206	-0.450	0.799 ***	-3.079
Real GDP									-0.074	-0.017	0.091 **	-0.003	0.015	-0.002	0.473 ***
R^2	0.108	0.197	0.210	0.078	0.318	0.066	0.379	0.934	0.130	0.427	0.693	0.894	0.801	0.917	0.872
p-value (F-statistic)	0.183	0.026	0.019	0.643	0.007	0.728	0.001	0.000	0.584	0.002	0.000	0.000	0.000	0.000	0.000

Table 3.9 – VAR results (July 2005 – June 2009)

Table 3.9 – continued:
All figures are estimated from monthly averaged time series of systemic risk measures at the banking system level and monthly (linearly interpolated) time series of financial market, aggregate balance sheet, and macro-economic variables covering the period from July 2005 to June 2009. We estimate the VAR system $\Delta y_t = a + B\Delta y_{t-1} + \epsilon_t$ with $y_t \equiv (SysRisk_t^{sys}, x_t)'$, where $SysRisk_t^{sys}$ represents any of the three systemic risk measures MultiCoVaR, MultiMES or SRISK at the banking system level and x_t is the vector of financial market, balance sheet or macro-economic variables. Parameter vector a denotes the intercepts, B is the coefficient matrix of the lagged regression variables y_{t-1}, and ϵ_t is a vector of standard Gaussian error terms. The Δs indicate that we are running the regression in first differences. The table is organized as follows. Panel A presents the results for the VAR systems with $SysRisk$ = MultiMES, Panel B the results for $SysRisk$ = SRISK, and Panel C the results for $SysRisk$ = ΔMultiCoVaR. The names of the lagged explanatory variables to which the regression coefficients refer are given in the respective rows and the dependent variables' names are given in the respective column headers. For a detailed description of the regression variables, we refer to Table 3.6. For ease of exposition, we suppress the intercepts' values. The regression coefficients are assigned asterisks if they are statistically significant. (*** = 1%-confidence level; ** = 5%-confidence level; * = 10%-confidence level)

	FINANCIAL MARKET			BALANCE SHEET					MACRO-ECONOMY						
	Systemic Risk	EURIBOR-OIS Spread	Volatility	Systemic Risk	Leverage	Market-to-Book	Profitability	Nonperforming Loans	Systemic Risk	Sentiment	Production	House Prices	Credit Private	Government Debt	Real GDP
Panel A – MultiMES (in %)															
MultiMES	-0.045	0.058 ***	3.537 ***	-0.006	0.597 *	-0.011	-0.008 *	-0.007	-0.128	-0.449 *	0.217 *	-0.007	-0.010	-0.008	0.350
EURIBOR-OIS Spread	1.883	0.330 **	-2.422												
Volatility	-0.061 **	0.002	-0.081												
Leverage				0.136	1.323 ***	-0.028 *	-0.008	-0.024 ***							
Market-to-Book				6.644	40.561 **	-0.867 *	-0.272	-0.756 ***							
Profitability				4.066	21.749 **	-0.760 **	0.624 ***	-0.759 ***							
Nonperforming Loans				-1.562	-0.461	0.015	0.014	0.951 ***							
Sentiment									0.053	0.308 *	0.139 *	0.019	0.006	0.005	0.247
Production									0.125	-0.390	-0.286 *	0.043	0.008	0.008	0.742 *
House Prices									1.110	-0.454	0.744	0.635 ***	0.088	0.090	-0.157
Credit Private									-8.180	-3.088	-7.186 *	0.374	0.875	0.051	-18.869 *
Government Debt									8.355	7.122	8.231 **	-0.504	-0.069	0.771	21.573 *
Real GDP									-0.136 *	0.021	-0.020	0.009	-0.002	-0.001	0.604 ***
R^2	0.099	0.345	0.354	0.047	0.249	0.176	0.566	0.907	0.108	0.566	0.456	0.648	0.869	0.895	0.805
p-value (F-statistic)	0.221	0.000	0.000	0.882	0.064	0.216	0.000	0.000	0.776	0.000	0.003	0.000	0.000	0.000	0.000
Panel B – SRISK (in *bn* EUR)															
SRISK	0.182	0.091 ***	5.359 ***	-0.024	0.755	-0.012	-0.007	-0.002	0.130	-1.185 ***	0.118	0.009	-0.016	-0.012	0.064
EURIBOR-OIS Spread	-1.675	0.305 **	-4.015												
Volatility	-0.010	-0.001	-0.309 **												
Leverage				0.152	0.982 **	-0.022	-0.004	-0.021 **							
Market-to-Book				1.874	34.603 **	-0.739	-0.172	-0.643 **							
Profitability				4.219	18.721 *	-0.703 **	0.662 ***	-0.727 ***							
Nonperforming Loans				0.666	-1.053	0.025	0.019	0.952 ***							
Sentiment									0.048	0.198	0.176 **	0.018	0.003	0.003	0.303
Production									0.081	-0.164	-0.347 **	0.044	0.012	0.011	0.658
House Prices									0.775	-0.870	1.093	0.620 ***	0.075	0.080	0.449
Credit Private									5.865	0.211	-8.412 **	0.403	0.942 *	0.101	-20.746 *
Government Debt									-7.117	3.403	9.322 **	-0.519	-0.138	0.720	23.138 *
Real GDP									0.041	0.066	-0.037	0.009	-0.001	0.000	0.577 ***
R^2	0.113	0.443	0.486	0.070	0.202	0.153	0.530	0.902	0.131	0.741	0.411	0.648	0.870	0.896	0.798
p-value (F-statistic)	0.166	0.000	0.000	0.752	0.144	0.299	0.000	0.000	0.665	0.000	0.009	0.000	0.000	0.000	0.000
Panel C – ΔMultiCoVaR (in %)															
ΔMultiCoVaR	-0.019	0.018 ***	1.646 ***	0.146	0.188	-0.005	0.002	0.000	-0.095	-0.234 ***	0.011	-0.001	0.003	0.003	0.027
EURIBOR-OIS Spread	0.652	0.258	-7.276												
Volatility	-0.028	0.003	-0.070												
Leverage				0.882	1.136 **	-0.024	-0.005	-0.022 **							
Market-to-Book				39.682	36.244 **	-0.843 *	-0.063	-0.636 **							
Profitability				10.497	21.440 **	-0.776 **	0.685 ***	-0.730 ***							
Nonperforming Loans				-1.636	-0.483	0.016	0.013	0.950 ***							
Sentiment									0.128	0.236	0.172 **	0.018	0.004	0.003	0.301
Production									1.198 *	-0.220	-0.338 **	0.045	0.009	0.009	0.657
House Prices									4.242	-0.506	1.097	0.626 ***	0.058	0.067	0.384
Credit Private									0.872	-0.872	-8.311 **	0.409	0.931 *	0.093	-20.681 *
Government Debt									-3.642	4.901	9.154 **	-0.534	-0.108	0.743	23.078 *
Real GDP									-0.192	0.056	-0.036	0.009	-0.001	0.000	0.577 ***
R^2	0.003	0.275	0.538	0.089	0.211	0.184	0.541	0.902	0.148	0.615	0.400	0.647	0.869	0.895	0.798
p-value (F-statistic)	0.987	0.003	0.000	0.636	0.124	0.191	0.000	0.000	0.579	0.000	0.012	0.000	0.000	0.000	0.000

Table 3.10 – VAR results (July 2009 – June 2013)

Table 3.10 – continued:
All figures are estimated from monthly averaged time series of systemic risk measures at the banking system level and monthly (linearly interpolated) time series of financial market, aggregate balance sheet, and macro-economic variables covering the period from July 2009 to June 2013. We estimate the VAR system $\Delta y_t = a + B\Delta y_{t-1} + \epsilon_t$ with $y_t \equiv (SysRisk_t^{sys}, x_t)'$, where $SysRisk_t^{sys}$ represents any of the three systemic risk measures MultiCoVaR, MultiMES or SRISK at the banking system level and x_t is the vector of financial market, balance sheet or macro-economic variables. Parameter vector a denotes the intercepts, B is the coefficient matrix of the lagged regression variables y_{t-1}, and ϵ_t is a vector of standard Gaussian error terms. The Δs indicate that we are running the regression in first differences. The table is organized as follows. Panel A presents the results for the VAR systems with $SysRisk$ = MultiMES, Panel B the results for $SysRisk$ = SRISK, and Panel C the results for $SysRisk$ = ΔMultiCoVaR. The names of the lagged explanatory variables to which the regression coefficients refer are given in the respective rows and the dependent variables' names are given in the respective column headers. For a detailed description of the regression variables, we refer to Table 3.6. For ease of exposition, we suppress the intercepts' values. The regression coefficients are assigned asterisks if they are statistically significant. (*** = 1%-confidence level; ** = 5%-confidence level; * = 10%-confidence level)

The inferior predictive power of the measures during the Euro Crisis may be explained by the following two reasons: First, a result of the European Central Bank's government bond purchase program, the informativeness of the market-based measures might be biased. Second, the Euro Crisis can be – for the most part – regarded as a government debt crisis. In addition, the downturn in the real economy (that might be even reinforced by austere government spending policies) is – in contrast to the Subprime Crisis – much more concentrated in the peripheral Euro countries and thus less substantial for the European economy as a whole.

3.6 Summary and conclusion

In this paper we propose a framework to assess the potential of systemic risk measures as a monitoring tool for regulators. We compare three commonly cited systemic risk measures – the Marginal Expected Shortfall (MES), the related SRISK, and the Conditional Value at Risk (CoVaR) – in a DCC GARCH framework. We do so by investigating directionalities between the measures and several balance sheet, financial market, and macro-economic variables in a VAR system and assess the systemic risk measures' aptitude as a regulatory tool on the basis of their predictive power. Employing a representative sample of important European institutions, we ensure that the systemic risk measures are evaluated both by their perfomance in the Subprime Crisis *and* the Euro Crisis.

At the banking system level, we find that systemic risk measures possess substantial forecasting power for a variety of balance sheet (leverage, market-to-book ratio, and profitability), financial market (EURIBOR-OIS spread and volatility), and macro-economic variables (GDP, housing prices, and economic sentiment). At the individual bank level, systemic importance is well explained by an institutions' balance sheet characteristics. However, aggregate balance sheet characteristics cannot explain systemic risk at the banking system level. When evaluated in comparison to the MES related measures, the CoVaR's predictive power for financial market and macro-economic variables is rather poor and the direction of influence often misleading.

Our results have paramount implications. Regulators should rely on MES-based systemic risk measures as these possess superior predictive power compared to the commonly applied CoVaR. In the long run, more complex measures such as the SRISK tend to produce better results than simple market indicators such as interest rate spreads that are prone to capturing market conditions specific to certain types of crises.

3.A DCC GARCH

Recalling the bivariate return process from Equation (3.7) and the setup of the univariate GARCH(1,1) models from Equations (3.8a) and (3.8b), the following relationship holds:

$$\xi_{sys,t} = \epsilon_{sys,t} \tag{3.15a}$$

$$\xi_{i,t} = \rho_{i,sys,t}\epsilon_{sys,t} + \sqrt{1-\rho^2_{i,sys,t}}\epsilon_{i,t}. \tag{3.15b}$$

It is obvious that within the bivariate process the correlation variable $\rho_{sys,i,t}$ entirely captures the correlation between institution i and the banking system. Therefore, the residuals $\epsilon_{i,t}$ and $\epsilon_{sys,t}$ are uncorrelated by definition. However, this is not the case for the (correlated) residuals $\xi_{i,t}$ and $\xi_{sys,t}$ from the univariate GARCH(1,1) processes. This fact is used by Engle (2002) to estimate time-varying return correlations.

