CFR Working Paper NO. 12-10

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Abstract

In this paper we study systemic risk for the US and Europe. We show that banks' exposures to common risk factors are crucial for systemic risk. We come to this conclusion by first showing that relations between US and European banks are smaller than within each region. We then show that European banks react more strongly to the onset of the financial crisis than US ones. Regarding the consequences of systemic risk, we show that dependence between the banking sector and a wide range of real sectors is limited. Our results imply that regulators and supervisors should address international bank dependencies arising from common risk factors, while recessions in real sectors due to bank defaults should be a secondary concern.

JEL classification: G01, G15, G18, G21, G28

Keywords: systemic risk, banking sector, real sectors, regulation, copula

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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

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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 disaggregated 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 it were available, portfolio-level information may not sufficiently reflect interbank exposures. Given most banks' limited exposures[3] 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 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

[3] 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.

traded assets, and directly infer systemic risk by adopting 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 (2009a, 2009b, 2009c), 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 our 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, exactly 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., 2010; 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 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, being 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, we give an overview over the CDS time series used to compute systemic risk. We motivate and develop our systemic risk measures in Section 3, and present the empirical results of our study in Section 4. Section 5 summarizes and concludes.

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:

1. 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.
2. 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.[4] As Arora et al. (2012) show, counterparty risk has a very lim-

[4] 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.

ited effect on CDS premia of around 1 bp.[5] Hence, fluctuations of counterparty risk are likely to have almost no effect on CDS premia overall.

3. 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.[6] Second, we manually verify whether firms with the "Financial" sector tag are banks or non-banks,[7] 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 all CDS contracts

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

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

[7] 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.

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.[8] 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.[9] Table 1 reports descriptive statistics of all CDS contracts in our final sample.

[INSERT TABLE 1 ABOUT HERE]

As Panel A of Table 1 shows, the number of firms is not evenly distributed across sectors with only 19 firms in the technology sector, and 174 firms in the consumer sector. The joint financial sector (bank and non-bank) is the second-largest sector with 105 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

[8] 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.

[9] 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.

measure would severely underestimate upper tail dependence.[10]

Regarding the US and European sub-samples in Panels B and C of Table 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 1 and 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.

[INSERT FIGURES 1 AND 2 ABOUT HERE]

Figures 1 and 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 co-movement of CDS premia for different sectors. As Figure 1 shows, the co-movement 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 implies a higher co-movement between banks and non-bank sectors such as the industrial or the technology sector. The two latter time-

[10] 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.

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 4.4.

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.[11] Hence, we use an upside risk measure derived using extreme value theory.

[11] 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 $360 \cdot 24$ 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

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

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

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 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

$$\mathrm{UTDC}(i,j) = \lim_{x\uparrow 1} P\left[s_i > G_i^{-1}(x) \,|\, s_j > G_j^{-1}(x)\right], \tag{2}$$

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.

thus approaches infinity.

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

$$C_{i,j}\left(x_i,x_j\right)=\exp\left(-\left[\left(-\ln x_i\right)^{d(i,j)}+\left(-\ln x_j\right)^{d(i,j)}\right]^{\frac{1}{d(i,j)}}\right), \tag{3}$$

where $d\left(i,j\right)>1$ measures the degree of dependence between firm i and firm j, $x_i=G_i\left(s_i\right)$ is the value of the marginal distribution function G_i evaluated at s_i, and $x_j=G_j\left(s_j\right)$ 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

$$\text{UTDC}\left(i,j\right)=2-2^{\frac{1}{d(i,j)}}. \tag{4}$$

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 (1) for each firm i via maximum likelihood.[12] Second, we determine the 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 $d\left(i,j\right)$ for each firm-combination (i,j) using the Gumbel copula in Equation (3) by maximum likelihood, and compute the upper tail coefficient $\text{UTDC}\left(i,j\right)$ according to Equation (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 $\left(a_i,b_i,c_i\right)_t$ as well as copula parameters $d\left(t;i,j\right)$ and upper tail dependence coefficients $\text{UTDC}\left(t;i,j\right)$.[13]

[12] 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 4 and is addressed there. The two latter properties are accommodated by the chosen marginal distribution.

