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Credit risk connectivity in the financial industry and stabilization effects of government bailouts

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Abstract:

We identify the connections between financial institutions from different sectors of the financial industry based on joint extreme movements in credit default swap (CDS) spreads. First, we estimate pairwise co-crash probabilities (CCP) to identify significant connections among 193 international financial institutions and explain CCPs with shared country and/or sectoral origin indicators. Second, we use network centrality measures to identify systemically important financial institutions. Third, we test if bailouts stabilized network neighbors and thus this financial system. Financial firms from the same sector *and* country are most likely significantly connected. Inter-sector and intra-sector connectivity across countries also increase the likelihood of significant links. Central network indicators based on significant CCPs identify many institutions that failed during the 2007/2008 crisis. Excess equity returns in response to bank bailouts are overall negative and significantly lower for connected banks.

Keywords: Extreme Value Theory, CDS Spreads, Systemic Institutions, Network Stability

JEL-Classification: C14, G14, G 21, H12

Non-technical summary

The failure of Lehman Brothers and the distress of AIG in September 2008 touched off a cascading series of financial shocks. These events were the catalyst of the global financial crisis and subsequently demonstrated that risks can propagate quickly in the financial industry both across countries and sectors. The set up of rescue schemes in numerous countries and a series of bailouts of distressed financial institutions signaled that any systemically important financial institution will be saved. While such policies potentially contributed to stabilize the financial system they bode ill for market discipline and moral hazard. This has led to calls for a centralized prudential regulator with a far reaching mandate to regulate systemic risks and discipline the management. Against this background, this paper contributes to the literature on financial stability by providing evidence on two important questions. First, which financial institutions are systemically relevant due to their connectivity? And secondly, how effective were national bailout policies in stabilizing the financial system?

Methodologically, we approach these two questions using Extreme Value Theory to estimate so-called co-crash probabilities (CCP). CCPs measure the likelihood of an extreme joint deterioration in CDS spreads for pairs of financial institutions. We use daily CDS spreads of 193 financial intermediaries from eight different sectors and 37 different countries between January 2004 and January 2011 to estimate an overall number 18,528 bilateral connections. The focus on connections between individual intermediaries allows us to examining links between individual institutions allows us to obtain a network perspective, which is largely neglected in previous literature. To shed light on the first question, we use bootstrap methods to identify significant pair wise CCPs and investigate the degree and intensity of connections across countries and sectors. Concerning the effectiveness of bailout policies, we test in an event study setting if bailouts during the crisis caused cumulative abnormal returns (CARs). More specifically, we expect to see that significantly connected peers exhibit significantly positive and higher CARs compared to non-connected peers. We identify connected peers by making use of the information contained in significant CCPs.

Our empirical analysis provides three key insights for financial stability. First, our results suggest that the connectivity of financial firms as measured by significant CCPs decreased substantially during the crisis. Before the crisis, regional connectivity within Europe was higher compared to the U.S., but lower afterwards. Second, connectivity is most likely among financial institutions from the same country and sector. While the intensity of ties is largest for pairs of financial institutions within regions, sectoral ties across countries are also positive and sizeable. Third, we find that average cumulative abnormal equity returns around government bailouts are overall negative for both connected and unconnected peers. However, domestic peers from the banking sector that are not connected to rescued banks exhibit significantly positive CARs. Largely national rescue schemes thus appear to primarily stabilize domestic financial systems by generating abnormal returns of non-connected banks.

Nichttechnische Zusammenfassung

Der Zusammenbruch von Lehman Brothers und die Schieflage von AIG im September 2008 lösten eine Reihe von sich selbstverstärkenden Schocks im Finanzsystem aus. Diese Ereignisse waren die Auslöser der globalen Finanzkrise und demonstrierten, wie schnell sich Risiken über das gesamte Finanzsystem ausbreiten können. Die Rettung von in Schieflage geratener Finanzintermediäre durch dafür eigens eingerichtete Rettungsfonds verdeutlichte, dass vor allem systemrelevante Banken künftig gerettet werden. Obwohl diese Rettungsmaßnahmen zur Stabilisierung des Finanzsystems beigetragen haben, können sie sich auch nachteilig auf die Marktdisziplin und das Risikoverhalten der Finanzintermediäre auswirken. Vor diesem Hintergrund werden in diesem Papier zwei Fragestellungen untersucht. Erstens, welche Finanzintermediäre sind aufgrund ihrer Vernetztheit systemisch relevant? Zweitens, wie effektiv waren die Rettungsmaßnahmen tatsächlich bei der Stabilisierung des Finanzsystems?

Zur Beantwortung dieser beiden Fragen wird die Methode der Extremwerttheorie verwendet, um die Wahrscheinlichkeit einer gemeinsamen Schieflage von zwei Finanzintermediären (CCP) zu ermitteln. Da CCPs die Wahrscheinlichkeit einer gleichzeitigen, extremen Verschlechterung der CDS-Spanne angeben, können sie auch als ein Maß der Verbindung zwischen zwei Finanzintermediären interpretiert werden. Der zugrundeliegende Datensatz enthält tägliche CDS-Spannen für 193 Finanzintermediäre aus 8 Sektoren und 37 Ländern zwischen Januar 2004 und Januar 2011. Daraus werden insgesamt 18528 bilaterale Verbindungen abgeleitet. Durch die Ermittlung der einzelnen Verbindungen zwischen allen Finanzintermediären wird ein Einblick in das gesamte Netzwerk gewährt. Um die erste Frage zu beantworten, werden zunächst die signifikanten CCPs identifiziert und anschließend die Anzahl und die Intensität der Verbindungen zwischen Ländern und Sektoren untersucht. Zur Beantwortung der zweiten Frage wird im Rahmen einer Event-Studie getestet, ob die Rettungsmaßnahmen während der Krise zu kumulativen, abnormalen Aktienrenditen (CARs) geführt haben. Zu erwarten ist, dass Finanzintermediäre, die mit geretteten Finanzintermediären in Verbindung gestanden haben, signifikant höhere CARs aufweisen als Finanzintermediäre ohne eine solche Verbindung. Verbundene und nicht-verbundene Intermediäre werden mittels statistisch signifikanten CCPs differenziert.

Die empirischen Befunde dieser Studie lassen drei wesentliche Rückschlüsse für die Finanzstabilität zu. Erstens deuten die Ergebnisse auf einen deutlichen Rückgang der Vernetztheit zwischen Finanzintermediären während der Finanzkrise hin. Vor der Krise war die regionale Verbundenheit innerhalb Europas größer als in den USA und kleiner während der Krise. Zweitens bestätigen die Ergebnisse die Erwartung, dass zwei Finanzintermediäre aus der gleichen Region und dem gleichen Sektor stärker miteinander verbunden sind als Finanzintermediäre aus unterschiedlichen Ländern oder Sektoren. Während die Stärke der Verbindungen besonders für Finanzinstitute innerhalb der gleichen Region am höchsten ist, sind auch Verbindungen über Sektoren hinweg bedeutsam. Drittens sind die durchschnittlichen kumulativen, abnormalen Renditen an Tagen, an denen staatliche Rettungsmaßnahmen stattgefunden haben, insgesamt negativ. Für Banken innerhalb eines Landes, die nicht verbunden waren, lassen sich jedoch signifikant positive CARs feststellen. Nationale Rettungsprogramme scheinen daher im Wesentlichen zu einer Stabilisierung des inländischen Finanzsystems geführt zu haben, von der überwiegend nicht-verbundene Banken profitieren konnten.