Using matrix notation the return vector of the market and institution i is given by

$$R_t = \Sigma_t^{\frac{1}{2}}\epsilon_t \tag{3.16}$$

where

$$\Sigma_t = \begin{bmatrix} \sigma^2_{sys,t} & \rho_{i,sys,t}\sigma_{i,t}\sigma_{sys,t} \\ \rho_{i,sys,t}\sigma_{i,t}\sigma_{sys,t} & \sigma^2_{i,t} \end{bmatrix} \tag{3.17}$$

is the covariance matrix of the return vector $R_t = (r_{sys,t}, r_{i,t})$ and $\Sigma_t^{1/2}$ the corresponding Cholesky transformation of Σ_t. The covariance matrix can be further decomposed to the following form:

$$\Sigma_t = D_t P_t D_t \tag{3.18a}$$

$$= \begin{bmatrix} \sigma_{sys,t} & 0 \\ 0 & \sigma_{i,t} \end{bmatrix} \begin{bmatrix} 1 & \rho_{i,sys,t} \\ \rho_{i,sys,t} & 1 \end{bmatrix} \begin{bmatrix} \sigma_{sys,t} & 0 \\ 0 & \sigma_{i,t} \end{bmatrix} \tag{3.18b}$$

with P_t representing the correlation matrix of the return vector R_t. Since the residuals $\xi_{i,t}$ and $\xi_{sys,t}$ have *zero* mean and *unit* variance, the covariance matrix of the return vector and the covariance matrix of the residuals are equivalents and can be used to calculate the time-varying correlation variable $\rho_{i,sys,t}$. Following Engle (2009), the bivariate DDC

GARCH model at time t is fully specified by:

$$\rho_{i,sys,t} = \frac{q_{i,sys,t}}{\sqrt{q_{i,i,t} q_{sys,sys,t}}} \tag{3.19a}$$

$$q_{i,sys,t} = (1-\alpha-\beta)\,\overline{q}_{i,sys} + \alpha\xi_{i,t-1}\xi_{sys,t-1} + \beta q_{i,sys,t-1} \tag{3.19b}$$

$$q_{sys,sys,t} = (1-\alpha-\beta)\,\overline{q}_{sys,sys} + \alpha\xi_{sys,t-1}\xi_{sys,t-1} + \beta q_{sys,sys,t-1} \tag{3.19c}$$

$$q_{i,i,t} = (1-\alpha-\beta)\,\overline{q}_{i,i} + \alpha\xi_{i,t-1}\xi_{i,t-1} + \beta q_{i,i,t-1} \tag{3.19d}$$

$$\overline{q}_{i,sys} = \frac{1}{n}\sum_{t=1}^{n} \xi_{i,t}\xi_{sys,t} \tag{3.19e}$$

where $\overline{q}$ is the average correlation within the sample period and the q values are the quasi-correlations extracted from residuals $\xi_{i,t}$ and $\xi_{sys,t}$. The decomposition of ρ_t into quasi-correlations ensures that the correlation matrix is positive definite. In analogy to the volatility GARCH models, the time-varying correlation of the DCC GARCH is heteroscedastic and depends on the lagged quasi-correlation values as well as on the lagged values of the GARCH(1,1) residuals $(\xi_{sys,t}, \xi_{i,t})$. Again, parameters α and β are estimated using the maximum likelihood method. For a detailed discussion of the DCC GARCH framework, we refer to Engle (2009).

3.B Time series diagnostics

We conduct several diagnostic checks for the time series employed in our regressions. Table 3.11 contains test results for the (monthly) series of aggregate systemic risk measures as well as the (monthly) series of financial market, balance sheet, and macro-economic variables. Table 3.12 displays the test results for the individual banks' series of daily log returns.

	SYSTEMIC RISK			FINANCIAL MARKET		BALANCE SHEET				MACRO-ECONOMY					
	MultiMES	SRISK	ΔMultiCoVaR	EURIBOR-OIS Spread	Volatility	Leverage	Market-to-Book	Profitability	Nonperforming Loans	Sentiment	Production	House Prices	Credit Private	Government Debt	Real GDP
Panel A – Unit roots & stationarity: Augmented Dickey-Fuller test															
p-value	0.990	0.788	0.990	0.990	0.990	0.987	0.969	0.705	0.529	0.780	0.867	0.721	0.699	0.177	0.509
statistic	-4.215	-2.885	-5.203	-4.147	-4.726	-4.002	-3.677	-2.684	-2.255	-2.867	-3.077	-2.724	-2.670	-1.399	-2.207
Panel B – Heteroscedasticity: Breusch-Pagan test															
p-value	0.840	0.870	0.876	0.943	0.779	0.517	0.007	0.951	0.000	0.891	0.577	0.102	0.000	0.954	0.555
statistic	0.041	0.027	0.024	0.005	0.079	0.421	7.202	0.004	24.825	0.019	0.310	2.674	23.388	0.003	0.348
Panel C – Auto-correlation: Durbin-Watson test															
p-value	0.941	0.006	0.749	0.002	0.785	0.001	0.370	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
statistic	2.008	1.452	1.955	1.387	1.965	1.345	1.832	0.698	0.229	0.720	1.301	0.213	0.230	0.109	0.210
Panel D – Non-normality: Jarque-Bera test															
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.397	0.000	0.006	0.018	0.000	0.787	0.000	0.111	0.000
statistic	572.167	33.903	39.231	808.111	607.850	68.634	1.846	394.547	10.344	8.006	47.433	0.480	30.112	4.399	70.487

Table 3.11 – **Time series diagnostics (first differences): *p*-values and test statistics**
The above table exhibits p-values of various statistical diagnostic tests on the first differenced monthly (interpolated) time series used in our regressions in Section 3.5. The financial market and balance sheet data are obtained from Datastream; the macro-economic data is obtained from the European Central Bank (government debt), the Worldbank (domestic credit to the private sector and nonperforming loans), and Datastream (all other macro-economic data). All time series of observations range from 2005 to 2013. The table is organized as follows: *Panel A* exhibits the results of the Augmented Dickey-Fuller test with the null hypothesis that the time series are stationary, i.e., there is no unit root. *Panel B* presents the results of the Breusch-Pagan test with the null hypothesis that the time series are homoscedastic, i.e., there is no heteroscedasticity. *Panel C* gives the results of the Durbin-Watson test with the null hypothesis that the time series exhibit no auto-correlation. *Panel D* presents the results of the Jarque-Bera test with the null hypothesis that the time series follow the Gaussian distribution.

Statistic	#series	mean	min	$q = 0.25$	$q = 0.50$	$q = 0.75$	max	$\#p : p < 0.1$ (in %)	$\#p : p < 0.05$ (in %)	$\#p : p < 0.01$ (in %)
Augmented Dickey-Fuller	86	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.00	0.00	0.00
Breusch-Pagan	86	0.1705	0.0000	0.0000	0.0004	0.2127	0.9883	70.93	62.79	55.81
Durbin-Watson	86	0.1617	0.0000	0.0001	0.0428	0.1792	0.9510	67.44	54.65	37.21
Jarque-Bera	86	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	100.00	100.00	100.00

Table 3.12 – Diagnostics of sample bank's daily log return series: p-values and test statistics
The above table exhibits p-values of various statistical diagnostic tests on the daily log return series. All stock price data are obtained from Datastream and the analyzed time series range from 2005 to 2013. We perform the following tests: the Augmented Dickey-Fuller statistic tests the null hypothesis that the time series are stationary, i.e., there is no unit root; the Breusch-Pagan statistic tests the null hypothesis that the time series are homoscedastic, i.e., there is no heteroscedasticity. The Durbin-Watson statistic tests the null hypothesis that the time series exhibit no auto-correlation and the Jarque-Bera statistic tests the null hypothesis that the time series follow the Gaussian distribution. Column one gives the abbreviations for the respective test statistics. Column two gives the number of series tested and thus the number of test results. Column three gives the mean p-value of the test results, columns four to eight the quantiles, and columns nine to eleven provide the percentage of test results significant at the 10%, 5%, and 1% confidence levels.

4 Are earthquakes less contagious than bank failures?

4.1 Introduction

Can stock market reactions following a natural disaster be just as contagious as stock market reactions arising from a shock with its origin in the financial markets? The last decades have shown that increasingly integrated international stock markets catalyze the propagation of financial shocks of various origins. Events such as *Black Monday* on October 19, 1987 or the terrorist attacks launched by Al-Qaeda on *September 11, 2001* demonstrate that, regardless of the nature of the event, substantial shocks have the potential to cause contagion to international stock markets.

This paper compares contagion arising from natural disasters and financial shocks. We define contagion as a *substantial, measurable increase in stock price comovement following an event* which is in line with a number of previous works (e.g., Claessens et al., 2001; Forbes and Rigobon, 2002). We focus on two events that are commonly recognized to have caused substantial economic cost both at the national and international level – the bankruptcy of the investment bank *Lehman Brothers* on September 15, 2008 and the Japanese *Tohoku earthquake* including the subsequent tsunami disaster and the nuclear accident at Fukushima Daiiachi.[1,2,3] In total, the *superdisaster* caused massive destruction of both financial and production capital and thus serves as an ideal object of investigation for the question of whether a natural disaster has the potential to cause contagion to the

[1] The term *Tohoku* refers to the Northeast of Japan's main island *Honshu* and represents the region that was most severely affected by the earthquake.

[2] The earthquake that was measured to be of magnitude 8.9 and therefore considered to be one of the strongest on record since the beginning of seismic measurement (Chang, 2011) triggered two further devastating disasters: a tsunami locally reaching a height of up to 133*ft* (at Miyako, Iwate, Tohoku) and a severe accident at the nuclear power plant *Fukushima Daiichi* which caused the radioactive contamination of vast areas of land. Aoki and Rothwell (2013) analyze various aspects of the accident at Fukushima Daiichi and classify the latter as one of the most serious nuclear disasters in history drawing comparisons to the Three Mile Island (March 1979) and Chernobyl (April 1986) nuclear accidents.

[3] The nearly simultaneous occurence of the Tohoku earthquake, the subsequent tsunami, and the nuclear accident at Fukushima Daiichi complicates disentagling the latter. Since the earthquake can be assumed to have triggered the subsequent disasters, we mostly refer to the three simultaneous disasters as the *Tohoku earthquake* for the ease of exposition. Bertero (2011) and Kushida (2012) provide comprehensive narratives and overviews on both disasters.

national and international stock markets to a degree that is comparable to an event such as the Lehman bankruptcy.

We study cross-country contagion for thirteen countries investigating industry-specific effects analyzing contagion at the individual stock price level. To evaluate the relative degree of contagion, we employ the Lehman bankruptcy as benchmark event. To the best of our knowledge, this study is the first to compare contagion arising from the Tohoku earthquake and the Lehman bankruptcy and thus one of the first to compare the impact of a disaster of natural cause to a disaster with its cause in the financial markets. Contrary to previous studies, we investigate contagion at the individual stock price level.

We find that contagion arising from both events is substantial. Whereas the Lehman bankruptcy was more contagious at the international level, the Tohoku earthquake's impact was particularly strong at the national level suggesting that contagion arising from natural disasters is most severe to the event country and thus more regional than contagion following a pure financial market shock. While the Lehman bankruptcy caused contagion to a wide range of industries and countries, the Tohoku earthquake primarily affected utilities and insurance stocks. Moreover, the Tohoku earthquake resulted in particularly strong contagion to the German and South African stock markets.

Our results' implications are paramount. Both the Tohoku earthquake and the Lehman bankruptcy caused substantial contagion to national and international stock markets. However, our results suggest that contagion arising from natural disasters is more regional than contagion arising from pure financial market shocks. We argue that this difference in global stocks' response is best explained by the distinct nature of contagion. Whereas natural disasters primarily affect (real) assets in the event region, financial market driven shocks may cause panics at the international stock markets triggering substantial drops in global stock prices. The results suggest that international supply chain disruptions arising from destroyed production facilities impact global stock only to a lesser degree than information-based shocks or panics. The results furthermore suggest that geographic diversification is less effective in post- than in pre-disaster periods.

The remainder of the paper is structured as follows: Section 4.2 surveys related literature, Section 4.3 describes the data applied to our analysis, and Section 4.4 explains the methodology employed for the assessment of contagion. In Section 4.5 we present our results and Section 4.6 deals with some robustness issues. Section 4.7 summarizes and concludes.

4.2 Literature survey

Our study contributes to various strands of literature. Literature on stock price comovement can be systemized into financial market integration literature and contagion literature. The liberalization of capital markets in the 1990s has precipitated a number of studies on the integration of international stock markets. Chou et al. (1994) find that US and Canadian stock price indexes are cointegrated with those of the largest European countries and that the degree of cointegration has even increased over time. Contrary, Kanas (1998) finds that the US stock market is not pairwisely cointegrated with any of the six analyzed European markets suggesting that the potential for diversification across the Atlantic is substantial.

Karolyi and Stulz (1996) study fundamental variables driving the comovement of US and Japanese Stocks. They find that macro-economic news and exchange rate shocks have no measurable impact on cross-market correlation. However, the latter increases in case the NIKKEI or the S&P 500 indexes incur substantial losses. Cashin et al. (1995) examine international integration of industrial and emerging country equity markets and find that cross-country linkages have strengthened with global shocks being most persistent.

In the aftermath of *Black Monday* on October 19, 1987, a series of papers documents contagious effects from the US on other national stock markets (e.g., King and Wadhwani, 1990; Hamao et al., 1990; Bertero and Mayer, 1990). It has been found that only a small proportion of contagion can be attributed to fundamental variables (King et al., 1994) inducing researchers to study contagion on the basis of correlation increases, following the definitions of Claessens et al. (2001) and Forbes and Rigobon (2002).

Calvo and Reinhart (1996) and Edwards (1998) explore contagious effects arising from the Mexican Peso Crisis in December 1994. Calvo and Reinhart (1996) find that the onset of the crisis increases stock price comovement in Latin America and Asia. However, the effects are found to be stronger regionally than globally suggesting that geographic proximity is one determinant of contagion. Edwards (1998) analyzes interest volatility contagion to Chile and Argentina in a GARCH framework. He finds that contagion is limited and can only be detected for Argentina but not for Chile. Kaminsky and Reinhart (2000) explore the role of trade and financial linkages for the emergence of conatgion and conclude that the latter are likely to be a major determinant. Moreover, they find evidence that contagion is more regional than global. Forbes (2004) investigates how the Asian flu and Russian virus affected firms around the world and finds that firms with sales exposures to crisis countries were significantly adversely affected. Thus, their results suggest that trade channels are crucial for the transmission of shocks.