[13] We also compute statistics that allow us to evaluate the goodness of fit of the marginal distributions

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 $\bar{\boldsymbol{R}}$:

$$\bigcup_{t,i,j} \mathrm{UTDC}(t; i, j), \tag{5}$$

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.[14] In Section 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 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, we give

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and the copula. 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%.

[14] 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 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 $\boldsymbol{I}^{\bar{R}}$.

a detailed overview of the nine sectors) and define the rank of systemic risk in the regional banking sectors as

$$\#\left\{\text{sectors } J: \quad \widetilde{\text{UTDC}}\left(\boldsymbol{J}^R, \boldsymbol{J}^R\right) > \widetilde{\text{UTDC}}\left(\text{Bank}^R, \text{Bank}^R\right)\right\}. \tag{6a}$$

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:

$$\#\left\{\text{sectors } J: \quad \widetilde{\text{UTDC}}\left(\boldsymbol{I}^R, \boldsymbol{J}^R\right) > \widetilde{\text{UTDC}}\left(\boldsymbol{I}^R, \text{Bank}^R\right)\right\}. \tag{6b}$$

We thus assign rank 1 to the most systemic sector and rank 9 to the least systemic sector. In Section 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 (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 $j \in \boldsymbol{J}^{\bar{R}}$:

$$\bigcup_{i,j} \text{UTDC}(t; i, j). \tag{7}$$

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:

$$\bigcup_{t} \overline{\text{UTDC}}\left(t; \boldsymbol{I}^R, \boldsymbol{J}^{\bar{R}}\right). \tag{8}$$

We display the corresponding means, standard deviations, and percentiles in Panel B1 in all tables of Section 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:

$$\text{countstat}\left(\text{UTDC}^{R}_{\boldsymbol{I},\boldsymbol{J}}\right) = \frac{\#\left\{t: \quad \overline{\text{UTDC}}\left(t;\boldsymbol{I}^{R},\boldsymbol{J}^{R}\right) > \overline{\text{UTDC}}\left(t;\boldsymbol{I}^{\bar{R}},\boldsymbol{J}^{\bar{R}}\right)\right\}}{T}. \tag{9}$$

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 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 (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:

$$\begin{aligned}&\text{rankcount}\left(\text{UTDC}^{R}_{\text{Bank}}\right) = \\ &\quad \frac{\#\left\{t: \quad \text{rank}_t\left(\overline{\text{UTDC}}\left(t;\text{Bank}^{R},\text{Bank}^{R}\right)\right) < \text{rank}_t\left(\overline{\text{UTDC}}\left(t;\text{Bank}^{\bar{R}},\text{Bank}^{\bar{R}}\right)\right)\right\}}{T}.\end{aligned} \tag{10a}$$

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 $\boldsymbol{I}^{\bar{R}}$:

$$\begin{aligned}&\text{rankcount}\left(\text{UTDC}^{R}_{\boldsymbol{I},\text{Bank}}\right) = \\ &\quad \frac{\#\left\{t: \quad \text{rank}_t\left(\overline{\text{UTDC}}\left(t;\boldsymbol{I}^{R},\text{Bank}^{R}\right)\right) < \text{rank}_t\left(\overline{\text{UTDC}}\left(t;\boldsymbol{I}^{\bar{R}},\text{Bank}^{\bar{R}}\right)\right)\right\}}{T}.\end{aligned} \tag{10b}$$

The corresponding results are displayed in Panel D of each table in Section 4.

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 4.1, we determine systemic risk among US and among European banks. Then, we explore the relation between US and European banks in Section 4.2. Third, we determine the increase in systemic risk among and between US and European banks during the financial crisis in Section 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 4.4. There, we find that the relation between banks and non-banks is comparatively low, especially when we consider large banks.

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 3 depicts the evolution of upper tail dependence in the US and European banking sectors.

[INSERT FIGURE 3 ABOUT HERE]

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[15]:

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

Table 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 (5); statistics in Panel B1 are determined according to Expressions (7) and (8).

[INSERT TABLE 2 ABOUT HERE]

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%.[16] 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 $\overline{\text{UTDC}}\left(t; \boldsymbol{I}^R, \boldsymbol{J}^{\bar{R}}\right)$ 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.[17]

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

[16] 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 A.1.