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Credit risk connectivity in the financial industry and stabilization effects of government bailouts[1]

I. Introduction

The September 2008 coincidence of the Lehman Brothers failure and the bailout of AIG, an U.S. insurance company, shows that risks can propagate in the financial industry both across countries *and* sectors (Brunnermeier, 2009). Subsequent wide-spread bailout policies for distressed financial institutions by policy makers signaled that any systemically important financial institution (SIFI) will be saved (Freixas and Rochet, 2010). Clearly, such policies bode ill for market discipline and moral hazard (Voelz and Wedow, 2011). Any financial institution considered too big or too connected to fail has strong incentives to misbehave. Freixas and Rochet (2010) argue therefore that a centralized prudential regulator with a far reaching mandate to tax systemic risks and discipline SIFI management is needed instead of national authorities. But which financial institutions are systemically relevant due to their connectivity? And how effective were national bailout policies in stabilizing the financial system? These are the two questions this paper answers.

First, to identify financial institutions that are too connected too fail, we use Extreme Value Theory (EVT) to estimate so-called co-crash probabilities (CCP), which measure the likelihood of an extreme joint deterioration in CDS spreads for pairs of financial institutions. We use daily CDS spreads of 193 financial intermediaries from eight different sectors and 37 different countries between January 2004 and January

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2011 to measure interconnectedness. CDS markets exhibited a rampant increase and writing CDS contracts in opaque over-the-counter (OTC) markets were directly related to the fall of AIG (Stulz, 2010; Duffie, 2010). More generally, CDS spreads reflect directly market participants' perceptions of credit risk. Given that contagion of credit risk is arguably one of the most relevant considerations whether or not to bail out financial institutions, CDS-based CCPs are a natural point of departure to assess which institutions may qualify as SIFI.

Second, prudential regulation and supervision is still organized for the most part at the national level and only responsible for separate sectors of the financial industry, e.g. either banks or insurances. We ask if government support measures for financial institutions were effective in stabilizing the financial system. Using bootstrap methods, we identify significant pairwise CCPs and investigate the degree and intensity of connections across countries and sectors. We generate measures of network centrality based on CCPs to identify very connected institutions and test if bailouts during the crisis of 2007/2008 caused cumulative abnormal returns (CARs). We utilize capital injections and asset support measures issued by governments to rescue distressed banks and insurance companies from Stolz and Wedow (2010). If national rescue policies were effective, we expect that significantly connected peers exhibit significantly positive and higher CARs compared to non-connected peers.

Our paper relates to two important strands in recent financial economic literature. The first models networks of financial institutions (Allen and Babus, 2009) and emphasize the interbank market's role as a source of liquidity.[2] Numerous empirical studies assess the contagion potential of interbank markets.[3] But given the proprietary nature

[2]See, for example, Allen and Gale (2000), Nier et al. (2007), Allen et al. (2009), and Acharya and Merrouche (2009).

[3]Upper and Worms (2004) and Memmel et al. (2011) (Germany), van Lelyveld and Liedorp (2006) (Netherlands), Iori et al. (2006) (Italy), Degryse and Nguyen (2007) (Belgium), and Cocco et al. (2009) (Portugal), and Gai and Kapadia (2010) (UK).

of interbank market data, most studies typically neither consider cross-country nor cross-sectoral linkages. In addition, interbank loans reflect credit risk only to a limited extent, which restricts their appeal to provide evidence on the potential of systemic risk contagion in empirical work.[4]

The second strand of literature to which we relate are models that measure systemic risk and the contribution of individual institutions to it. Systemic risk is a notoriously vaguely defined term. A common feature in most studies is it's low probability-high impact nature. Often, systemic risk results from "extreme events". In Acharya (2009), these events are shocks to shared exposures to real investments that trigger a flight for safe assets that induces a market crash. Wagner (2010, 2011) focuses on the risk that investors might have to liquidate portfolios simultaneously. If agents hold diversified portfolios that are, however, identical, he shows that a trade-off exists between diversification (of individual portfolios) and diversity (across different portfolios). Hence, completely diversified asset holdings might actually increase systemic risk. Ibragimov et al. (2011) show that these extreme risks are not normally distributed and typically underestimated (see also Duffie et al., 2009). Individual diversification can thus lead to high interconnectedness of risks[5] that is undesirable from a societal perspective.

A number of recent studies aim to measure the contribution of individual financial institutions to systemic risk (Tarashev et al., 2010). Systemic risk is usually defined as an aggregate loss in equity value based on some variation of value-at-risk (VaR) approaches. For instance, Acharya et al. (2010) estimate the expected shortfall of an individual financial institution if the system as a whole faces a certain extreme VaR loss. Conversely, Adrian and Brunnermeier (2010) obtain their measure from a VaR for

[4]For instance, Angelini et al. (2009) find that only after the 2007/2008 financial crisis interbank interest rates came to depend on the creditworthiness of the counterparty. Two additional practical issues in empirical work are that interbank exposures are often imputed based on large credit exposures, and thus subject to selection bias, and low reporting frequency.

[5]Either through common real asset exposures as in Acharya (2009) or joint liquidation risk as in Wagner (2010, 2011).

the financial system with and without considering the institution in question, the so-called Co-VaR measure, and estimate marginal values applying quantile regressions.[6]

The main differences between our EVT approach to measure CDS based CCPs and these studies are fourfold. First, we focus on the conditional probability of all possible pairings of individual intermediaries crashing jointly whereas the literature on systemic risk measurement concentrates on the effect of an individual institution's default on the overall financial system. Second, examining links between individual institutions allows us to obtain a network perspective, which is largely neglected in previous literature. Third, while all systemic risk approaches also focus on tail events, they impose considerably more structure a priori on the investigated equity returns data compared to the non-parametric EVT-based estimation, which requires much lighter distributional assumptions (Longines and Solnik, 2001; Hartmann et al., 2004). In addition, EVT permits the estimation of significance levels of connections. Finally, most systemic risk measures are confined to the study of bank's equity prices. But financial instability and contagion concerns apply equally to non-bank financial intermediaries and should arise in particular from credit risk connectivity, which is not directly reflected by equity returns or debt yield series (Jorion and Zhang, 2007).[7]

Indeed, Jorion and Zhang (2007) find evidence for credit contagion among U.S. non-financial firms filing for Chapter 11 bankruptcy. They distinguish in Jorion and Zhang (2009) between contagion (through intra- and inter-industry effects) from counterparty effects (due to direct credit exposures between pairs of firms *across* industries). To our knowledge, we are the first using CDS spread co-movements across financial firms from different sectors of the financial industry. Thereby, we fill the gap between

[6]Other systemic risk metrics mushroom, see for example, Lehar (2005) or Huang et al. (2009).