Several studies investigate contagion on the basis of correlation increases. Collins and Biekpe (2003) analyze contagion to African equity markets in the aftermath of the Hong Kong stock market crash in October 2007. Lee et al. (2007) investigate contagion arising from the 2004 Indian Ocean earthquake and tsunami. They find no contagion on international stock prices but on some countries' foreign exchange markets. Adopting the methodology of Lee et al. (2007), Asongu (2012) explores contagion to 33 national stock and foreign exchange markets arising from the Japanese Tohoku earthquake but only finds limited contagion. However, emerging markets are found to be particularly prone to contagious effects confirming the widely held view that these markets are less resilient to financial shocks. Our study is methodologically closely linked to Lee et al. (2007) and Asongu (2012).

A series of empirical studies has documented increasing stock price correlation in time periods of high volatility (Longin and Solnik, 2001; Ang and Bekaert, 2002). In line with this notion, Loretan and English (2000) and Forbes and Rigobon (2002) argue that contagion tests based on correlation increases are prone to substantial heteroscedasticity biases and propose a method to correct correlation coefficients for volatility that we apply in the robustness section.

Lastly, this study contributes to the strands of literature on the economic impact of the Lehman bankruptcy and the Tohoku earthquake including the subsequent tsunami and nuclear disaster at Fukushima Daiichi. Whereas the number of studies on international stock market contagion resulting from the Lehman bankruptcy and the subsequent financial crisis is abundant (e.g., Hwang et al., 2010; Bekaert et al., 2011), corresponding research on contagious effects arising from natural disasters including the Tohoku earthquake remains scarce. To our knowledge, the only study to explore stock market and exchange rate contagion in the aftermath of the Tohoku earthquake so far is Asongu (2012). However, the latter study investigates contagion only at the index level.

Other existing literature on the Tohoku Earthquake and the nuclear disaster at Fukushima Daiichi primarily focuses on the economy. Noy (2011) analyzes the over-all impact of the Tohoku earthquake on economic activity in the context of other natural disasters comparable in magnitude. He argues that the economies of developed countries are much more resilient to natural disasters than the ones of developing countries. Nanto et al. (2011) provide a report on the consequences of the disasters on manufacturing as well as financial and currency markets. They predict that the superdisaster had a significant impact on the US economy through trade and supply chain disruptions increasing volatility in the financial markets.

Kawashima and Takeda (2012) investigate the effect of the nuclear accident at Fukushima Daiichi on electric power utilities in Japan and find that stock prices of utilities in charge of nuclear power plants dropped more sharply than those of utilities not in charge of such plants. Ferstl et al. (2012) extend the geographical scope examining the disasters' impact on French, German, Japanese, and US nuclear utility and alternative energy firms and generally find significant abnormal returns within the one-week post-event window except for US entities. Moreover, Lopatta and Kaspereit (2012) find that the share of nuclear power in an energy firm's portfolio is negatively related with the abnormal return following the accident.

Kojima (2011) examines the impact of the natural disaster on the Japanese housing market and Takao et al. (2013) study the effects on the value of Japanese insurance companies. In the post-eartquake period, they find abnormal returns for insurance stock with particularly strong effects for life insurers. However, high capital buffers and the *Earthquake Insurance System on Dwelling Risks* in Japan are found to have substantial stabilizing effects on the stock market (Takao et al., 2013).

4.3 Data

Our study is based on a broad cross-section of international stock prices and stock price indexes covering 4,350 stocks from 13 countries. We obtain all stock price data from Datastream. The time series of daily closing stock prices and stock price indexes cover the period from January 2006 to December 2012 and hence include both the Lehman bankruptcy on September 15, 2008 as well as the Tohoku Earthquake on March 11, 2011. Our study focuses on the Group of Eight (G8) countries as these are comparable with respect to the degree of development of their financial markets. To cover a wider global range of countries and to analyze regional effects arising from both events, we add Australia, Brazil, China, South Africa, and South Korea.[4]

Stocks are classified with respect to country of origin and industry. Datastream categorizes stocks according to the Industry Classification Benchmark (ICB) which sorts firms into the following ten industries: Oil & Gas, Basic Materials, Industrials, Consumer Goods, Health Care, Consumer Services, Telecommunications, Utilities, Financials, and Technology. With a total of 992 stocks, we have more observations for the Financial industry than for any other industry. For our later analyses, the distinction between banking and insurance stocks is worthwile such as to analyze contagious effects separately.

[4] Whereas Brazil, China, and South Africa are BRICS countries, we add South Korea because of its geographic proximity to Japan. Australia is added because it represents one of Japan's most important trade partners.

Country	Oil & Gas	Basic Materials	Industrials	Consumer Goods	Health Care	Consumer Services	Telecommunications	Utilities	Banks	Insurance	Real Estate	Financial Services	Technology	SUM
Panel A – In Absolute Terms														
Canada	49	53	32	9	2	27	6	13	8	9	20	15	7	250
United States	100	46	172	98	80	134	12	49	33	47	71	47	103	992
Brazil	3	12	11	12	1	12	5	18	7	3	7	7	1	99
France	8	9	49	38	20	35	1	8	9	5	26	16	24	248
Germany	4	20	62	35	19	26	4	9	7	7	14	15	25	247
Italy	6	2	41	22	5	14	4	13	17	10	3	16	4	157
Russian Federation	13	12	1	1	1	1	4	6	9	–	–	2	–	50
United Kingdom	23	32	101	31	13	79	7	7	6	19	33	163	21	535
South Africa	1	14	9	7	4	11	2	–	6	5	5	6	-	70
Australia	11	25	27	5	8	29	2	6	6	4	21	15	1	160
China & Hong Kong	13	80	100	59	42	35	2	21	24	9	22	22	19	448
Japan	10	87	225	176	67	160	6	19	71	6	66	36	66	995
South Korea	5	11	28	21	1	7	3	2	7	5	–	5	4	99
ALL	246	403	858	514	263	570	58	171	210	129	288	365	275	4,350
Panel B – In Percentage Terms														
Canada	19.6	21.2	12.8	3.6	0.8	10.8	2.4	5.2	3.2	3.6	8.0	6.0	2.8	100.0
United States	10.1	4.6	17.3	9.9	8.1	13.5	1.2	4.9	3.3	4.7	7.2	4.7	10.4	100.0
Brazil	3.0	12.1	11.1	12.1	1.0	12.1	5.1	18.2	7.1	3.0	7.1	7.1	1.0	100.0
France	3.2	3.6	19.8	15.3	8.1	14.1	0.4	3.2	3.6	2.0	10.5	6.5	9.7	100.0
Germany	1.6	8.1	25.1	14.2	7.7	10.5	1.6	3.6	2.8	2.8	5.7	6.1	10.1	100.0
Italy	3.8	1.3	26.1	14.0	3.2	8.9	2.5	8.3	10.8	6.4	1.9	10.2	2.5	100.0
Russian Federation	26.0	24.0	2.0	2.0	2.0	2.0	8.0	12.0	18.0	–	–	4.0	–	100.0
United Kingdom	4.3	6.0	18.9	5.8	2.4	14.8	1.3	1.3	1.1	3.6	6.2	30.5	3.9	100.0
South Africa	1.4	20.0	12.9	10.0	5.7	15.7	2.9	–	8.6	7.1	7.1	8.6	–	100.0
Australia	6.9	15.6	16.9	3.1	5.0	18.1	1.2	3.8	3.8	2.5	13.1	9.4	0.6	100.0
China & Hong Kong	2.9	17.9	22.3	13.2	9.4	7.8	0.4	4.7	5.4	2.0	4.9	4.9	4.2	100.0
Japan	1.0	8.7	22.6	17.7	6.7	16.1	0.6	1.9	7.1	0.6	6.6	3.6	6.6	100.0
South Korea	5.1	11.1	28.3	21.2	1.0	7.1	3.0	2.0	7.1	5.1	–	5.1	4.0	100.0
ALL	5.7	9.3	19.7	11.8	6.0	13.1	1.3	3.9	4.8	3.0	6.6	8.4	6.3	100.0

Table 4.1 – Sample composition by country and industry
The above table exhibits the composition of the sample of stocks by country and industry (Panel B). All data are obtained from Datastream. Panel A gives the distribution of the number of stocks per country and industry in absolute numbers and Panel B expresses these figures in percentage terms.

Thus, we split the Financial industry into the four ICB supersectors: Banks, Insurance, Real Estate, and Financial Services. For our subsequent analyses we employ the S&P 500 and the NIKKEI 225 indexes as base criteria. Both indexes cover a wide range of large caps ensuring a sector composition that is representative for their country's equity markets.[5]

[5] According to the Standard&Poor's website `http://www.spindices.com/indices/equity/sp-500`

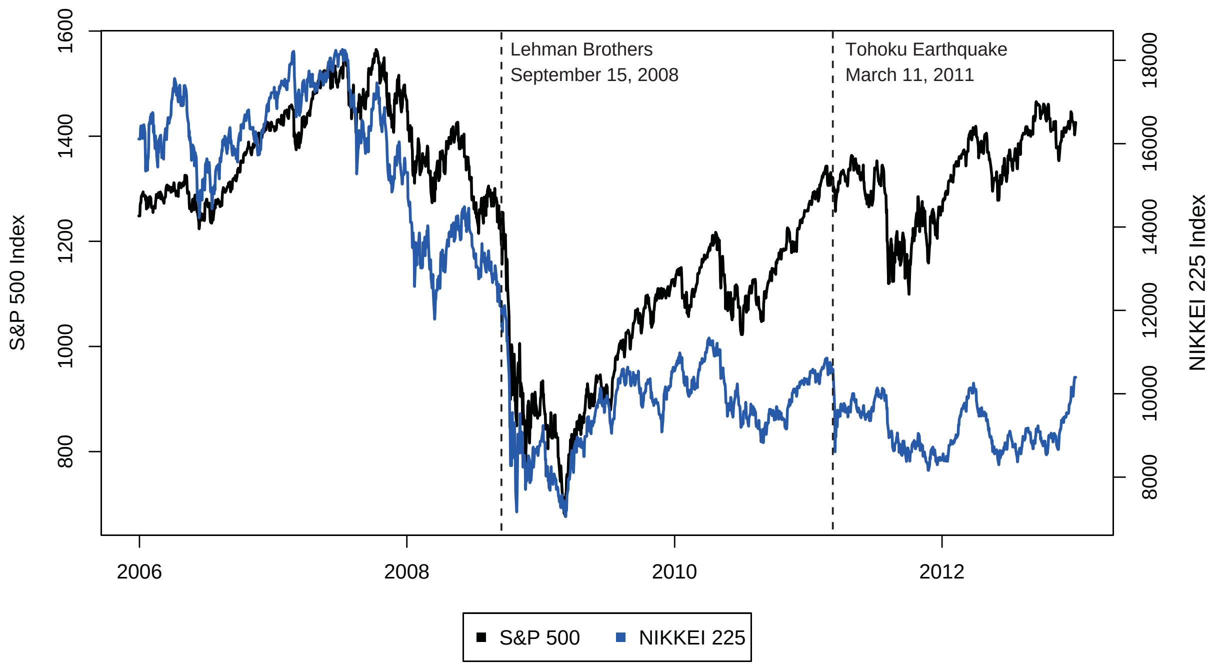

Figure 4.1 – Time evolution of daily S&P 500 and NIKKEI 225 stock market index levels
The figure presents the series of daily S&P 500 and NIKKEI 225 stock market index levels used in our analysis. All data are obtained from Datastream; the time series of observations cover the period from January 2006 to December 2012 and hence include both the Lehman Bankruptcy on September 15, 2008 as well as the Tohoku Earthquake on March 11, 2011.

Hence, the indexes ideally proxy the state of the United States' and Japanese stock markets.

Table 4.1 exhibits the composition of our sample providing the number of stocks per country and industry. According to Panel A, most stocks in our sample are from the United States or Japan. Most countries are represented by around 200 stocks. For the Russian Federation, we only have 50 stocks in our sample. However, with 55,033 observations for Russian stock returns, we are confident that our estimates reliably capture the dynamics in the Russian stock market. Table 4.1 furthermore reveals that the number of stocks is not evenly distributed across industries with 58 telecommunications stocks and 858 industrials stocks.

Figure 4.1 exhibits the time series of daily index levels of the S&P 500 and the NIKKEI 225 indexes in the period from January 2006 to December 2012. The Lehman

and the S&P 500 factsheet, the index covers approximately 75% of US equities with respect to market capitalization; no corresponding information can be found on the NIKKEI website `http://indexes.nikkei.co.jp/en/nkave/index`, however, around the globe the index is employed as a leading indicator for Japanese equity markets.

bankruptcy, which occured on September 15, 2008, marks a steep decline in stock prices for both indexes triggering a 25% drop of the NIKKEI 225 and the S&P 500 within the first post-event month. Moreover, the post-event period is characterized by high volatility levels. The Tohoku earthquake on March 11, 2011 and the subsequent nuclear disaster at Fukushima Daiichi triggered a 18% plunge of the NIKKEI 225 within the first few days following the disaster. Though no abnormal dynamics are visible for the S&P 500 for the same period, other stock price indexes suffered substantial drops.[6] We will discuss the stock market responses to both the Lehman bankruptcy and the Tohoku earthquake in Section 4.5.

4.4 Methodology

We measure contagion comparing cross-market stock price comovement from the pre- and post-event periods. Applying correlations as a measure for contagion, we examine if individual stocks' participation at index losses increases in the aftermath of an event. Put in other words, we investigate if the index' explanatory power for individual stock returns grows as a result of the events. This approach is in line with Claessens et al. (2001) and Forbes and Rigobon (2002) – see Section 4.1.