[17] By construction, the series of UTDC exhibit significant auto-correlation. 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

Panel B2 reports results obtained applying the count statistic from Expression (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. 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 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.

[INSERT FIGURES 4 AND 5 ABOUT HERE]

Figures 4 and 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 exhibit the results obtained applying Expressions (6a) (pooling over firms and time) and (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

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main results in Panel A of Tables 2 to 5. For each of our calculations, we obtain highly significant p-values below 0.01%. The results are presented in Appendix-Table A.2.

banks ranks first among all sectors. In Europe, systemic risk in the banking sector ranks only sixth.[18] 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.

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

[18] We present more detailed results of the sectoral ranking in Appendix-Table B.2.

leads to a 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 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.[19] The aggregate results are exhibited in Table 3.

[INSERT TABLE 3 ABOUT HERE]

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 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

[19] 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.

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.

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[20], 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.[21] 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.[22]

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.

[20] 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.

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

[22] 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.

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 4 reports the results. Panel A is calculated in the same fashion as Panel A of Table 2.

[INSERT TABLE 4 ABOUT HERE]

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 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 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 (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.

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.[23] 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.*

[23] See Sections 1 and 2 for references.

Table 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) 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).

[INSERT TABLE 5 ABOUT HERE]

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 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.*

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 (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 (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 overestimate 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.[24] 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 6.

[INSERT TABLE 6 ABOUT HERE]

Table 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, 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 6 to Table 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

[24] 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.

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. This suggests that the main beneficiaries of bailouts for large banks (that might be considered 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.

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 market and (ii) continue to limit exposures between large international banks and those banks providing the largest share of loans to real-sector firms.

Acknowledgments

Monika Trapp acknowledges financial support from the Centre for Financial Research (CFR) and the Fritz Thyssen Foundation. Claudio Wewel acknowledges financial support from the Institute for Bank Management and Banking Law at the University of Cologne. We thank an anonymous referee, Thomas Hartmann-Wendels, Alexander Kempf, Wolfgang Bühler, and our discussants at the Eastern Finance Association Annual Meeting 2012 in Boston, the FMA European Conference 2012 in Istanbul, and the Southwestern Finance Association Annual Meeting 2013 in Albuquerque for valuable comments on earlier versions of this paper. A first version of this paper was circulated under the title "Systemic Risk Beyond the Banking Sector".