[7]CDS spreads directly reflect debt default expectations. Alternatives, such as the spread between corporate and Treasury bond yields, can reflect also other factors, for instance differential tax treatment between two types of bonds. Equity prices, in turn, reflect changes in the expected profitability of a firm rather than credit risk and a change in leverage affects equity prices and CDS spreads differently.

de Jonghe (2010), who analyzes equity CCPs of banks and conditions those on firm-specific traits, and Jorion and Zhang (2007, 2009), who investigate credit contagion based on CDS spreads for non-financial firms.

Our main results are as follows. Across sectors and countries, the connectivity of financial firms as measured by significant CCPs decreased substantially during the crisis. Regional connectivity within Europe is higher compared to the U.S. before the crisis, but lower afterwards. Regression analysis shows that connectivity is *most likely* among financial institutions from the same country and sector. But also sectoral ties across countries contribute positively. The *intensity* of ties, in turn, is largest for pairs of financial institutions within regions, especially the U.S. "League" tables of connectivity based on network centrality measures reveal that a number of arguably important banks are identified well by our method (e.g. Lehman Brothers, Bear Stearns, and Commerzbank). But we also find a number of unusual suspects to be very connected according to our measures of centrality that originate from other than the banking sector, such as insurance companies, REITS, and investment firms. Average cumulative abnormal equity returns around government bailouts of banks (and insurances) are overall negative for both connected and unconnected peers, but differ across sectors. In sum, our results support the claim for a more holistic approach to prudential supervision across national borders and sectors of the financial industry.

This paper is organized as follows. In section II we introduce the data and methods to estimate the tail dependence index and discuss the co-crash probabilities. Section III shows how we construct the network centrality measures and identify SIFIs. Section IV discusses the method to estimate cumulative abnormal equity returns around bailout events and discusses the results. We conclude in Section V.

II. Credit default swaps and co-crash probabilities

A. Data

Credit contagion between two financial institutions can be driven by direct counterparty risk when an obligor fails to meet its obligations to the creditor, or through joint exposures to common factors. Either reason affects the likelihood of a financial firm failing in part or completely to repay it's debt. A CDS contract insures the buyer against a credit event specified in the contract, thereby transferring credit risk.[8] The CDS buyer makes periodic payments to the seller of the contract until the contract expires or the predefined credit event occurs. In case of a credit event, the seller compensates the buyer for the difference between the par value and the market value. Two ways of settlement exist. First, the protection buyer delivers the security of the underlying reference entity, for which it bought the CDS, to the protection seller and receives the notional amount of the security. Second, the CDS contract is settled by cash payment of the difference in the par value and the market price of the security.

CDS contracts are traded in (opaque) OTC markets (Nicolò and Pelizzon, 2008), which expanded considerably. Outstanding notional amounts peaked according to the International Swaps and Derivatives Association at around USD 60 trillion just before the onset of the crisis. We obtain CDS spread data from the Markit Group for the period January 2004 through January 2011. The sample consists of quotes contributed by more than 30 dealers for all trading days during the period. Once the quotes are delivered by the dealers, Markit screens the quotes, removes outliers and stale observations. Only when more than two contributors remain, Markit calculates a daily composite spread. CDS spread quotes are the most widely used source of CDS data in the literature (Mayordomo et al., 2010).

We select financial institutions using the weekly list of the 1000 single reference

[8]See Stulz (2010) for a comprehensive review of CDS contracts and markets.

entities with the largest notional amounts of CDS contracts outstanding published by the Depository Trust & Clearing Corporation (DTCC) to acknowledge that the information content of CDS spreads is related to firm size (Mayordomo et al., 2010).[9] We identify around 360 financial institutions and obtain CDS spreads for 193 (Table I).

We only use CDS spreads of senior contracts with a maturity of five years, which are traded more frequently and are more liquid (BBA, 2006). For each underlying entity, we choose the CDS contract in the currency with the potentially highest liquidity.[10]

Finally, we select CDS spreads based on the different restructuring clauses applicable for financial institutions in the US, Europe and Asia. We selected the CDS spreads based on the ex-restructuring clause for institutions from North America, modified-modified restructuring for Western Europe and old restructuring for Asia.

–Table I around here–

Table I contains the average CDS spread by financial sector and region. Most financial institutions are banks and, to a lesser extent, insurance companies as well as intermediaries from other sectors of the financial industry. Banks and financial service providers exhibit the lowest mean (and median) CDS spreads. Subsidiaries, lease companies, and also insurance companies are in turn significantly more risky as reflected by higher mean (and median) CDS spreads. From a geographical perspective, financial firms from Europe and the US account for about 76% of sampled institutions. The remainder is from other developed (O.D.) and emerging market (E.M.) economies.[11]

[9] See http://www.dtcc.com/products/derivserv/data/index.php.
[10] According to DTCC, the majority of CDS contracts are denominated in USD (62%) and EUR (35%).
[11] See Table X for a list of countries per region.

B. Tail dependence index estimation

News about the credit worthiness of counter parties are well reflected in CDS spreads, which is why they are meaningful indicators of credit events. For example, Blanco et al. (2005) find that the CDS market leads the bond market in determining the price of credit risk. Therefore, we measure the potential for credit risk contagion between two financial institutions by the joint probability of extreme CDS spread changes, where $X_{i,t}$ is the percentage change in institution i's CDS spread at time t:

$$p_{i,j} := \text{Prob}[X_{i,t} > x_j \cap X_{j,t} > x_i], \quad i \neq j. \tag{1}$$

This co-crash probability (CCP) captures the likelihood that the CDS spreads of institutions i and j exceed jointly the respective critical thresholds x_i and x_j. Joint exceedance of markets' expectations about credit events are rare by definition. Therefore, we employ multivariate extreme value theory to estimate the probability of the joint event. Ledford and Tawn (1996) suggest a semi-parametric approach to estimate Equation (1). The main advantage of the approach is to permit inferring dependence or independence of CDS changes in the tails of the joint distribution.[12] We develop a bootstrap technique to test for dependence that is outlined in section II.D.

Dependence implies the existence of a credit risk connection between two institutions since both are jointly exposed to extreme credit event expectations reflected by CDS spreads. Note that connections can exist due to both actual credit exposures to another or mutual dependence on third factors.

To extract information on the dependence between the maximum values of the two series, it is important to address the biasing impact of the marginal densities on

[12]See also Poon et al. (2004), Hartmann et al. (2007), Straetmans et al. (2008), and de Jonghe (2010). Dependence, or more precisely asymptotic dependence, implies that Equation (1) does not tend to zero as the sample size grows large. Asymptotic independence implies that Equation (1) tends to zero for a large sample size.

the joint probability estimate. Therefore, we follow the semi-parametric approach of Draisma et al. (2004) and Drees et al. (2004) that only involves the estimation of the tail index η of a univariate Pareto marginal distribution to infer dependence of the extreme values of two series. The approach consists of two steps.