We define the pre-event period as the year prior to the event. Thus, the pre-Lehman-bankruptcy period is from September 14, 2007 to September 12, 2008 and the pre-Tohoku-earthquake period from March 11, 2010 to March 10, 2011, respectively.[7] We define the post-event period as the month subsequent to the event including the event day. Thus, the post-Lehman-bankruptcy period is from September 15 to October 15, 2008 and the post-Tohoku-earthquake period is from March 11 to April 11, 2011.

We measure stock price comovement in the pre- and post-event periods applying the *Pearson* correlation coefficient ρ given by

$$\rho_{ij} = \frac{\sigma_{ij}}{\sigma_i \sigma_j} = \frac{\frac{1}{T}\sum_{t=1}^{T}(r_{it} - \overline{r_i})(r_{jt} - \overline{r_j})}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(r_{it} - \overline{r_i})^2}\sqrt{\frac{1}{T}\sum_{t=1}^{T}(r_{jt} - \overline{r_j})^2}}, \tag{4.1}$$

[6] E.g., the German blue chip DAX 30 performance index suffered a drop of more than 8% within the first few days following the Tohoku earthquake.

[7] September 15, 2007 is a Saturday and September 14, 2008 is a Sunday. To account for this, we adapt the pre-Lehman-bankruptcy period as stated above.

with

$$\overline{r_i} = \frac{1}{T}\sum_{t=1}^{T} r_{it} \quad \text{and} \quad \overline{r_j} = \frac{1}{T}\sum_{t=1}^{T} r_{jt},$$

where r_{it} and r_{jt} denote the daily log returns of base criterion i and stock j; σ_i and σ_j denote the standard deviations and σ_{ij} is the covariance between base criterion i and stock j's daily log returns.

For both events we calculate the pre- $\left(\rho_{ij}^{pre}\right)$ and the post-event correlation $\left(\rho_{ij}^{post}\right)$ between base criterion i and all stocks j. Thus, for each event we obtain around 4,000 pre- and 4,000 post-event correlations subject to the availability of stock prices for the respective time interval. We then pool these estimates once with respect to stock j's industry $\boldsymbol{S}$, i.e. $\bigcup_j \rho_{ij}$ with $j \in \boldsymbol{S}$, and once with respect to stock j's country $\boldsymbol{R}$, i.e., $\bigcup_j \rho_{ij}$ with $j \in \boldsymbol{R}$. For the pooled estimates we compute means and medians and subsequently use these to test for contagion applying the following hypotheses:

$$H_0: \quad \widetilde{\rho_{ij,S}^{post}} - \widetilde{\rho_{ij,S}^{pre}} < 0 \ ; \qquad H_1: \quad \widetilde{\rho_{ij,S}^{post}} - \widetilde{\rho_{ij,S}^{pre}} > 0 \ , \tag{4.2a}$$

and

$$H_0: \quad \widetilde{\rho_{ij,R}^{post}} - \widetilde{\rho_{ij,R}^{pre}} < 0 \ ; \qquad H_1: \quad \widetilde{\rho_{ij,R}^{post}} - \widetilde{\rho_{ij,R}^{pre}} > 0 \tag{4.2b}$$

where $\widetilde{\rho_{ij,S}^{reg}}$ $\left(\widetilde{\rho_{ij,R}^{reg}}\right)$ denotes the mean or median correlation coefficient with respect to industry $\boldsymbol{S}$ (country $\boldsymbol{R}$) for either the pre-event or the post-event regime, i.e., $reg = \{pre, post\}$. A rejection of the null hypotheses indicates an increase in cross-market correlation that we interpret as contagion.

4.5 Results

We conduct two main analyses. We first investigate contagion at the industry level. This allows us to determine which industries are particularly prone to bank failures and earthquakes. Subsequently, we investigate contagion at the country level such as to identify geographical propagation channels of contagion.

4.5.1 Contagious effects by industry

In contrast to many previous event studies on the Lehman bankruptcy and the Tohoku earthquake including the subsequent nuclear disaster at Fukushima Daiichi, our analysis compares both events in a common framework analyzing contagious effects in all industries and thereby covering a multitude of countries. Whereas it is well documented in literature that real sector firms were strongly affected by banks' liquidity freezes following the Lehman bankruptcy, industries other than utilities and insurance were as well likely to have been affected by the Tohoku earthquake and the nuclear accident at Fukushima Daiichi, e.g., through disrupted supply chains resulting from the destruction of production facilities.

Table 4.2 displays the results of our industry analysis and reads as follows. Panel A displays our correlation estimates for the Lehman bankruptcy and Panel B the estimates for the Tohoku earthquake. Both panels are organized in the same fashion: Column 1 gives the name of the ICB industry to which the figures in columns 2–10 refer. Columns 2–4 display figures for the pre-event window and columns 5–7 exhibit figures for the post-event window. Column 8 reports the difference of means from columns 3 and 6, column 9 the *p*-value of the corresponding *t*-statistic, and column 10 the *p*-value of the Wilcoxon median difference test.

The numbers reveal that – as a result of the Lehman bankruptcy – correlations increase for all industries. The increase in correlation is especially steep for oil & gas (0.3848), utilities (0.2783), and basic materials (0.1965). Interestingly, the increase in correlation is substantially lower for stocks from financial firms (banks, insurance, real estate, and financial services). This result indicates that prior to the Lehman bankruptcy, the awareness of the risks prevalent in financial markets must have been substantially higher among financial firms than among real sector firms reflecting potential informational advantages of financial companies. For all industries, however, the increase in correlation is significant at the 1%-level. Overall, the Lehman bankruptcy leads to an increase in correlation of 0.1618.

The Tohoku earthquake also leads to significant correlation increases in a number of industries. The increases are most substantial for consumer services (0.1245), health care (0.1149), utilities (0.1110), telecommunications (0.1079), and consumer goods (0.0847) stocks, which is in line with reports on the destruction of manufacturing and power plants – either as a result of the earthquake or the subsequent tsunami (see, e.g., Noy, 2011). Oil & gas stocks are least affected by the Tohoku earthquake. However, this may be simply explained by the fact that stocks on Japanese oil firms only represent less than 5% of oil stocks in our sample. Moreover, insurance stock reacts less strongly to the earthquake.[8] The overall correlation (as indicated by the last row in Panel B) increases from 0.2698 to 0.3391 on average, which is significant at the 1%-level.

[8] We refer to footnote 10 on page 124.

	PRE PERIOD			POST PERIOD			STATISTICS		
Industry	# stocks	mean	median	# stocks	mean	median	Δmean	*t*-test	Wilcoxon
Panel A – Lehman Bankruptcy									
Oil & Gas	211	0.1913	0.1733	205	0.5761	0.6165	0.3848	0.0000	0.0000
Basic Materials	377	0.1252	0.0932	354	0.3217	0.2974	0.1965	0.0000	0.0000
Industrials	796	0.2183	0.1444	773	0.3625	0.3324	0.1442	0.0000	0.0000
Consumer Goods	469	0.1890	0.1270	456	0.3054	0.2550	0.1165	0.0000	0.0000
Health Care	235	0.1722	0.1348	225	0.3779	0.3951	0.2058	0.0000	0.0000
Consumer Services	523	0.2290	0.1650	511	0.3382	0.3211	0.1092	0.0000	0.0000
Telecommunications	54	0.2582	0.2475	53	0.4295	0.4718	0.1713	0.0030	0.0014
Utilities	163	0.2176	0.1895	153	0.4960	0.5730	0.2783	0.0000	0.0000
Banks	193	0.2428	0.1501	188	0.3458	0.3212	0.1030	0.0001	0.0001
Insurance	115	0.3796	0.3833	112	0.5108	0.5541	0.1312	0.0003	0.0001
Real Estate	268	0.2483	0.1662	253	0.3480	0.3648	0.0997	0.0002	0.0002
Financial Services	318	0.2347	0.1963	313	0.3886	0.3926	0.1539	0.0000	0.0000
Technology	256	0.2588	0.1912	254	0.4444	0.4608	0.1857	0.0000	0.0000
ALL	3,978	0.2156	0.1539	3,850	0.3773	0.3729	0.1618	0.0000	0.0000
Panel B – Tohoku Earthquake									
Oil & Gas	230	0.2129	0.1947	228	0.1575	0.1375	-0.0554	0.0102	0.0063
Basic Materials	391	0.2877	0.2390	381	0.3605	0.3230	0.0728	0.0011	0.0054
Industrials	838	0.3115	0.2536	815	0.3467	0.3085	0.0352	0.0160	0.2828
Consumer Goods	492	0.3033	0.2306	484	0.3880	0.3305	0.0847	0.0000	0.0006
Health Care	251	0.2123	0.1832	248	0.3272	0.2565	0.1149	0.0000	0.0013
Consumer Services	550	0.2511	0.2203	534	0.3756	0.3132	0.1245	0.0000	0.0000
Telecommunications	56	0.1896	0.1658	55	0.2975	0.2731	0.1079	0.0114	0.0866
Utilities	168	0.1929	0.2017	159	0.3039	0.2969	0.1110	0.0000	0.0000
Banks	201	0.3445	0.2917	196	0.4194	0.3896	0.0749	0.0144	0.1195
Insurance	123	0.2306	0.2036	121	0.2711	0.2802	0.0405	0.1190	0.0575
Real Estate	278	0.2096	0.1813	261	0.2926	0.2049	0.0831	0.0006	0.1871
Financial Services	344	0.2768	0.2776	329	0.3457	0.3258	0.0690	0.0001	0.0033
Technology	267	0.2736	0.2115	264	0.3289	0.2497	0.0554	0.0336	0.5768
ALL	4,189	0.2698	0.2248	4,075	0.3391	0.2917	0.0693	0.0000	0.0000

Table 4.2 – Cross-market correlations by industry (international stock incl. event country) The above table exhibits statistics of pre- and post-event correlations between individual stocks and the base criterion, calculated according to Expression (4.1). The correlations are estimated from series of daily log returns and pooled according to ICB industries across all countries *including* the event country. The *pre*-event period covers the year prior to the event and the *post*-event period the month subsequent to the event including the event day. Panel A displays estimates for the Lehman bankruptcy and Panel B estimates for the Tohoku earthquake applying the S&P 500 (Panel A) and the NIKKEI 225 stock market (Panel B) indexes as base criteria. Both panels are organized as follows: Column 1 gives the name of the ICB industry to which the figures in columns 2–10 refer. Columns 2–4 display pre-event figures and columns 5–7 post-event figures. Column 8 reports the residual between the industry-specific mean post-event (in column 6) and mean pre-event (in column 3) figures and column 9 the p-value of a t-test with the null hypothesis stating that *pre-event correlation equals post-event correlation*. Column 10 reports the p-value of the corresponding Wilcoxon median difference test. Each panel's last row exhibits international cross-industry averages.

Industry	PRE PERIOD # stocks	PRE PERIOD mean	PRE PERIOD median	POST PERIOD # stocks	POST PERIOD mean	POST PERIOD median	STATISTICS Δmean	STATISTICS *t*-test	STATISTICS Wilcoxon
Panel A – Lehman Bankruptcy									
Oil & Gas	85	0.3328	0.3287	85	0.8270	0.8451	0.4942	0.0000	0.0000
Basic Materials	45	0.5224	0.5602	45	0.7973	0.8514	0.2749	0.0000	0.0000
Industrials	160	0.5938	0.6205	160	0.7965	0.8205	0.2026	0.0000	0.0000
Consumer Goods	89	0.5156	0.5232	89	0.7412	0.7435	0.2256	0.0000	0.0000
Health Care	77	0.4006	0.3971	77	0.7739	0.8063	0.3732	0.0000	0.0000
Consumer Services	120	0.5528	0.5672	121	0.7407	0.7858	0.1879	0.0000	0.0000
Telecommunications	12	0.5239	0.5459	12	0.8649	0.8878	0.3411	0.0000	0.0000
Utilities	49	0.5039	0.5229	49	0.8067	0.8157	0.3028	0.0000	0.0000
Banks	31	0.6349	0.6685	31	0.6629	0.6864	0.0281	0.2460	0.2224
Insurance	46	0.6030	0.6089	46	0.7292	0.7609	0.1262	0.0000	0.0000
Real Estate	64	0.6799	0.7062	63	0.7014	0.7023	0.0215	0.2685	0.4950
Financial Services	41	0.6737	0.7271	41	0.7878	0.8033	0.1142	0.0000	0.0000
Technology	92	0.5062	0.5311	92	0.7784	0.8113	0.2722	0.0000	0.0000
ALL	911	0.5335	0.5480	911	0.7694	0.7966	0.2359	0.0000	0.0000
Panel B – Tohoku Earthquake									
Oil & Gas	10	0.5324	0.5464	10	0.7379	0.7204	0.2055	0.0000	0.0000
Basic Materials	85	0.6280	0.6406	85	0.8853	0.9059	0.2573	0.0000	0.0000
Industrials	224	0.5917	0.6170	223	0.7702	0.8459	0.1786	0.0000	0.0000
Consumer Goods	170	0.5467	0.5663	170	0.8022	0.8589	0.2555	0.0000	0.0000
Health Care	63	0.3788	0.3568	61	0.8137	0.8489	0.4349	0.0000	0.0000
Consumer Services	159	0.4255	0.4262	157	0.8309	0.8722	0.4054	0.0000	0.0000
Telecommunications	6	0.4539	0.5056	6	0.8349	0.8546	0.3810	0.0024	0.0022
Utilities	18	0.2946	0.2576	18	0.7418	0.7496	0.4472	0.0000	0.0000
Banks	69	0.5391	0.5528	69	0.8606	0.8858	0.3215	0.0000	0.0000
Insurance	6	0.5953	0.6281	6	0.6715	0.6395	0.0762	0.3642	0.4848
Real Estate	63	0.3552	0.2890	62	0.7937	0.8543	0.4385	0.0000	0.0000
Financial Services	35	0.5271	0.5835	35	0.8437	0.8716	0.3166	0.0000	0.0000
Technology	66	0.5555	0.5440	66	0.8534	0.8954	0.2979	0.0000	0.0000
ALL	974	0.5154	0.5396	968	0.8137	0.8645	0.2983	0.0000	0.0000