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Tables and Figures

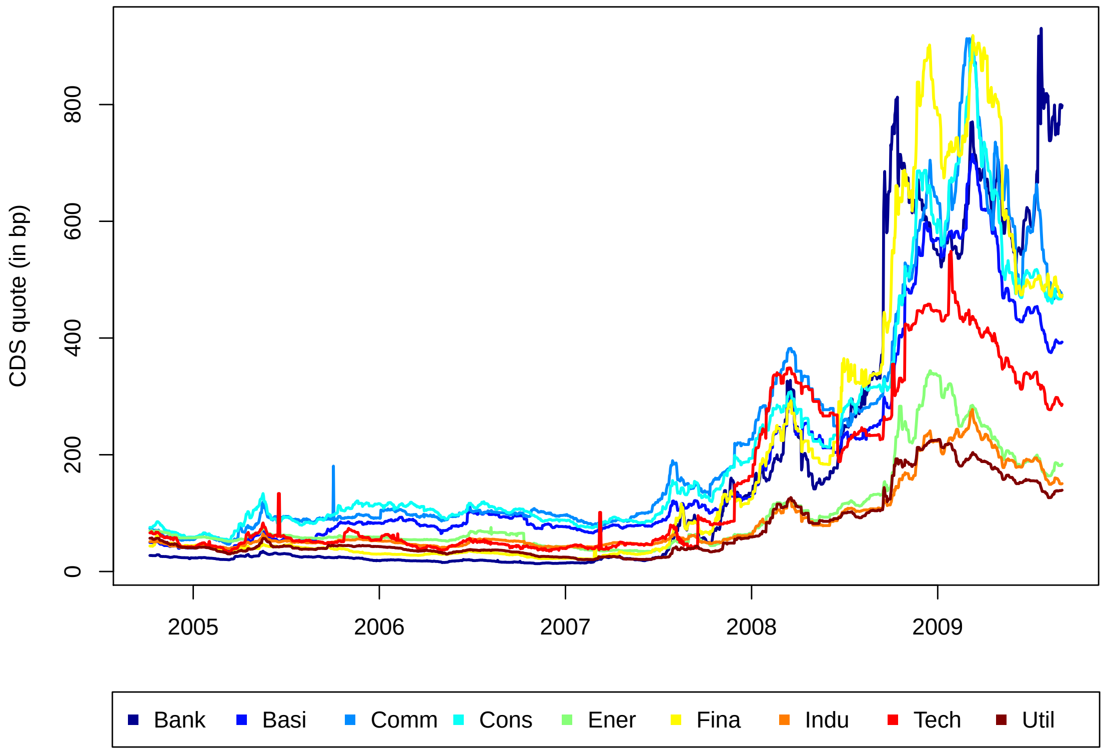

Figure 1 – Time Evolution of CDS Premia Averaged Across Sectors (United States)

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.

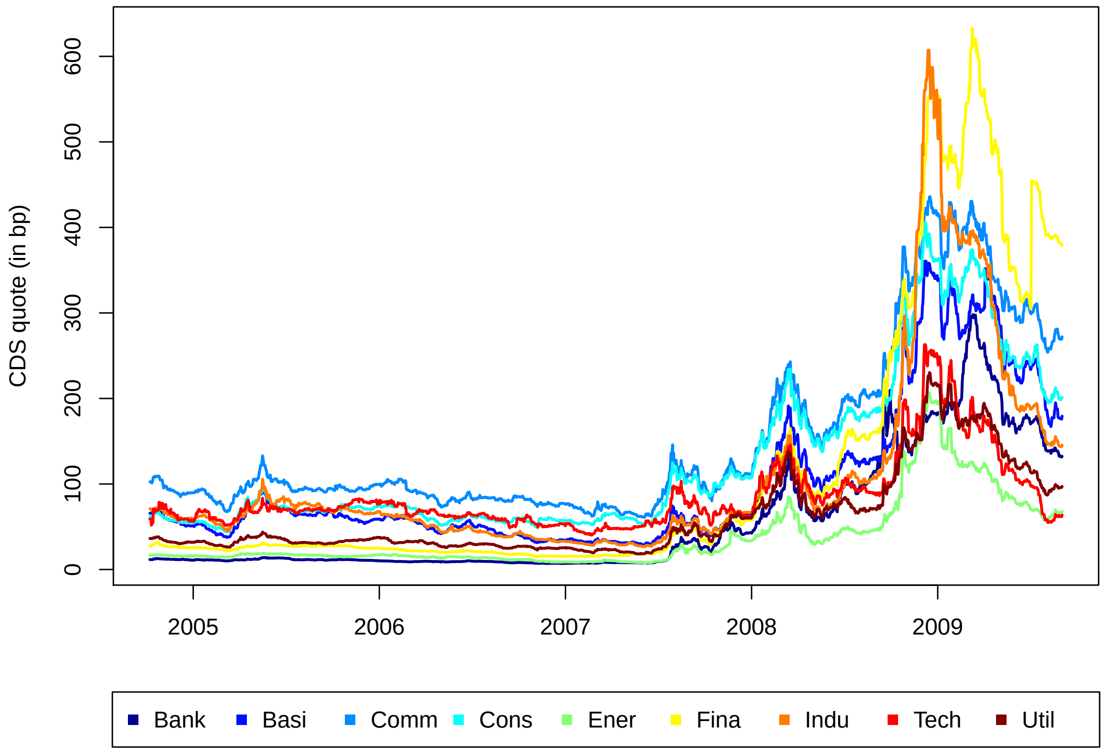

Figure 2 – Time Evolution of CDS Premia Averaged Across Sectors (Europe)
The figure presents sector-averaged time series of daily CDS bid quotes used in our analysis. All CDS data are obtained from Bloomberg; the time series of observations ranges from October 2004 to October 2009. Daily averages are taken across all firms belonging to the given sector.