First, we transform the percentage changes in CDS spreads of two institutions i and j to unit Pareto marginals. This ensures that the marginal distributions of the series have no impact on the joint tail probabilities. Thus, differences in the estimated tail index are only due to differences in the dependency of extreme percentage changes in CDS spreads. We denote the unit Pareto marginal transformation of the series by $\tilde{X}_{i,t} := (n_i + 1)/(n_i + 1 - R(X_{i,t}))$, where n_i is the number of observations of institution i and $R()$ returns the rank order statistic of the argument. Between any two institutions, the transformed series $\tilde{X}_{i,t}$ and $\tilde{X}_{j,t}$ have the same density. Therefore, the critical threshold values q are the same across institutions and Equation (1) can be stated as:

$$\begin{aligned}\text{Prob}[X_{i,t} > x_j \cap X_{j,t} > x_i] &= \text{Prob}[\tilde{X}_{i,t} > q \cap \tilde{X}_{j,t} > q] \\ &= \text{Prob}[\min\{\tilde{X}_{i,t}, \tilde{X}_{j,t}\} > q].\end{aligned}$$

Note that the multivariate probability is now changed into a univariate probability. This transformation permits the use of standard maximum likelihood techniques to estimate a generalized Pareto distribution for the minimized series

$$Z_t := \min\{\tilde{X}_{i,t}, \tilde{X}_{j,t}\}.$$

For notational convenience, the subscripts i and j are dropped for Z_t. Suppose that two institutions exhibit a perfect credit risk connection and as a result their CDS spreads move identically. Therefore, Z_t equals the transformed variable $\tilde{X}_{i,t}$ and its density exhibits a unit tail index. In contrast, if no connection exists, the minimized series Z_t

exhibits a minimal fat tail and the tail index of its density is smaller than one.

Thus, the extent to which institutions are credit-risk connected can be estimated as the tail index of the generalized Pareto density of the minimized series Z_t. We employ the maximum likelihood estimator suggested by Hill (1975) to compute the estimate of the tail index η. This estimate is denoted by:

$$\hat{\eta}(k) := \frac{1}{k}\sum_{m=1}^{k} \ln\Big[\frac{Z(n-m+1)}{Z(n-k)}\Big]. \tag{2}$$

A typical problem in calculating Equation (2) is the nontrivial choice of k, i.e. the sample of "large" CDS spread changes in the joint series that is used to predict truly extreme CDS changes occurring simultaneously. If k is too small, an insufficient amount of observations enter the estimation of the tail index. In contrast, too high levels of k result in a biased tail index estimate because too many observations enter the estimation that are from the central mass of the distribution and do not represent tail events. The decision on the optimal number of observations to estimate Equation (2), k^* thus represents a trade-off between a too high variance of the estimator for low values of k versus a lower variance for large values of k at the expense of introducing bias.

We follow Huisman et al. (2001) to determine k^* and approximate the bias in estimating the tail index to be linear in k.[13] The bias is modeled as a linear relation between the estimated tail index and the number of observations included for estimation:

$$\hat{\eta}(k) = \gamma_0 + \gamma_1 k + \varepsilon_k, \quad \forall k \in \{1, ..., n-1\}, \tag{3}$$

where ε_k denotes a random noise term and the coefficient parameters γ_0 and γ_1 represent the bias relation between the tail index estimate Equation (2) and the number of

[13] Alternatively, one can plot Equation (2) for different k, evaluate the range of tail index estimates that are stable across k, and choose k^* in a region with minimal tail indeces. Danielsson et al. (2001) provide a double bootstrap procedure to determine k^*. Our time series are too short for this procedure.

observations included for its computation. Huisman et al. (2001) suggest to estimate Equation (3) with weighted least squares using weights equal to $\sqrt{k}$ to obtain unbiased and consistent estimates of $\hat{\gamma}_0$ and $\hat{\gamma}_0$. The weighting scheme ensures that less weight is given to the tail index estimates in the region where they are least consistent, which is likely to be the case for low values of k. The unbiased estimate of the tail index is obtained from $\hat{\gamma}_0$, which is substituted in Equation (2) to determine k^*

To determine k^*, we choose k by minimizing $(\hat{\eta}(k) - \hat{\gamma}_0)^2$. The k that minimizes this sequence in a stable area is denoted as k^*.[14] Substitution into Equation (2) yields the tail dependence index of the two series of percentage changes in CDS spreads.

–Table II around here–

Table II contains summary statistics of the percentage changes in CDS spreads for the 193 sampled financial institutions in the periods before and after August 9, 2007. This date marks the first of major public interventions by central authorities that preceded and are related to the Global Financial Crisis. In order to alleviate market worries about widespread exposure of financial institutions to U.S. subprime mortgage lending markets, the ECB opened lines of USD 130 billions in low-interest credit, and the Federal Reserve followed suit with USD 12 billions in temporary reserves. Therefore, the period until August 9, 2007 is denoted as the pre-crisis period, and is followed by the during-crisis period. Additionally, summary statistics of the percentage changes in CDS spreads included for estimating the CCPs are reported.

On average, we use only observations above the 85^{th} percentile in the joint CDS change series to predict truly extreme movements, i.e. the tail index. It is important not to confuse the percentiles shown in Table 2 with those specified, for example, in Value-at-Risk based approaches to calculate "extreme" events. Related, the percentiles of

[14]We conduct a grid search to choose k^* in an area where neighboring k values also yield squared prediction errors around zero to avoid obtaining k^* based on inconsistent estimates of η.

threshold values of critical CDS spread changes may differ across institutions because we do not impose a priori percentiles to denote extreme percentage changes in CDS spreads. Instead, the Huisman et al. (2001) method determines, which observations to include for calculating CCPs properly accounting for the consistency-bias tradeoff in estimating the tail index for the CCP.

C. *Co-crash probability*

Draisma et al. (2004) extend the model by Ledford and Tawn (1996) and develop an estimator for the probability of an extreme event reflected by Equation (1) that allows for both asymptotic dependence as well as independence between two series. This estimator is semi-parametric because no distributional assumptions are necessary about the joint density of the percentage changes in CDS spreads. Constructing the joint probability estimator suggested by Draisma et al. (2004) requires to revisit the assumptions and notation regarding the marginal densities of each institution's maximum CDS spread percentage change. Let the maximum of $X_{i,t}$ for institution i follow the generalized Pareto distribution with shape parameter ξ_i, scaling parameter a_i, and location parameter b_i, such that the cumulative density of $X_{i,t}$ is denoted by

$$F_i(x) := 1 - \left(1 + \xi_i \frac{x - b_i}{a_i}\right)^{-\frac{1}{\xi_i}}. \tag{4}$$

Parameters are estimated with standard maximum likelihood techniques and calculated independently for each institution in the sample. Parameter estimates are denoted by $\hat{\xi}_i$, scaling parameter $\hat{a}_i$, and location parameter $\hat{b}_i$. Since Equation (4) is estimated for each individual institution, heterogeneity with respect to idiosyncratic failure probabilities of institutions is preserved.