Table 4.3 – Cross-market correlations by industry (event country stock)
The above table exhibits statistics of pre- and post-event correlations between individual stocks and the base criterion, calculated according to Expression (4.1). The correlations are estimated from series of daily log returns and pooled according to ICB industries *within* the event country. The *pre*-event period covers the year prior to the event and the *post*-event period the month subsequent to the event including the event day. Panel A displays estimates for the Lehman bankruptcy and Panel B estimates for the Tohoku earthquake applying the S&P 500 (Panel A) and the NIKKEI 225 stock market (Panel B) indexes as base criteria. Both panels are organized as follows: Column 1 gives the name of the ICB industry to which the figures in columns 2–10 refer. Columns 2–4 display pre-event figures and columns 5–7 post-event figures. Column 8 reports the residual between the industry-specific mean post-event (in column 6) and mean pre-event (in column 3) figures and column 9 the p-value of a t-test with the null hypothesis stating that *pre-event correlation equals post-event correlation*. Column 10 reports the p-value of the corresponding Wilcoxon median difference test. Each panel's last row exhibits national cross-industry averages.

For both events, however, it remains unclear whether the overall increase in correlation is driven by the event country's stock or by stock from countries other than the event country. We investigate this question by conducting partial analysis. Thus, we compute industry means of US stock correlations for the Lehman bankruptcy (applying the S&P 500 index as base criterion) and industry means of Japanese stock correlations for the Tohoku earthquake (applying the NIKKEI 225 index as base criterion).

Table 4.3 presents the figures for our analyses of event country stock correlations. Panel A exhibits industry mean and median values of US stock correlations for the Lehman bankruptcy with the S&P 500 index as base criterion and Panel B exhibits industry mean and median values of Japanese stock correlations for the Tohoku earthquake with the NIKKEI 225 index as base criterion. The remainder is organized in the same fashion as Table 4.2.

For most US industries, we detect substantial contagious effects. The increases in correlation are significant at very high significance levels for both the t- and the Wilcoxon median difference test. This finding is intuitive since the Lehman bankruptcy affected the US economy as a whole and even resulted in credit crunches in many other countries across the globe. Interestingly, correlations do not increase for US bank and real estate stocks. Apparently, the distress had already materialized in the interbank and real estate markets.[9]

The results from Panel B indicate significant contagious effects in Japan as a result of the Tohoku earthquake. The increases are significant for all Japanese industries except for the insurance industry.[10] The results indicate severe distress in the stock markets in the post-event period. The contagious effects are particularly strong for utilities, real estate, and health care stocks. Concerning the overall increases in correlation (exhibited in each Panel's last row), it is remarkable that the increase in Japanese stock correlations following the Tohoku earthquake is higher than the increase in US stock correlations

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[9] By September 15, 2008 the US government had already taken various steps to ensure the soundness of institutions providing mortgage credit. E.g., on July 13, 2008 the Board of Governors of the Federal Reserve System announced that it had granted the Federal Reserve Bank of New York the authority to lend to Funnie Mae and Freddie Mac *should such lending prove necessary*. See `http://www.federalreserve.gov/newsevents/press/other/20080713a.htm`

[10] In insurance literature, two opposing effects are well documented. On the one hand, a natural disaster may have a negative effect on firm value resulting from an increased number of policy holders' claims. On the other hand, a positive effect on firm value has been documented as a result of higher expected future policy purchases and premium payments (see, e.g., Angbazo and Narayanan, 1996). Generally, high capital buffers and the Earthquake Insurance System on Dwelling Risks in Japan are documented to have had stabilizing effects on the stock market (Takao et al., 2013). (Though the increase in correlation is substantial for Japanese insurance stocks, the reason for its insignificance may lie in the small number of Japanese insurers within our sample.)

following the Lehman bankruptcy. This implies that regionally, contagion arising from a natural disaster may be more severe than contagion arising from a foreign financial shock such as the Lehman bankruptcy which is in line with the findings of Kaminsky and Reinhart (2000).

Following our analysis of contagious effects within the event country, we now turn towards the analysis of contagion to countries *beyond* the event country. Table 4.4 exhibits our results from the analysis of international stock market contagion by industry. Panel A exhibits industry mean and median values of international stock (excluding US stock) correlations for the Lehman bankruptcy applying the S&P 500 index as base criterion and Panel B exhibits industry mean and median values of international stock (excluding Japanese stock) correlations for the Tohoku earthquake applying the NIKKEI 225 index as base criterion. The remainder is organized in the same manner as the previous tables.

From Panel A of Table 4.4 we observe that international stock from all industries experienced significant contagion following the Lehman bankruptcy and the subsequent turmoil in the financial markets. This is in line with research documenting the Lehman bankruptcy's severe impact on real sectors. In contrast, the impact of the Tohoku earthquake on international stock is somewhat ambiguous. The corresponding figures reported in Panel B of Table 4.4 show that only some industries experienced contagion at the international level. Significant contagious effects occured for international utilities, financial services, and insurance stocks.

The utilities industry is likely to have been most affected by the nuclear disaster at Fukushima Daiichi (that was caused by the Tohoku earthquake and the tsunami in the first place). Being classified as one of the most serious nuclear disasters in history, the incidents at Fukushima Daiichi triggered political discussions on the adequacy of nuclear power generation around the globe. As a result, some studies document abnormal returns for French and German nuclear utility and alternative energy stocks (Betzer et al., 2013; Ferstl et al., 2012).

Insurance stock was heavily affected through claims resulting from the destruction of production plants either by the earthquake itself or the subsequent tsunami floodings. This can be observed from the stock prices of the world's leading reinsurance companies such as Munich Re, Swiss Re, and Berkshire Hathaway whose stock prices plunged by roughly 10% in the first few days following the event. Contrarily, oil & gas as well as banking stocks experienced a significant decrease in correlation. Thus, when averaging across all industries globally, the contagion effect diminishes.

Industry	PRE PERIOD # stocks	PRE PERIOD mean	PRE PERIOD median	POST PERIOD # stocks	POST PERIOD mean	POST PERIOD median	STATISTICS Δmean	STATISTICS *t*-test	STATISTICS Wilcoxon
Panel A – Lehman Bankruptcy									
Oil & Gas	126	0.0959	0.1002	120	0.3984	0.4423	0.3026	0.0000	0.0000
Basic Materials	332	0.0713	0.0744	309	0.2524	0.2441	0.1810	0.0000	0.0000
Industrials	636	0.1238	0.1097	613	0.2492	0.2367	0.1254	0.0000	0.0000
Consumer Goods	380	0.1125	0.1024	367	0.1997	0.1723	0.0873	0.0000	0.0002
Health Care	158	0.0608	0.0629	148	0.1719	0.1546	0.1111	0.0000	0.0003
Consumer Services	403	0.1326	0.1133	390	0.2133	0.2072	0.0807	0.0000	0.0001
Telecommunications	42	0.1823	0.1758	41	0.3020	0.3649	0.1197	0.0249	0.0058
Utilities	114	0.0946	0.0759	104	0.3496	0.3410	0.2550	0.0000	0.0000
Banks	162	0.1678	0.1213	157	0.2832	0.2447	0.1154	0.0000	0.0000
Insurance	69	0.2306	0.2387	66	0.3586	0.4173	0.1279	0.0011	0.0005
Real Estate	204	0.1128	0.0839	190	0.2308	0.2551	0.1179	0.0000	0.0000
Financial Services	277	0.1698	0.1588	272	0.3285	0.3640	0.1587	0.0000	0.0000
Technology	164	0.1200	0.1196	162	0.2548	0.2536	0.1348	0.0000	0.0000
ALL	3,067	0.1211	0.1075	2,939	0.2558	0.2556	0.1347	0.0000	0.0000
Panel B – Tohoku Earthquake									
Oil & Gas	220	0.1984	0.1893	218	0.1309	0.1285	-0.0675	0.0009	0.0019
Basic Materials	306	0.1932	0.1941	296	0.2098	0.2084	0.0166	0.3535	0.1885
Industrials	614	0.2093	0.2114	592	0.1871	0.1691	-0.0222	0.0556	0.0137
Consumer Goods	322	0.1748	0.1718	314	0.1638	0.1681	-0.0110	0.4381	0.6743
Health Care	188	0.1565	0.1604	187	0.1685	0.1611	0.0120	0.5097	0.3851
Consumer Services	391	0.1802	0.1757	377	0.1860	0.1807	0.0058	0.6735	0.8082
Telecommunications	50	0.1579	0.1592	49	0.2317	0.2327	0.0738	0.0288	0.1351
Utilities	150	0.1808	0.1943	141	0.2480	0.2777	0.0673	0.0049	0.0014
Banks	132	0.2427	0.2163	127	0.1797	0.1819	-0.0630	0.0110	0.0116
Insurance	117	0.2119	0.1958	115	0.2502	0.2550	0.0384	0.1158	0.0580
Real Estate	215	0.1669	0.1489	199	0.1365	0.1277	-0.0304	0.0987	0.0494
Financial Services	309	0.2484	0.2575	294	0.2865	0.2638	0.0381	0.0125	0.0338
Technology	201	0.1810	0.1795	198	0.1541	0.1467	-0.0269	0.1507	0.0654
ALL	3,215	0.1954	0.1908	3,107	0.1913	0.1894	-0.0042	0.4026	0.3085

Table 4.4 – Cross-market correlations by industry (international stock excl. event country) The above table exhibits statistics of pre- and post-event correlations between individual stocks and the base criterion, calculated according to Expression (4.1). The correlations are estimated from series of daily log returns and pooled according to ICB industries across all countries *excluding* the event country. The *pre*-event period covers the year prior to the event and the *post*-event period the month subsequent to the event including the event day. Panel A displays estimates for the Lehman bankruptcy and Panel B estimates for the Tohoku earthquake applying the S&P 500 (Panel A) and the NIKKEI 225 stock market (Panel B) indexes as base criteria. Both panels are organized as follows: Column 1 gives the name of the ICB industry to which the figures in columns 2–10 refer. Columns 2–4 display pre-event figures and columns 5–7 post-event figures. Column 8 reports the residual between the industry-specific mean post-event (in column 6) and mean pre-event (in column 3) figures and column 9 the p-value of a t-test with the null hypothesis stating that *pre-event correlation equals post-event correlation.* Column 10 reports the p-value of the corresponding Wilcoxon median difference test. Each panel's last row exhibits international cross-industry averages.