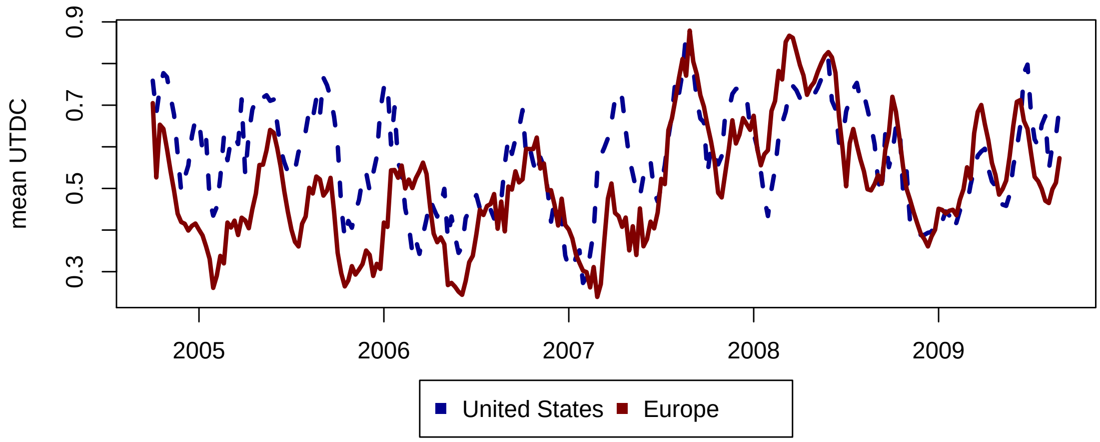

Figure 3 – Time Evolution of Upper Tail Dependence Within the Regional Banking Sectors

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.

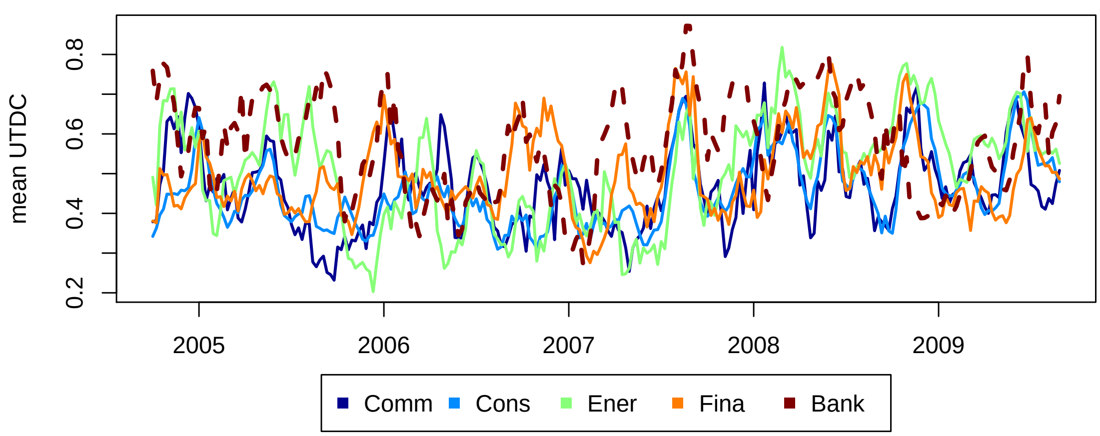

Figure 4 – Time Evolution of Intra-sectoral Upper Tail Dependence (United States)

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.