For ease of exposition, $\hat{F}_i$ denotes Equation (4) with parameters replaced by estimates. Let $\hat{\boldsymbol{F}}_{i,j} := (\hat{F}_i, \hat{F}_j)$, a two dimensional vector with elements reflecting the idiosyncratic probabilities of the events, in which percentage changes in CDS spreads are smaller than the critical levels of institutions i and j. Similarly, $\hat{\boldsymbol{F}}_{i,j}^{-1} := (\hat{F}_i^{-1}, \hat{F}_j^{-1})$, and contains elements of $\hat{\boldsymbol{F}}_{i,j}$ inverted. This term identifies CDS spread percentage changes that are larger than the given thresholds. Last, let $\boldsymbol{D}_{i,j} := (1 - \hat{F}_i, 1 - \hat{F}_j)$ a row vector with probabilities of the event in which both institutions' CDS spread percentage changes exceed their critical thresholds. The estimator of Equation (1) is:

$$\hat{p}_{i,j} := c_{i,j}^{1/\hat{\eta}_{i,j}} \frac{1}{n_{i,j}} \sum_{t=1}^{n_{i,j}} \mathbf{1}\{(X_{i,t}, X_{j,t}) \in \hat{\boldsymbol{F}}_{i,j}^{-1}(\boldsymbol{\iota} - \boldsymbol{D}_{i,j}/c_{i,j})\}, \tag{5}$$

where the operator $\mathbf{1}\{.\}$ returns a 1 if the condition in braces is fulfilled and a zero if not. The operand $\{(X_{i,t}, X_{j,t}) \in \hat{\boldsymbol{F}}_{i,j}^{-1}(.)\}$ identifies the set of CDS spread percentage changes that are larger than the critical values returned by $\hat{\boldsymbol{F}}_{i,j}^{-1}(.)$. Hence, the summation over the $n_{i,j}$ days in Equation (5) yields the number of observations for which both institutions experience contemporaneously a detrimental credit event.

The constant $c_{i,j} \in (0, 1]$ inflates the set of critical exceedance values. Note that for smaller values of $c_{i,j}$, the critical levels in $\hat{\boldsymbol{F}}_{i,j}^{-1}(.)$ are larger. Smaller values of $c_{i,j}$ essentially imply a reduction in the number of observations for which both institutions experience simultaneously a detrimental credit event. Because the domain of $\hat{\boldsymbol{F}}_{i,j}^{-1}(.)$ is $[0, 1]$, the choice of $c_{i,j}$ is limited to $(\max\{\boldsymbol{D}_{i,j}\}, 1]$. Throughout, $c_{i,j}$ is set at $\max\{\boldsymbol{D}_{i,j}\} + e$, where e is an arbitrary small constant. $\hat{\eta}_{i,j}$ denotes the estimator of the tail index, and larger estimates imply that both institutions experience more frequent extreme credit events jointly as shown in Equation (5). There, an increase in $\hat{\eta}_{i,j}$ results in a higher probability of extreme co-movement in CDS spread percentage changes.

D. Test for significance of CCPs

Draisma et al. (2004) investigate the asymptotic properties of the tail index estimate $\hat{\eta}_{i,j}$ as defined by Equation (2) and find that the estimate exhibits asymptotic normality as the number of observations becomes large. This result motivates the use of a bootstrap procedure to obtain a standard error of $\hat{\eta}_{i,j}$ for the purpose of developing a statistical test to infer dependence between extreme credit events of two institutions. We employ the stationary bootstrap procedure suggested by Politis and Romano (1994) to allow for weakly dependent observations on CDS spread percentage changes in calculating the standard error of the tail index estimate in Equation (5). The bootstrap procedure consists of the following steps:

1. A tail index estimate $\hat{\eta}_{i,j}$ is calculated along the lines of the estimation technique of Huisman et al. (2001) as described in section II.B.

2. For each of the B bootstrap replications the percentage changes in CDS spreads $X_{i,t}$ and $X_{j,t}$ are resampled in blocks of consecutive observations of random block length to yield a bootstrap sample $X^b_{i,t}$ and $X^b_{j,t}$ of equal length as the original sample, where b indexes the b^{th} replication.[15] From these bootstrap samples B tail index estimates $\hat{\eta}^b_{i,j}$ are produced, as in step 1.

3. The bootstrap standard error of $\hat{\eta}_{i,j}$ is denoted by $s(\hat{\eta}_{i,j}) = \sqrt{\frac{\sum_{b=1}^{B}(\hat{\eta}^b_{i,j}-\hat{\eta}_{i,j})^2}{B-1}}$.

4. Let η_0 be the hypothesized true value of $\hat{\eta}_{i,j}$ under the null. Then the test statistic $\frac{\hat{\eta}_{i,j}-\eta_0}{s(\hat{\eta}_{i,j})}$ can be computed and follows a student-t distribution with $B-1$ degrees of freedom. A t-test can be conducted to evaluate whether the test statistic lies in a pre-specified rejection region.

[15] For one particular block the starting value and the length are chooses uniformly at random across the number of observations.

Dependence in large percentage changes of CDS spreads between two institutions can now be determined by means of a basic statistical test. One tests the null of dependence against the alternative of independence. In terms of the tail index value, dependence is the case if $\eta = 1$ and independence is characterized by $\eta < 1$. For $\eta = 1$, the extreme percentage changes in CDS spreads between two institutions co-move sufficiently such that the joint crash probability eventually converges to a nonzero value. In case the null is not rejected, we assume the existence of a credit link between institutions i and j. Throughout, the number of bootstrap replications is 10,000, and a one percent significance level is applied.

Table III reports descriptive statistics of the estimated co-crash probabilities. Note that a distinction is made between all co-crash probabilities and the ones for which dependence in credit events could not be rejected. Since 193 institutions are sampled, a maximum of 18,528 potential links can exist.[16]

–Table III here–

The descriptive statistics illustrate a right-skewed distribution for the co-crash probabilities. The number of CCPs for which we find dependence is considerably lower during the crisis period relative to the pre-crisis period. Potentially, this reduction of significant ties reflects attempts of financial institutions during the crisis to insulate themselves from former peers as reflected by absenteeism in interbank markets and liquidity hoarding (Acharya and Skeie, 2011). The relevant mean CCP pertaining to significant linkages increased significantly from 11.9 basis points prior to the onset of the crisis to 15.5 basis points in the period after August 9, 2007. Thus, while the level of extreme CDS spread changes occurring at two institutions at the same time remains low, as can be expected for tail events, it doubled during the crisis sample period.

[16]Each institution can share a credit connection with 192 institutions and not counting a connection twice results in $\frac{193(193-1)}{2} = 18,528$ potential credit risk connections.