	PRE PERIOD			POST PERIOD			STATISTICS		
Country	# stocks	mean	median	# stocks	mean	median	Δmean	t-test	Wilcoxon
Panel A – Lehman Bankruptcy									
Canada	233	0.2323	0.2044	223	0.4326	0.4679	0.2003	0.0000	0.0000
United States	911	0.5335	0.5480	911	0.7694	0.7966	0.2359	0.0000	0.0000
Brazil	87	0.3168	0.3507	80	0.7056	0.7036	0.3887	0.0000	0.0000
France	238	0.1791	0.1772	222	0.4344	0.4798	0.2553	0.0000	0.0000
Germany	232	0.1838	0.1883	217	0.4782	0.5194	0.2943	0.0000	0.0000
Italy	146	0.2204	0.2308	145	0.4187	0.4428	0.1983	0.0000	0.0000
Russian Federation	39	0.0855	0.0977	31	0.1290	0.1053	0.0435	0.1779	0.2159
United Kingdom	497	0.2033	0.2173	492	0.3769	0.4071	0.1736	0.0000	0.0000
South Africa	67	0.1031	0.1055	64	0.3010	0.3110	0.1979	0.0000	0.0000
Australia	150	0.0162	0.0160	146	0.1070	0.1164	0.0909	0.0000	0.0000
China & Hong Kong	338	-0.0888	-0.0921	293	0.2837	0.2877	0.3725	0.0000	0.0000
Japan	952	0.0881	0.0934	939	0.0206	0.0265	-0.0675	0.0000	0.0000
South Korea	88	0.0545	0.0522	87	0.1285	0.1325	0.0740	0.0003	0.0000
ALL	3,978	0.2156	0.1539	3,850	0.3773	0.3729	0.1618	0.0000	0.0000
Panel B – Tohoku Earthquake									
Canada	243	0.1103	0.1160	239	0.1352	0.1380	0.0248	0.1055	0.0700
United States	952	0.1661	0.1722	953	0.0733	0.0708	-0.0928	0.0000	0.0000
Brazil	94	0.0697	0.0695	87	-0.0277	-0.0213	-0.0974	0.0002	0.0002
France	243	0.2339	0.2523	219	0.2756	0.2719	0.0417	0.0115	0.0275
Germany	241	0.1742	0.1858	219	0.3862	0.4312	0.2120	0.0000	0.0000
Italy	151	0.1948	0.2074	149	0.1767	0.1614	-0.0182	0.3841	0.4871
Russian Federation	40	0.2005	0.2141	35	0.2472	0.2731	0.0468	0.2774	0.0844
United Kingdom	518	0.2417	0.2507	509	0.2114	0.2121	-0.0303	0.0078	0.0033
South Africa	69	0.1929	0.1944	69	0.3685	0.3979	0.1756	0.0000	0.0000
Australia	156	0.3514	0.3632	145	0.4179	0.4407	0.0664	0.0026	0.0011
China & Hong Kong	415	0.2025	0.2066	389	0.2332	0.2818	0.0307	0.0273	0.0000
Japan	974	0.5154	0.5396	968	0.8137	0.8645	0.2983	0.0000	0.0000
South Korea	93	0.2495	0.2263	94	0.3228	0.3413	0.0732	0.0139	0.0017
ALL	4,189	0.2698	0.2248	4,075	0.3391	0.2917	0.0693	0.0000	0.0000

Table 4.5 – Cross-market correlations by country (international stock)
The above table exhibits statistics of pre- and post-event correlations between individual stocks and the base criterion, calculated according to Expression (4.1). The correlations are estimated from series of daily log returns and pooled according to countries across all ICB industries. The *pre*-event period covers the year prior to the event and the *post*-event period the month subsequent to the event including the event day. Panel A displays estimates for the Lehman bankruptcy and Panel B estimates for the Tohoku earthquake applying the S&P 500 (Panel A) and the NIKKEI 225 stock market (Panel B) indexes as base criteria. Both panels are organized as follows: Column 1 gives the name of the country to which the figures in columns 2–10 refer. Columns 2–4 display pre-event figures and columns 5–7 post-event figures. Column 8 reports the residual between the country-specific mean post-event (in column 6) and mean pre-event (in column 3) figures and column 9 the p-value of a t-test with the null hypothesis stating that *pre-event correlation equals post-event correlation.* Column 10 reports the p-value of the corresponding Wilcoxon median difference test. Each panel's last row exhibits cross-country averages.

4.5.2 Contagious effects by country

In the first part of Section 4.5.1, we analyzed contagion by industry. However, we are interested if any geographical patterns of the "shock waves'" propagation through global stock markets become visible if we analyze contagion by country. Thus, we dedicate this subsection to the analysis of country-specific contagious effects.

Table 4.5 displays the results of our contagion analysis with respect to countries and is organized in the same fashion as the previous tables. Panel A displays our correlation estimates for the Lehman bankruptcy and Panel B the estimates for the Tohoku earthquake.

Overall, Panel A reveals that the Lehman bankruptcy leads to a significant increase in correlation that is significant for almost all countries. This result is in line with our previous findings and intuitive given the tremendous impact of the Lehman bankruptcy to other countries' economies. It is astonishing that Russia is the only country in our sample not suffering from contagion, however, stock price dynamics in Russia exhibit a very low correlation with the US stock market in general, which might be attributed to relatively weak economic ties between Russia and the United States.[11]

The Tohoku earthquake's impact on cross-market correlation, however, is not that clear cut. Whereas for most countries correlation with the Japanese market decreases (e.g., United States, Brazil, Italy, and United Kingdom), it significantly increases only for some countries. Most notable is the increase of cross-market correlation for German stocks amounting to 0.2120. Indeed, the German stock index DAX 30 declined substantially in the first days following the Tohoku disaster. This result reflects fears that amongst others the automobile industry (including suppliers) that constitutes an important share of the German economy was indirectly hit by Japanese production breakdowns.[12] Moreover, South African stocks experienced a dramatic increase in cross-market correlation from 0.1929 to 0.3685.[13] On a smaller scale, we find significant contagion for South Korean, Chinese, Australian, Canadian, and French stocks.

We find that geographic proximity to the event country is only one determinant for the occurence of contagion in a country. However, trade links and the relative importance of insurance and utilities firms within a country's economy governed the degree to which a country experienced contagion in the aftermath of the Tohoku earthquake. Moreover,

[11] E.g., Russia did not become a member of the World Trade Organization until August 22, 2012.

[12] "Erdbeben/Roundup: Europäische Autozulieferer indirekt betroffen", Handelsblatt, March 30, 2011 (only available in German)

[13] This finding is in line with Asongu (2012), who furthermore finds contagion for the Taiwanese, the Bahrain, and the Saudi-Arab stock markets.

some country's energy politics responded stongly to the nuclear disaster at Fukushima Daiichi leaving a significant print on cross-market correlation (see, e.g., Lopatta and Kaspereit, 2012; Betzer et al., 2013).

4.6 Robustness issues

4.6.1 Forbes-Rigobon correction for volatility

In the literature it has been noted that the standard Pearson correlation coefficient suffers from a heteroscedasticity bias. Forbes and Rigobon (2002) show that the correlation coefficient increases in periods of high volatility and vice versa. To test if our results are affected by this type of bias, we apply the following adjustment proposed by Forbes and Rigobon (2002) to our correlation estimates:

$$\tilde{\rho} = \frac{\rho}{\sqrt{1 + \delta(1 - \rho^2)}} \quad \text{with} \quad \delta = \frac{\sigma_{ii}^{post}}{\sigma_{ii}^{pre}} - 1. \tag{4.3}$$

σ_{ii}^{pre} $\left(\sigma_{ii}^{post}\right)$ stands for the pre(post)-event variance of base criterion i's daily log return r_{it}. Parameter δ adjusts for the heteroscedasticity bias and is thus applied to standardize the Pearson correlation coefficient ρ.

Tables 4.6 and 4.7 exhibit the results obtained for Forbes and Rigobon (2002) correction of correlations and are organized in the same fashion as the previous tables. Overall, the standardization of correlation coefficients leads to lower levels of correlation. However, Tables 4.6 and 4.7 both confirm our previous results from Tables 4.2 and 4.5.

4.6.2 Base criterion

For our analyses, the choice of an adequate base criterion is crucial. We investigate contagion from the event country to other countries' stock markets. Thus, it is straightforward to apply the event region's leading stock market index as base criterion.

However, alternate spill-over mechanisms are conceivable. In contrast to the direct contagion presumed in our study, contagion could occur through an indirect contagion mechasnism, where contagion propagates from event country A to country B via country C. To confirm that the previously applied base criteria adequately capture distress in the event countries' markets, we switch the base criteria for our event studies, i.e., for the Lehman bankruptcy we apply the NIKKEI 225 index and for the Tohoku earthquake we apply the S&P 500 index as base criteria.

	PRE PERIOD			POST PERIOD			STATISTICS		
Industry	# stocks	mean	median	# stocks	mean	median	Δmean	*t*-test	Wilcoxon
Panel A – Lehman Bankruptcy									
Oil & Gas	210	0.0572	0.0517	205	0.2485	0.2340	0.1912	0.0000	0.0000
Basic Materials	373	0.0411	0.0285	354	0.1243	0.0888	0.0832	0.0000	0.0000
Industrials	793	0.0712	0.0436	773	0.1408	0.0985	0.0697	0.0000	0.0000
Consumer Goods	469	0.0589	0.0392	456	0.1133	0.0742	0.0544	0.0000	0.0000
Health Care	235	0.0520	0.0385	225	0.1512	0.1167	0.0992	0.0000	0.0000
Consumer Services	523	0.0728	0.0498	510	0.1290	0.0984	0.0562	0.0000	0.0000
Telecommunications	54	0.0805	0.0703	53	0.1796	0.1574	0.0991	0.0003	0.0011
Utilities	162	0.0681	0.0546	153	0.2019	0.1949	0.1337	0.0000	0.0000
Banks	193	0.0818	0.0474	188	0.1226	0.0939	0.0409	0.0001	0.0002
Insurance	115	0.1281	0.1129	112	0.1956	0.1788	0.0676	0.0000	0.0001
Real Estate	268	0.0866	0.0515	253	0.1256	0.1078	0.0390	0.0002	0.0002
Financial Services	318	0.0761	0.0548	313	0.1381	0.1174	0.0620	0.0000	0.0000
Technology	256	0.0812	0.0562	254	0.1806	0.1456	0.0994	0.0000	0.0000
ALL	3,969	0.0695	0.0456	3,849	0.1459	0.1114	0.0764	0.0000	0.0000
Panel B – Tohoku Earthquake									
Oil & Gas	230	0.0813	0.0712	228	0.0677	0.0504	-0.0136	0.1530	0.0057
Basic Materials	390	0.1218	0.0880	381	0.2013	0.1244	0.0795	0.0000	0.0087
Industrials	835	0.1326	0.0957	815	0.1871	0.1152	0.0545	0.0000	0.3770
Consumer Goods	491	0.1284	0.0860	483	0.2175	0.1269	0.0891	0.0000	0.0010
Health Care	251	0.0824	0.0675	247	0.1719	0.0971	0.0895	0.0000	0.0011
Consumer Services	548	0.1002	0.0825	533	0.2072	0.1199	0.1069	0.0000	0.0000
Telecommunications	56	0.0725	0.0614	55	0.1374	0.1044	0.0648	0.0050	0.0803
Utilities	166	0.0752	0.0744	159	0.1370	0.1121	0.0618	0.0000	0.0000
Banks	199	0.1424	0.1093	196	0.2440	0.1451	0.1016	0.0000	0.1397
Insurance	123	0.0893	0.0761	121	0.1144	0.1055	0.0251	0.0392	0.0599
Real Estate	278	0.0814	0.0659	261	0.1556	0.0747	0.0743	0.0000	0.2010
Financial Services	342	0.1094	0.1045	329	0.1625	0.1241	0.0531	0.0000	0.0059
Technology	267	0.1131	0.0798	264	0.1884	0.0933	0.0753	0.0000	0.5998
ALL	4,176	0.1106	0.0838	4,072	0.1811	0.1094	0.0705	0.0000	0.0000

Table 4.6 – Robustness: Cross-market Forbes-Rigobon (2002) correlations by industry
The above table exhibits statistics of pre- and post-event correlations between individual stocks and the base criterion, calculated according to Expressions (4.1) and (4.3). The correlations are estimated from series of daily log returns and pooled according to ICB industries across all countries *including* the event country. The *pre*-event period covers the year prior to the event and the *post*-event period the month subsequent to the event including the event day. Panel A displays estimates for the Lehman bankruptcy and Panel B estimates for the Tohoku earthquake applying the S&P 500 (Panel A) and the NIKKEI 225 stock market (Panel B) indexes as base criteria. Both panels are organized as follows: Column 1 gives the name of the ICB industry to which the figures in columns 2–10 refer. Columns 2–4 display pre-event figures and columns 5–7 post-event figures. Column 8 reports the residual between the industry-specific mean post-event (in column 6) and mean pre-event (in column 3) figures and column 9 the p-value of a t-test with the null hypothesis stating that *pre-event correlation equals post-event correlation.* Column 10 reports the p-value of the corresponding Wilcoxon median difference test. Each panel's last row exhibits international cross-industry averages.