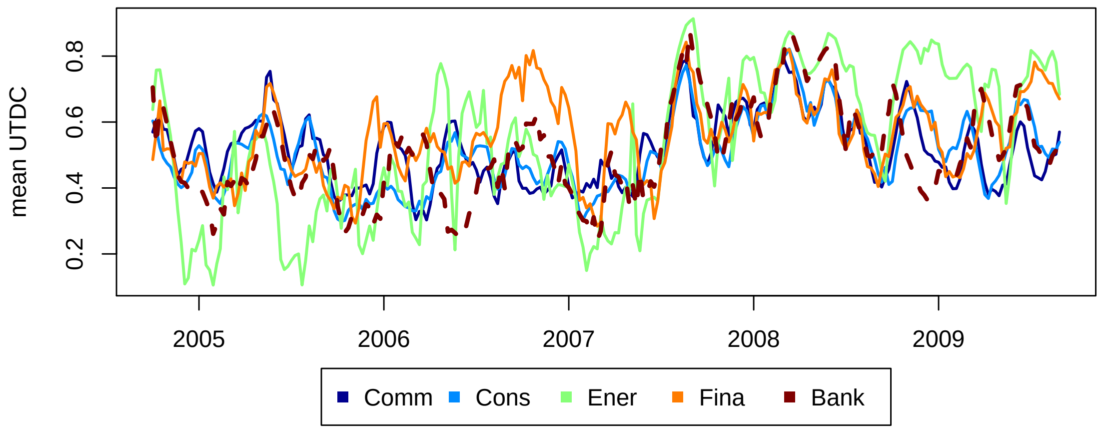

Figure 5 – Time Evolution of Intra-sectoral Upper Tail Dependence (Europe)

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.

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 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 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 B.1 presents the names of the US and European banks in our sample.

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 – 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 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 (5) (Expressions (7) and (8)); the count statistics in Panel B2 are determined according to Expression (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 (6a) and (10a). Appendix-Table B.2 provides detailed statistics supplementary to the determination of ranks in Panel C.

Table 2 – continued:

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 ($\Delta\%$) or in absolute (Δ) terms.

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 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 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 (5) (Expressions (7) and (8)); the count statistics in Panel B2 are determined according to Expression (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 (6a) and (10a). Appendix-Table B.3 provides detailed statistics supplementary to the determination of ranks in Panel C.

Table 3 – continued:

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.

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 4 – continued on the next page

– continued –

Panel C	pre-crisis		crisis		$\Delta_{\text{crisis}-\text{pre-crisis}}$			
	#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 4 – Pre-Crisis and Crisis Upper Tail Dependence

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 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 (5) (Expressions (7) and (8)); the count statistics in Panel B2 are determined according to Expression (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 (6a) and (10a). Appendix-Table B.4 provides detailed statistics supplementary to the determination of ranks in Panel C.

Table 4 – continued:

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.

	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 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 3. We present aggregate statistics of upper tail dependence coefficients between banks and firms from a non-bank sector ***I*** within the same region.

Table 5 – continued:

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 (5) (Expressions (7) and (8)); the count statistics in Panels B2 and B3 are determined according to Expression (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 (6b) and the rank count statistics presented in Panel D1 are calculated applying Expression (10b). Appendix-Tables B.5, B.6, B.7, and B.8 present detailed statistics supplementary to the figures given in Panels A, B, and C. 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 ($\Delta\%$) or in absolute (Δ) terms. We assign asterisks if these deviations are statistically significant. (*** = 1%-level; ** = 5%-level; * = 10%-level)

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 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 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 (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)

Appendix A. Robustness Issues

Panel A – Robustness of Table 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 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 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 A.1 – Upper Tail Dependence Coefficients

All figures are estimated from the full sample of daily CDS bid quotes applying the methodology outlined in Section 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).

Table A.1 – 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 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 ($\Delta\%$) terms. We assign asterisks if these deviations are statistically significant. (*** = 1%-level; ** = 5%-level; * = 10%-level)

Panel A – Robustness of Table 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 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 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 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 A.2 – 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 3. Instead of using a standard t-test for the difference tests, we use the non-parametric Wilcoxon W Statistic.

Table A.2 – 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 ($\Delta\%$) terms. We assign asterisks if these deviations are tested statistically significant according to the Wilcoxon Test. (*** = 1%-level; ** = 5%-level; * = 10%-level)

Appendix B. Supplementary Results Tables

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 B.1 – Description of Banks

All United States' CDS in USD; all European CDS in EUR.

Supplement to Table 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 B.2 – 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 (5) on page 13. (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 (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 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 B.3 – 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 (5) on page 13. The *rank* is identified by the mean upper tail dependence coefficient applying Expression (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 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 B.4 – 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 B.4 – 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 (5) on page 13. 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 (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 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 B.5 – 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 (5) on page 13. (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 (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 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 B.6 – 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 (8) on page 14. (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 (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 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 B.7 – 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 B.7 – 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 B.7 – 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 B.7 – 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 (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 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 B.8 – 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 B.8 – continued on the next page

– **continued** –

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 B.8 – 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 B.8 – 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 (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.

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