To gauge a first impression on the connectivity of financial institutions both across regions and sectors of the financial industry, consider Table IV. It shows the proportion of significant CCP estimates as a share of all CCPs for different regions and sectors, respectively.

–Table IV around here–

Intra-regional connectivity, i.e. the ratio of significant CCPs relative to all possible links among financial firms within a region, declined substantially after August 9, 2007. Especially the connectivity within U.S. and European regions declined substantially from around 60% and 85%, respectively, to around 18% and 11%. The Euro area, but also emerging markets, are the most intra-connected regions while in the U.S. only 60% of all possible ties between domestic financial institutions are significant.

Inter-regional connectivity, i.e. the ratio of significant CCPs relative to all possible links between financial firms across regions, is generally lower than intra-regional connectivity. This result indicates that financial institutions are more likely subject to credit-risk contagion through connections with other domestic rather than international peers.

The bottom panel of Table IV provides analogous summary statistics of significant CCPs for different sectors of the financial industry. For the two most populated sectors, banks and insurances, inter- and intra-sector connectivity is on a similar order than the regional indicators.[17] Intensive sectoral ties illustrate the potential for contagion not only across international borders, but also across different sectors of the financial industry. Declining intra- and inter-sectoral connectivity during the crisis mimics potential insulation attempts that also prevailed from a regional perspective.

[17] The complete networks indicated by 100% intra-sectoral connectivity for Financial Services and Leasing firms prior to the crisis reflects the low number of observations in these sectors.

E. Explaining CCPs

Two issues are important when assessing the connectivity of financial institutions and their actual potential to be systemically relevant. First, whether CCPs between firms *i* and *j* are significantly different from zero and, second, if the distress of an institution can spill over across borders and sectors. Table V shows a Heckman selection model, which specifies dummies for shared regional and sectoral origin financial institution pairs to explain either aspect for the entire *Pooled sample* as well as the *Pre-crisis period* until August 9, 2007 and the *During-crisis period* thereafter.

–Table V around here–

The dependent variable in columns 1, 3 and 5 of Table V is an indicator equal to one if a CCP connection between firms *i* and *j* is significant. We use a probit model and calculate subsequently inverse Mill's ratios to control for potential selection bias when regressing levels of significant CCPs only on the same set of dummies in the second specification in using OLS in each pair of columns.

The first group of dummies shows the effects if a certain pair of institutions is from the same country and/or sector of the financial industry. The reference group are financial-firm pairs from the same sector and country. For the full as well as for the subsamples, the existence of significant CCP ties is most likely for financial firms with a shared geographic and sectorial origin. This corroborates the current practice to organize prudential supervision primarily at the national level separately for each financial industry sector. However, the negative coefficients for the first two dummies distinguishing cross-sectoral and cross-national ties are very much alike, also in the subsamples. Therefore, it is not a priori clear that contagion potential through credit links between financial firms from different sectors, e.g. banks and insurances, should be of a lesser importance compared to cross-border ties. Recent reforms establishing supranational supervisory agencies, such as the European Banking Authority, thus seem a sensible step. But the focus on cross-border assessment of systemic risks might falsely neglect potentially equally important cross-sectoral channels of contagion.

To some extent, the importance of sectoral rather than international linkages is corroborated by the results in Columns 2, 4, and 6, which explain the level of significant CCPs. While overall insignificant, we find that prior to the crisis inter-sectoral links within a country increased the level of CCPs by 4.7 basis points, which is substantial given a mean of 11.9 basis points (see Table III). In contrast, potential cross-border links within an industry only exhibit an effect on the order of 2.1 basis points. The effect of neither shared origin or sector on CCP levels is even larger, amounting to 7.1 basis points. Thus, while the existence of significant ties is certainly most likely for financial firms from the same country within the same sector, the intensity of ties between firms is highest across borders and sector. Holistic supervision prior to the crisis across both these dimensions might thus have been warranted.

The second group of dummies captures links within and between the regions defined in Table VIII. In line with the simple descriptive evidence in Table IV, European, other developed, and emerging market regions are all more likely to host financial institutions that are connected compared to the U.S. financial network. The intensity of these intra-regional ties is, however, around 2.5 basis points lower in Europe compared to the U.S. financial system, a result that is driven by the pre-crisis period. During the crisis, we find hardly any evidence that regional connectivity plays a role other than increasing the odds for observing significant ties inside other developed and emerging regions.

Inter-regional dummies between regions indicate for the full sample that the U.S. is a less open financial system since the likelihood to observe significant CCPs between it and any other region is significantly lower compared to the odds of observing national ties. Europe, but also emerging markets, are in turn more likely connected across regional borders. The key difference between the two regions is that the intensity of inter-regional ties is significantly lower for Europe while it is larger for emerging economies. These results are also driven by the pre-crisis sample as well.

III. Connectivity

A. Measurement method

The previous results showed that both regional and sectorial origin are relevant to explain differences in both the likelihood of significant CCPs, but also the intensity of such a resulting network. Given the drastic concentration of the network during the crisis, i.e. much fewer significant connections, it is crucial to identify those financial intermediaries that are central to the network.

We measure the connectivity of financial institutions in the network represented by significant credit risk links. First, we assess how the institutions are connected in the overall financial system. In this context the co-crash probability in Equation (5) provides an indicator for the strength with which two institutions are linked. A simple measure for the centrality of an institution is the ratio of the number of co-crash probabilities for which dependence is found and the number of other institutions that enter the sample. Let $l_{i,j}$ denote a credit link variable that takes a value of 1 if dependence is found between the institutions' percentage changes in CDS spreads. The degree centrality is computed by Jackson (2010) as:

$$degree_i = \frac{1}{I-1} \sum_{j \in \{1,\dots,I | j \neq i\}} l_{i,j}. \tag{6}$$

Note that $degree_i$ ranges from zero to one, where zero indicates that the institution has no direct credit links with other institutions and one full connection to all institutions.

But as discussed in subsection E., it is not only the question whether a connection exists, but also how intensive this tie is. Therefore, we use in addition the degree centrality multiplied with the average CCP of an institution as a centrality measure. This approach also accounts for the overall strength of the credit risk connection.

IV. Bailout events and return effects

A. Bailout events

Numerous financial institutions were bailed out during the financial crisis of 2007/2008 in the wake of unparalleled concerted efforts of central banks and governments around the world. Many of these bailed out banks are actually among those identified as SIFIs based on (weighted) network centrality represented by significant CDS co-crash probabilities. This result begs the question, whether these interventions helped to stabilize the global financial system?

We therefore use an event study methodology, described below, to test whether bailouts of banks and insurance companies caused cumulative abnormal equity returns (CAR) among non-bailed out competitors. Specifically, to test if bailouts have had the desired system-wide stabilizing effects, we estimate if CARs of peers that are significantly connected in terms of CCP are higher compared to those of non-connected peers.