	PRE PERIOD			POST PERIOD			STATISTICS		
Country	# stocks	mean	median	# stocks	mean	median	Δmean	*t*-test	Wilcoxon
Panel A – Lehman Bankruptcy									
Canada	232	0.0800	0.0681	223	0.1661	0.1693	0.0861	0.0000	0.0000
United States	911	0.1799	0.1762	910	0.3427	0.3386	0.1628	0.0000	0.0000
Brazil	87	0.0930	0.0998	80	0.2921	0.2605	0.1991	0.0000	0.0000
France	237	0.0511	0.0512	222	0.1428	0.1471	0.0917	0.0000	0.0000
Germany	231	0.0531	0.0522	217	0.1629	0.1608	0.1098	0.0000	0.0000
Italy	145	0.0631	0.0656	145	0.1344	0.1333	0.0713	0.0000	0.0000
Russian Federation	38	0.0255	0.0296	31	0.0364	0.0285	0.0108	0.2734	0.2769
United Kingdom	497	0.0579	0.0608	492	0.1176	0.1206	0.0597	0.0000	0.0000
South Africa	67	0.0287	0.0314	64	0.0902	0.0913	0.0616	0.0000	0.0000
Australia	150	0.0045	0.0044	146	0.0314	0.0311	0.0269	0.0000	0.0000
China & Hong Kong	334	-0.0249	-0.0255	293	0.0826	0.0815	0.1075	0.0000	0.0000
Japan	952	0.0278	0.0293	939	0.0066	0.0082	-0.0212	0.0000	0.0000
South Korea	88	0.0145	0.0139	87	0.0356	0.0362	0.0211	0.0003	0.0000
ALL	3,969	0.0695	0.0456	3,849	0.1459	0.1114	0.0764	0.0000	0.0000
Panel B – Tohoku Earthquake									
Canada	243	0.0413	0.0435	239	0.0533	0.0513	0.0120	0.0538	0.0793
United States	952	0.0622	0.0642	952	0.0286	0.0259	-0.0336	0.0000	0.0000
Brazil	93	0.0296	0.0245	87	-0.0112	-0.0082	-0.0408	0.0002	0.0002
France	241	0.0892	0.0944	219	0.1125	0.1037	0.0232	0.0014	0.0416
Germany	241	0.0675	0.0695	219	0.1678	0.1739	0.1003	0.0000	0.0000
Italy	151	0.0782	0.0780	149	0.0705	0.0601	-0.0077	0.4175	0.3521
Russian Federation	38	0.0797	0.0802	35	0.1023	0.0990	0.0226	0.2431	0.1442
United Kingdom	517	0.0926	0.0950	509	0.0849	0.0779	-0.0077	0.1147	0.0019
South Africa	69	0.0723	0.0736	69	0.1547	0.1563	0.0824	0.0000	0.0000
Australia	156	0.1405	0.1395	145	0.1815	0.1805	0.0411	0.0002	0.0014
China & Hong Kong	408	0.0742	0.0739	388	0.0899	0.1027	0.0157	0.0046	0.0000
Japan	974	0.2290	0.2258	967	0.5118	0.5333	0.2828	0.0000	0.0000
South Korea	93	0.0955	0.0837	94	0.1365	0.1334	0.0410	0.0025	0.0016
ALL	4,176	0.1106	0.0838	4,072	0.1811	0.1094	0.0705	0.0000	0.0000

Table 4.7 – Robustness: Cross-market Forbes-Rigobon (2002) correlations by country
The above table exhibits statistics of pre- and post-event correlations between individual stocks and the base criterion, calculated according to Expressions (4.1) and (4.3). The correlations are estimated from series of daily log returns and pooled according to countries across all ICB industries. The *pre*-event period covers the year prior to the event and the *post*-event period the month subsequent to the event including the event day. Panel A displays estimates for the Lehman bankruptcy and Panel B estimates for the Tohoku earthquake applying the S&P 500 (Panel A) and the NIKKEI 225 stock market (Panel B) indexes as base criteria. Both panels are organized as follows: Column 1 gives the name of the country to which the figures in columns 2–10 refer. Columns 2–4 display pre-event figures and columns 5–7 post-event figures. Column 8 reports the residual between the country-specific mean post-event (in column 6) and mean pre-event (in column 3) figures and column 9 the p-value of a t-test with the null hypothesis stating that *pre-event correlation equals post-event correlation.* Column 10 reports the p-value of the corresponding Wilcoxon median difference test. Each panel's last row exhibits cross-country averages.

	PRE PERIOD			POST PERIOD			STATISTICS		
Industry	# stocks	mean	median	# stocks	mean	median	Δmean	*t*-test	Wilcoxon
Panel A – Lehman Bankruptcy									
Oil & Gas	211	0.1697	0.1289	199	0.3841	0.4301	0.2144	0.0000	0.0000
Basic Materials	376	0.2721	0.2014	292	0.4135	0.4761	0.1414	0.0000	0.0000
Industrials	796	0.2955	0.2185	717	0.3726	0.4333	0.0771	0.0000	0.0000
Consumer Goods	469	0.2907	0.2179	419	0.3882	0.4671	0.0975	0.0000	0.0000
Health Care	235	0.1962	0.1562	200	0.3253	0.3478	0.1292	0.0000	0.0000
Consumer Services	523	0.2344	0.1816	491	0.3451	0.4182	0.1107	0.0000	0.0000
Telecommunications	54	0.1798	0.1371	52	0.4236	0.4561	0.2438	0.0000	0.0000
Utilities	163	0.1623	0.1237	134	0.3524	0.3696	0.1901	0.0000	0.0000
Banks	193	0.3752	0.3052	172	0.5146	0.5846	0.1394	0.0000	0.0000
Insurance	115	0.1740	0.1552	109	0.3016	0.3482	0.1275	0.0002	0.0001
Real Estate	268	0.2184	0.1691	231	0.2423	0.3395	0.0240	0.4634	0.0311
Financial Services	318	0.3054	0.2869	301	0.4603	0.5324	0.1549	0.0000	0.0000
Technology	256	0.2454	0.1791	239	0.2825	0.3254	0.0371	0.2014	0.2425
ALL	3,977	0.2578	0.1960	3,556	0.3696	0.4283	0.1117	0.0000	0.0000
Panel B – Tohoku Earthquake									
Oil & Gas	230	0.4190	0.4358	228	0.3110	0.3156	-0.1081	0.0000	0.0000
Basic Materials	391	0.2854	0.2040	382	0.1634	0.1559	-0.1220	0.0000	0.0000
Industrials	838	0.3053	0.2071	822	0.2537	0.2249	-0.0515	0.0003	0.0003
Consumer Goods	492	0.2671	0.1928	484	0.2117	0.1683	-0.0554	0.0014	0.0004
Health Care	251	0.2526	0.1587	248	0.2453	0.2398	-0.0073	0.7568	0.9147
Consumer Services	550	0.2896	0.2255	535	0.2464	0.2173	-0.0431	0.0055	0.0061
Telecommunications	56	0.3121	0.2711	55	0.2502	0.2493	-0.0619	0.2113	0.3006
Utilities	168	0.3554	0.3124	160	0.3152	0.3170	-0.0402	0.2230	0.2462
Banks	201	0.3263	0.2290	196	0.1822	0.1254	-0.1441	0.0000	0.0000
Insurance	123	0.4776	0.5026	121	0.3747	0.3986	-0.1029	0.0024	0.0074
Real Estate	278	0.3225	0.2214	265	0.2925	0.2868	-0.0300	0.1952	0.4477
Financial Services	345	0.3449	0.3205	330	0.3426	0.3742	-0.0023	0.9098	0.7451
Technology	267	0.3457	0.2907	265	0.2918	0.3017	-0.0538	0.0287	0.0701
ALL	4,190	0.3151	0.2347	4,091	0.2567	0.2427	-0.0584	0.0000	0.0000

Table 4.8 – Robustness with respect to base criteria, cross-market correlations by industry
The above table exhibits statistics of pre- and post-event correlations between individual stocks and the base criterion, calculated according to Expression (4.1). The correlations are estimated from series of daily log returns and pooled according to ICB industries across all countries *including* the event country. The *pre*-event period covers the year prior to the event and the *post*-event period the month subsequent to the event including the event day. Panel A displays estimates for the Lehman bankruptcy and Panel B estimates for the Tohoku earthquake applying the NIKKEI 225 (Panel A) and the S&P 500 stock market (Panel B) indexes as base criteria. Both panels are organized as follows: Column 1 gives the name of the ICB industry to which the figures in columns 2–10 refer. Columns 2–4 display pre-event figures and columns 5–7 post-event figures. Column 8 reports the residual between the industry-specific mean post-event (in column 6) and mean pre-event (in column 3) figures and column 9 the *p*-value of a *t*-test with the null hypothesis stating that *pre-event correlation equals post-event correlation.* Column 10 reports the *p*-value of the corresponding Wilcoxon median difference test. Each panel's last row exhibits international cross-industry averages.

	PRE PERIOD			POST PERIOD			STATISTICS		
Country	# stocks	mean	median	# stocks	mean	median	Δmean	*t*-test	Wilcoxon
Panel A – Lehman Bankruptcy									
Canada	232	0.0930	0.0953	222	0.3430	0.3642	0.2501	0.0000	0.0000
United States	911	0.0704	0.0700	911	-0.0624	-0.0739	-0.1327	0.0000	0.0000
Brazil	87	0.0932	0.0964	79	0.2361	0.2326	0.1429	0.0000	0.0000
France	238	0.2100	0.2264	212	0.4528	0.4563	0.2428	0.0000	0.0000
Germany	232	0.1654	0.1714	209	0.3289	0.3768	0.1635	0.0000	0.0000
Italy	146	0.2035	0.2126	143	0.4743	0.4856	0.2708	0.0000	0.0000
Russian Federation	39	0.2171	0.2510	28	0.5719	0.6034	0.3548	0.0000	0.0000
United Kingdom	497	0.2284	0.2072	488	0.3774	0.4043	0.1490	0.0000	0.0000
South Africa	67	0.2007	0.2054	62	0.3501	0.3888	0.1494	0.0000	0.0000
Australia	150	0.3194	0.3296	141	0.5657	0.5838	0.2463	0.0000	0.0000
China & Hong Kong	338	0.2112	0.1894	35	0.5789	0.5908	0.3677	0.0000	0.0000
Japan	952	0.5503	0.5811	939	0.7117	0.7540	0.1614	0.0000	0.0000
South Korea	88	0.3974	0.4146	87	0.6140	0.6706	0.2165	0.0000	0.0000
ALL	3,977	0.2578	0.1960	3,556	0.3696	0.4283	0.1117	0.0000	0.0000
Panel B – Tohoku Earthquake									
Canada	243	0.3295	0.3154	239	0.2338	0.2325	-0.0957	0.0000	0.0000
United States	952	0.6494	0.6725	953	0.5248	0.5619	-0.1246	0.0000	0.0000
Brazil	94	0.3446	0.3251	87	0.1681	0.1971	-0.1765	0.0000	0.0000
France	243	0.2959	0.2985	222	0.4361	0.4781	0.1402	0.0000	0.0000
Germany	241	0.2501	0.2503	219	0.3836	0.3955	0.1335	0.0000	0.0000
Italy	152	0.3459	0.3824	149	0.3384	0.3537	-0.0076	0.7631	0.5436
Russian Federation	40	0.2835	0.3133	35	0.2732	0.3184	-0.0103	0.8143	0.8784
United Kingdom	518	0.3256	0.3370	512	0.3889	0.4134	0.0633	0.0000	0.0000
South Africa	69	0.2543	0.2661	69	0.1437	0.1656	-0.1107	0.0007	0.0022
Australia	156	0.1314	0.1395	147	0.1387	0.1408	0.0073	0.6915	0.6066
China & Hong Kong	415	0.1279	0.1408	397	-0.1228	-0.1129	-0.2507	0.0000	0.0000
Japan	974	0.1255	0.1309	968	0.0514	0.0536	-0.0740	0.0000	0.0000
South Korea	93	0.1238	0.1330	94	0.0877	0.0664	-0.0361	0.0625	0.0219
ALL	4,190	0.3151	0.2347	4,091	0.2567	0.2427	-0.0584	0.0000	0.0000

Table 4.9 – Robustness with respect to base criteria, cross-market correlations by country The above table exhibits statistics of pre- and post-event correlations between individual stocks and the base criterion, calculated according to Expression (4.1). The correlations are estimated from series of daily log returns and pooled according to countries across all ICB industries. The *pre*-event period covers the year prior to the event and the *post*-event period the month subsequent to the event including the event day. Panel A displays estimates for the Lehman bankruptcy and Panel B estimates for the Tohoku earthquake applying the NIKKEI 225 (Panel A) and the S&P 500 stock market (Panel B) indexes as base criteria. Both panels are organized as follows: Column 1 gives the name of the country to which the figures in columns 2–10 refer. Columns 2–4 display pre-event figures and columns 5–7 post-event figures. Column 8 reports the residual between the country-specific mean post-event (in column 6) and mean pre-event (in column 3) figures and column 9 the p-value of a t-test with the null hypothesis stating that *pre-event correlation equals post-event correlation.* Column 10 reports the p-value of the corresponding Wilcoxon median difference test. Each panel's last row exhibits cross-country averages.

Tables 4.8 and 4.9 present the results of our robustness check with respect to the base criterion. The estimates reveal that we adequately presume a direct contagion effect. As a result of the Lehman bankruptcy (Panel A of Tables 4.8 and 4.9), cross-market correlation still increases significantly but does so much more weakly than in our benchmark analysis where we apply the S&P 500 stock market index as base criterion.

In contrast, overall correlation decreases as a result of the Tohoku earthquake (Panel B of Tables 4.8 and 4.9). This result also holds for both – the industry-specific analysis (Panel B of Table 4.8) and the country-specific analysis (Panel B of Table 4.9). Overall, we may interpret these results as a strong indication that we are applying adequate base criteria.

4.6.3 Comovement intensity

Literature has proposed numerous alternatives to measure comovement and connectedness. These proposals include several measures based on Principal Components Analysis (see, e.g., Billio et al., 2012). Hence, we evaluate if our results hold in case we apply a principal components measure to the data.

More specifically, we compute the comovement intensity (CMI) of the bivariate return dynamics between base criterion i and stock j. CMI captures the fraction of the return dynamics' total variance that can be attributed to the first principal component. By definition, the relationship between the returns' covariance matrix Σ and the principal components' covariance matrix Λ is given by $\Lambda = A'\Sigma A$, where $A = [a_1, a_2]$ is the matrix of eigenvectors a_1 and a_2 and Λ the diagonal matrix of eigenvalues λ_1 and λ_2.[14] Thus, in mathematical terms, CMI is the ratio between Σ's first eigenvalue λ_1 and the sum of Σ's eigenvalues, $\lambda_1 + \lambda_2$:

$$\mathrm{CMI} = \frac{\lambda_1}{\lambda_1 + \lambda_2}. \tag{4.4}$$

In the following, we express CMI in percentage terms. We test if industrial and country CMI averages significantly increase following the Tohoku earthquake and the Lehman bankruptcy employing a test procedure in analogy to Expressions (4.2a) and (4.2b). Tables 4.10 and 4.11 present the results for our robustness check with respect to the applied measure.