Actual bailouts under the auspices of the various national schemes, such as the Troubled Asset Relief Program in the US or the Federal Agency for Financial Market Stabilisation (*"Bundesanstalt für Finanzmarktstabilisierung"*) fonds but also outside of such schemes, have been collected systematically by the European Central Bank (see Stolz and Wedow, 2010). Bailouts entail either capital injections by governmental institutions or various forms of asset support for financial institutions.[18] They are only

[18]More specifically, governmental institutions include federal and local governments. As a conse-

observed for banks and insurance companies in our sample period and shown in Table VI.

– Table VI here –

Since the stock price series are observed on a daily basis (see Table IX in the appendix for summary statistics), the day at which the first rescue measure is announced constitutes the event. If an institution experienced successive rescue measures during the sample, we denote these as one event. This results in a total of 51 institutions, mostly banks, in our sample.

B. Event study method

The event study is based on an estimation window of 50 adjacent trading days that is directly followed by an event window of 3 trading days after the event. This event is the bailout of a financial institution, to which the firm under consideration may be significantly connected or not. The second day constitutes the day at which the bailout was implemented. For the estimation window we estimate the following market model by means of least squares for each financial firm i:

$$r_{i,t} = \beta_{0,i} + \beta_{1,i} r_{i,t-1} + \beta_{2,i} r_{m,t} + u_{i,t}, \tag{7}$$

where $r_{i,t}$ denotes the return of the institution i on trading day t. $r_{i,t-1}$ denotes a lagged return and controls for momentum effects, and $r_{m,t}$ denotes the market return and represents a global financial index. $u_{i,t}$ is a random error term.

The least squares estimates obtained from estimating Equation (7) are denoted by $\hat{\beta}_{0,i}$, $\hat{\beta}_{1,i}$ and $\hat{\beta}_{2,i}$. Abnormal returns are calculated as $AR_{i,t} := r_{i,t} - \hat{\beta}_{0,i} + \hat{\beta}_{1,i} r_{i,t-1} +$

quence measures taken outside official schemes are also included. With regard to asset support, these measure include asset guarantees and asset removal. Under the former approach, the actual assets remain on the bank's balance sheet but are insured by the government while the latter typically implied the set up of a bad bank.

$\hat{\beta}_{2,i} r_{m,t}$, which show whether the bailout of a connected peer had an impact on institution i.

We test if this impact is statistically significant using the method suggested by Kolari and Pynnönen (2010) to account for correlations in stock returns between financial institutions. Ignoring cross sectional return correlation can lead to considerably overstating test statistics, and may therefore lead to over rejection of the null of no impact. A detailed account on the methodology can be found in appendix A.

Once abnormal returns are identified that are significantly different from zero, they can be compared across institutions in terms of whether dependence is inferred from their credit link with the institution that was rescued. Differences between abnormal returns for institution for which dependence is found in their co-crash probability versus the ones that do not yields further insights about the co-crash probability measure.

C. *Bailout effects*

Table VII reports the average cumulative abnormal returns (CAR) due to bailouts of connected peers. Most bailouts pertain to banks (upper panel) and two insurance companies that were rescued (bottom panel). Within each panel, we consider insignificant and significant CCP ties for three subsamples: within and between countries together as well as domestic and international connections separately.

–Table VII around here–

Overall, cumulative abnormal returns are negative. Markets appear to derive little faith in future earnings of any financial firm from government bailouts of competitors. This may be due to restrictions on dividends and restructuring requirements for institutions bailed out by governments.

Considering both domestic and international links, CARs in response to bank rescues in the upper panel are lower for connected peers compared to unconnected peers.

Bank bailouts generate on average 2.9% lower returns for non-connected financial institutions and they reduce returns of connected intermediaries by 5.0%. However, this difference is not statistically different, casting doubt on any potential systemic effects of government bailouts.

Returns differ significantly though between connected and unconnected banks in response to another bank being bailed out. The negative abnormal returns are on average 4.7 percentage points lower for banks connected to a bailed out bank in terms of significant CCPs, which is substantial. This result suggests that investors' doubt about future cash flows is aggravated for those banks that are tied to a distressed partner in the interbank system.

This result is corroborated when considering only the effects of bailouts on national ties. Negative abnormal returns of connected banks are 8.3%, while non-connected banks exhibit positive abnormal returns. Thus, domestic bank rescues appear to instill faith among investors in those institutions that are not close to the source of distress, i.e. the bank that is bailed out. Mainly national bank rescue schemes thus seem to be a double-edged sword. While they apparently help to foster confidence at home in those banks that are not connected, they do generate significant discounts for those institutions that are connected.

This explanation is supported when considering between country links alone. Banks exhibit negative CARs between 2.8% and 6.5%, which are however not significantly different. But the abnormal returns are large and significantly negative. Together, these results suggest that international rather than national bailout policies may be preferable to avoid beggar-thy-neighbor behavior among nations that prioritize the stabilization of domestic, unconnected banks.

The divergent return responses of insurances and other financial institutions across all three definitions of connectivity highlights that bank bailouts have different effects on the various sectors of the financial industry. The responses to insurance bailouts also highlights the potential need for such cross-sectoral policy coordination. Insurance rescues affect the financial industry much less than bank rescues. Recall that we only show mean CARs that are significant at the 5%-level. The substantially lower number of observations in responses thus indicates that cumulative abnormal returns were mostly zero.

Insurance bailouts generate substantial positive returns for banks on the order of 9.7% that are connected, but not for connected insurances. This may indicate that the important role of insurances as institutional investors requires particular attention from the perspective of banking system stability. The result that unconnected banks in fact face negative CARs, like unconnected insurances as well, indicates in turn that rescuing important suppliers of liquidity in one sector of the financial industry potentially distorts competition in another sector, namely banking. This result therefore also indicates that coordination of bailout, and potentially prudential supervision policy might be more effective when coordinated closely across affected sectors of the industry.

V. Conclusion

This paper uses Extreme Value Theory to measure tail risks of financial firms. Based on a comprehensive sample of daily CDS spreads for 193 financial firms, we calculate so-called co-crash probabilities (CCP) for all possible pairs of these financial firms. We use daily changes of credit default swap quotes between January 2004 and January 2011 and employ a bootstrap method to obtain standard errors of potential CCP ties. The main results are as follows.

First, connectivity decreased substantially after the financial crisis and significant mean CCPs increase from around 12 to 16 basis points. CCPs are more likely to be significant for pairs of financial firms that are from the same country and the same sector. But the level, i.e. the intensity of these ties, is largest for financial-firm pairs from different countries and sectors. Most of these effects vanish during the financial crisis.

Second, based on significant CDS co-crash probabilities, we calculate network centrality measures to identify systemically important financial institutions. A number of arguably important financial institutions, namely those that were rescued, are ranked among the top-40 most connected financial firms. These 'league tables' comprise mostly banks, but also a number of insurances and other financial institutions. Thus, considering more than just the banking sector is not irrelevant for supranational financial stability policy. Rankings before and during the crisis are only weakly correlated. Therefore, network measures of connectivity are not a panacea for macro-prudential early warning systems.