[14] For details on the calculation of principal components and the extraction of Σ's eigenvalues we refer to 4.A.

	PRE PERIOD			POST PERIOD			STATISTICS		
Industry	# stocks	mean	median	# stocks	mean	median	Δmean	*t*-test	Wilcoxon
Panel A – Lehman									
Oil & Gas	211	80.07	82.37	205	84.19	86.45	4.11	0.0001	0.0000
Basic Materials	377	85.53	87.21	354	75.92	74.99	-9.61	0.0000	0.0000
Industrials	796	82.64	83.89	773	75.52	75.04	-7.11	0.0000	0.0000
Consumer Goods	469	79.98	81.14	456	74.23	72.99	-5.76	0.0000	0.0000
Health Care	235	79.18	79.30	225	76.78	78.41	-2.40	0.0225	0.1487
Consumer Services	523	80.75	82.02	511	74.60	74.36	-6.16	0.0000	0.0000
Telecommunications	54	79.54	81.75	53	79.76	79.79	0.22	0.9049	0.9826
Utilities	163	75.71	77.09	153	78.59	80.17	2.88	0.0272	0.0092
Banks	193	81.33	81.21	188	74.82	73.40	-6.51	0.0000	0.0000
Insurance	115	81.42	81.38	112	81.03	82.22	-0.39	0.7615	0.8707
Real Estate	268	83.33	85.71	253	77.80	78.09	-5.53	0.0000	0.0000
Financial Services	318	77.20	79.08	313	77.46	76.59	0.26	0.7675	0.7178
Technology	256	84.30	85.11	254	77.91	78.80	-6.40	0.0000	0.0000
ALL	3,978	81.31	82.79	3,850	76.59	76.39	-4.72	0.0000	0.0000
Panel B – Tohoku									
Oil & Gas	230	73.70	75.17	228	82.78	84.13	9.08	0.0000	0.0000
Basic Materials	391	80.72	82.61	381	82.74	84.68	2.02	0.0044	0.0001
Industrials	838	77.11	77.83	815	85.40	87.44	8.29	0.0000	0.0000
Consumer Goods	492	76.27	78.08	484	85.51	87.89	9.24	0.0000	0.0000
Health Care	251	73.23	72.31	248	85.90	88.23	12.67	0.0000	0.0000
Consumer Services	550	73.81	74.26	534	86.41	88.87	12.60	0.0000	0.0000
Telecommunications	56	69.59	68.32	55	86.27	89.97	16.67	0.0000	0.0000
Utilities	168	67.20	64.81	159	89.22	91.26	22.02	0.0000	0.0000
Banks	201	75.54	77.64	196	88.73	90.72	13.19	0.0000	0.0000
Insurance	123	69.32	68.52	121	86.52	88.64	17.20	0.0000	0.0000
Real Estate	278	71.97	70.90	261	87.08	89.84	15.12	0.0000	0.0000
Financial Services	344	73.30	71.56	329	88.78	90.38	15.48	0.0000	0.0000
Technology	267	78.14	79.55	264	84.44	86.45	6.30	0.0000	0.0000
ALL	4,189	75.10	75.89	4,075	85.85	88.20	10.75	0.0000	0.0000

Table 4.10 – Robustness: Comovement intensity by industry

The above table exhibits statistics of pre- and post-event comovement intensities (CMI) between individual stocks and the base criterion, calculated according to Expression (4.4) and expressed in percentage terms. The CMI are estimated from series of daily log returns and pooled according to ICB industries across all countries *including* the event country. The *pre*-event period covers the year prior to the event and the *post*-event period the month subsequent to the event including the event day. Panel A displays estimates for the Lehman bankruptcy and Panel B estimates for the Tohoku earthquake applying the S&P 500 (Panel A) and the NIKKEI 225 stock market (Panel B) indexes as base criteria. Both panels are organized as follows: Column 1 gives the name of the ICB industry to which the figures in columns 2–10 refer. Columns 2–4 display pre-event figures and columns 5–7 post-event figures. Column 8 reports the residual between the industry-specific mean post-event (in column 6) and mean pre-event (in column 3) figures and column 9 the p-value of a t-test with the null hypothesis stating that *pre-event CMI equals post-event CMI*. Column 10 reports the p-value of the corresponding Wilcoxon median difference test. Each panel's last row exhibits international cross-industry averages.

	PRE PERIOD			POST PERIOD			STATISTICS		
Country	# stocks	mean	median	# stocks	mean	median	Δmean	*t*-test	Wilcoxon
Panel A – Lehman									
Canada	233	78.74	79.01	223	79.00	80.35	0.26	0.7667	0.6532
United States	911	85.56	87.23	911	90.50	91.51	4.94	0.0000	0.0000
Brazil	87	84.94	85.71	80	87.55	89.31	2.61	0.0098	0.0033
France	238	76.07	77.35	222	78.87	79.12	2.80	0.0003	0.0009
Germany	232	79.20	80.90	217	79.77	81.51	0.58	0.4954	0.6297
Italy	146	76.11	75.87	145	75.24	75.72	-0.87	0.3752	0.4075
Russian Federation	39	81.36	81.49	31	80.88	83.53	-0.48	0.8451	0.4376
United Kingdom	497	77.81	79.99	492	74.74	75.29	-3.07	0.0000	0.0000
South Africa	67	76.64	77.55	64	73.73	74.01	-2.91	0.0216	0.0155
Australia	150	81.72	81.98	146	67.96	67.42	-13.76	0.0000	0.0000
China & Hong Kong	338	89.79	90.26	293	67.47	66.90	-22.32	0.0000	0.0000
Japan	952	79.11	80.53	939	66.44	66.10	-12.66	0.0000	0.0000
South Korea	88	82.54	83.73	87	68.83	68.09	-13.71	0.0000	0.0000
ALL	3,978	81.31	82.79	3,850	76.59	76.39	-4.72	0.0000	0.0000
Panel B – Tohoku									
Canada	243	68.18	64.17	239	83.87	88.45	15.68	0.0000	0.0000
United States	952	70.75	70.04	953	86.41	88.84	15.66	0.0000	0.0000
Brazil	94	72.03	71.53	87	81.95	83.78	9.92	0.0000	0.0000
France	243	71.78	71.00	219	84.02	85.88	12.24	0.0000	0.0000
Germany	241	73.92	73.90	219	81.02	83.01	7.10	0.0000	0.0000
Italy	151	71.83	72.81	149	82.52	84.15	10.70	0.0000	0.0000
Russian Federation	40	78.00	76.89	35	83.60	85.72	5.60	0.0084	0.0017
United Kingdom	518	73.35	72.33	509	83.87	85.90	10.51	0.0000	0.0000
South Africa	69	66.13	65.99	69	86.13	87.54	20.00	0.0000	0.0000
Australia	156	75.27	75.45	145	87.17	89.32	11.89	0.0000	0.0000
China & Hong Kong	415	82.05	83.13	389	79.80	81.25	-2.24	0.0001	0.0151
Japan	974	81.23	82.52	968	92.33	94.40	11.10	0.0000	0.0000
South Korea	93	77.78	79.23	94	77.45	77.96	-0.33	0.7786	0.9171
ALL	4,189	75.10	75.89	4,075	85.85	88.20	10.75	0.0000	0.0000

Table 4.11 – Robustness: Comovement intensity by country

The above table exhibits statistics of pre- and post-event comovement intensities (CMI) between individual stocks and the base criterion, calculated according to Expression (4.4) and expressed in percentage terms. The CMI are estimated from series of daily log returns and pooled according to countries across all ICB industries. The *pre*-event period covers the year prior to the event and the *post*-event period the month subsequent to the event including the event day. Panel A displays estimates for the Lehman bankruptcy and Panel B estimates for the Tohoku earthquake applying the S&P 500 (Panel A) and the NIKKEI 225 stock market (Panel B) indexes as base criteria. Both panels are organized as follows: Column 1 gives the name of the country to which the figures in columns 2–10 refer. Columns 2–4 display pre-event figures and columns 5–7 post-event figures. Column 8 reports the residual between the country-specific mean post-event (in column 6) and mean pre-event (in column 3) figures and column 9 the *p*-value of a *t*-test with the null hypothesis stating that *pre-event CMI equals post-event CMI*. Column 10 reports the *p*-value of the corresponding Wilcoxon median difference test. Each panel's last row exhibits cross-country averages.

The results are more conservative than our previous results but confirm several findings. In the days following the Tohoku earthquake, CMI rises most sharply for utilities and insurance stocks. South African stocks remain to be most heavily affected by the Tohoku earthquake. Moreover, the strong increase of CMI across all industries and most countries in our sample underlines that contagion following the Tohoku earthquake is substantial. Interestingly, the Tohoku earthquake increases overall CMI more strongly than the Lehman bankruptcy.

4.7 Summary and conclusion

We study contagion on international stock markets comparing contagion arising from the Japanese Tohoku earthquake on March 11, 2011 and the bankruptcy of Lehman Brothers on September 15, 2008 by country and industry.

We find that contagion arising from both – disasters of natural cause and shocks originating from the financial markets – is substantial. The Lehman bankruptcy's impact is more global than the Tohoku earthquake's, which is particularly strong at the national level suggesting that contagion arising from natural disasters is most severe in the event country. While the Lehman bankruptcy caused contagion to a wide range of industries and countries, the Tohoku earthquake primarily affected utilities and insurance stocks. Despite their geographically distant location, German and South African stock markets were most heavily affected by the Tohoku earthquake.

We conclude that the difference in degree to which global stock responded to the Tohoku earthquake and the Lehman bankruptcy is best explained by the distinct nature of contagion mechanisms. Information-based financial shocks such as the Lehman bankruptcy have the potential to result in panics arising from fears of losses related to balance sheet exposures or liquidity freezes. Given tight global financial integration, such panics are easily transmitted through global stock markets. Natural disasters are less likely to be followed by panics simply because market participants anticipate price reactions to be fully materialized after the event. Moreover, natural disasters primarily impact (real) assets in the event country. International supply chain disruptions arising from destroyed production facilities impact global stock only to a lesser degree.

4.A Principal components analysis and comovement intensity

Principal components analysis (PCA) employs orthogonal transformation in order to convert a dataset of possibly correlated variables to a dataset of uncorrelated variables. The vector of original variables shall be replaced by a smaller number of synthetical variables that are linear combinations of the original variables and capable of explaining a large fraction of the data's total variance. The new synthetic variables are referred to as principal components and sorted with decreasing explanatory power.

More specifically, let $R = (R_1, \dots, R_n)$ be an n-dimensional vector of randomized daily returns with the expectation $\mathbb{E}(R) = \mu$ and covariance matrix Σ. We now construct a vector of principal components $Z = (Z_1, \dots, Z_n)$ such that

$$Z_j = a_{1j}R_1 + a_{2j}R_2 + \ldots + a_{nj}R_n = a_j{}'R, \tag{4.5}$$

where a_j is a vector of constants. The property $a_j{}'a_j = 1$ ensures that the data is scaled and the transformation orthogonal. By construction, the first principal component is designed such that its variance $\mathrm{Var}(Z_1) = \mathrm{Var}(a_1{}'R) = a_1{}'\Sigma a_1$ explains a maximum portion of the data's total variance. Thus, the maximization problem can be expressed as

$$\max a_1{}'\Sigma a_1 \quad s.t. \quad a_1{}'a_1 = 1 \tag{4.6}$$

with the Lagrange function given by

$$L(a_1) = a_1{}'\Sigma a_1 - \lambda(a_1{}'a_1 - 1), \tag{4.7}$$

where λ denotes the Lagrange multiplier. Equating the partial derivatives to *zero* yields

$$(\Sigma - \lambda I)a_1 = 0, \tag{4.8}$$

where I is the $n \times n$ identity matrix. It immediately follows that λ has to be an eigenvalue of the covariance matrix Σ for a solution to exist. Since Σ is positive semi-definite, it will have n eigenvalues $\lambda_1, \dots, \lambda_n$ in general. To ensure that the variance of the first principal component explains the maximum portion of the total variance, we set

$$\mathrm{Var}(a_1{}') = a_1{}'\Sigma a_1 = \lambda_1, \tag{4.9}$$

where a_1 is the eigenvector belonging to eigenvalue λ_1. Principal components $Z_2, \ldots, Z_n$ are determined iteratively. Eigenvalues $\lambda_1, \ldots, \lambda_n$ thus may be interpreted as the principal components' variances. The relationship between the covariance matrix of R, Σ, and the principle components' covariance matrix Λ is determined by the equality

$$\Lambda = A' \Sigma A, \tag{4.10}$$

where $A = [a_1, \ldots, a_n]$ is the matrix of eigenvectors and Λ the diagonal matrix of eigenvalues, $\mathrm{diag}(\lambda_1, \ldots, \lambda_n)$. Since by construction the first principal component is capable of explaining a maximum portion of the total variance, we define the comovement intensity (CMI) as

$$\mathrm{CMI} = \frac{\lambda_1}{\sum_{i=1}^{n} \lambda_i}. \tag{4.11}$$

The CMI captures the amount of total variance that can be explained by the first principal component. Hence, when stock price comovement increases, we would expect CMI to increase significantly.

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