Third, we find on average negative cumulative abnormal equity returns of financial firms in response to bank bailouts during the crisis. Banks that are significantly connected to bailed out banks exhibit actually larger negative CARs compared to unconnected competitors. This result casts doubt on the effectiveness of government bailout programs to stabilize the banking industry. Moreover, when considering only intra-regional connections, domestic peers from the banking sector that are not connected to rescued banks exhibit significantly positive CARs. Largely national rescue schemes thus might help to stabilize domestic financial systems by generating abnormal returns of non-connected banks. However, the negative CAR effect found for internationally connected peers underpins the need for international policy coordination to avoid "beggar-thy-neighbor" distress resolution policies in the international financial system.

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A Event study methodology

This section presents the details pertaining to the event study methodology proposed by Kolari and Pynnönen (2010) to deal with cross sectional correlation in returns in stock prices.

First, for statistical inference the abnormal returns, obtained from Equation (7) in the text, are rescaled (Patell, 1976):

$$A_{i,t} = \frac{AR_{i,t}}{s_i\sqrt{1+d_t}},$$

where s_i is the regression residual standard deviation, and d_t denotes a correction term of the form $\boldsymbol{x}_t'(\boldsymbol{X}'\boldsymbol{X})\boldsymbol{x}_t$. Matrix $\boldsymbol{X}$ contains the variables for all observations in the estimation period, and $\boldsymbol{x}_t$ the observations for day t in the event window; both $\boldsymbol{X}$ and $\boldsymbol{x}_t$ include the constant. This rescaling weighs more volatile observations less.

Second, the cross-sectional adjustments are considered. The cross-sectional standard deviation s of event-day scaled abnormal returns is defined by

$$s = \sqrt{\frac{1}{I-1}\sum_{i=1}^{I}(A_i - \bar{A})^2}, \tag{8}$$

where I denotes the number of institutions considered in the event study, A_i is the scaled abnormal return on the event day, and $\bar{A}$ is the mean scaled abnormal return of institutions for the event day. Let $\bar{r}$ be the mean of the sample correlations between the residuals across institutions obtained from estimating Equation (7) by least squares. Kolari and Pynnönen (2010) note that Equation (8) is biased due to cross-sectional return correlations and show that

$$s_A := \frac{s}{1-\bar{r}}$$

is an unbiased estimator of the standard deviation of scaled abnormal returns.

The main aim is to test whether the mean scaled abnormal returns taken over the event window for an institution, $\bar{A}_i$, differ significantly from zero. This allows for determining whether the bailout of a connected peer had an impact on institution i. Kolari and Pynnönen (2010) denote the standard deviation of $\bar{A}_i$ by

$$s_{\bar{A}_i} = \sqrt{\frac{s_A^2}{I}(1 + (I-1)\bar{r})}.$$

To test whether $\bar{A}_i$ differs from zero, and thereby whether the bailout had an impact, the test statistic $t_{\bar{A}_i} = \frac{\bar{A}_i}{s_{\bar{A}_i}}$ is tested to be significantly different from zero. $t_{\bar{A}_i}$ is student-t distributed with $I - 1$ degrees of freedom.

B Tables

TABLE I

Descriptive statistics of CDS spreads

Sector/Region	Mean	Std. Dev.	Obs.	N. of inst.	Min	25^{th} pct.	Median	75^{th} pct.	Max
Sector									
Banks	104.23	264.68	203,144	122	3.28	13.64	39.05	112.96	20,457.70
Financial Services	109.51	147.31	3,664	2	6.39	16.00	39.07	170.05	1,150.16
Insurance	249.31	732.09	62,386	35	4.84	23.78	51.42	154.81	26,990.08
Investment	160.67	267.69	10,899	7	6.41	27.73	53.15	188.39	2,668.87
Lease	288.97	447.41	3,660	2	12.12	31.04	46.39	382.40	3,312.36
PEIT	178.04	273.90	1,830	1	12.79	22.62	44.71	202.67	1,465.46
REIT	204.48	454.45	31,681	18	5.70	37.36	67.19	189.54	7,856.95
Subsidiaries	403.01	721.43	9,515	6	10.87	37.73	223.62	505.31	10,046.75
Region									
U.S.	230.43	642.41	99,400	58	4.79	26.37	53.34	170.28	26,990.08
Europe	105.54	236.01	154,097	88	3.28	13.12	39.03	118.14	10,046.75
O.D.	143.55	407.10	54,308	32	3.93	15.21	45.66	110.50	14,496.22
E.M.	190.31	406.10	18,974	15	10.87	34.42	77.89	189.83	20,457.70
Total	154.77	438.06	326,779	193	3.28	17.34	48.14	132.05	26,990.08

Notes: Daily CDS spreads are reported in basis points, pooled within sectors and regions, and are obtained from the Markit Group databases. "REIT" stands for Real Estate Investment Trust, "PEIT" stands for Private Equity Investment Trust. "U.S." stands for United States. "Europe" for the developed countries in Europe: Austria, Belgium, Denmark, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom. "O.D" stands for other developed countries and include Australia, Canada, Japan and Singapore. "E.M" stands for "emerging markets" and include China, Hong Kong (China), India, Kazakhstan, Korea, Malaysia and Russia.

TABLE II
Descriptive statistics: CDS changes and critical CDS changes

CDS changes in percentages/ percentiles	Mean	Std. Dev.	Obs.	Min	25^{th} pct.	Median	75^{th} pct.	Max
Pre-crisis period								
Overall sample	0.38	4.38	140,889	-127.33	-0.58	0.00	0.89	209.58
Critical changes only	2.60	4.79	78,760	0.00	0.37	1.18	2.99	209.58
Percentiles of critical changes	86.00	9.00	18,528	38.24	79.32	86.77	93.60	100.00
During-crisis period								
Overall sample	0.60	5.73	171,718	-120.82	-1.37	0.07	2.46	148.85
Critical changes only	3.77	4.88	89,245	0.00	0.84	2.33	4.97	148.85
Percentiles of critical changes	83.37	10.79	18,528	48.90	75.05	85.04	92.47	100.00
Both periods								
Overall sample	0.49	5.08	312,607	-127.33	-0.88	0.00	1.55	209.58
Critical changes only	3.22	4.87	168,005	0.00	0.57	1.70	4.11	209.58
Percentiles of critical changes	84.69	10.02	37,056	38.24	77.65	85.98	93.05	100.00

Notes: Top two rows for each period category report descriptive statistics on percentage changes in CDS spreads, both for the overall sample and for the critical changes that are included in calculating the Hill estimator for tail index in Equation (2). The total number of observations differ from Table I due to an unbalanced panel. The last row of each period category reports statistics on the percentiles of the minimum percentage change in CDS spreads included for estimation of the tail index, as outlined in section II.B. Since 193 institutions are sampled, the total number of minimum critical changes in CDS spreads per period amounts to $193(193-1)/2 = 18,528$. The "pre-crisis" and "during-crisis" period are respectively defined by before and after August 9, 2007.

TABLE III
Summary Statistics of co-crash probabilities

Sample covers both pre and during-crisis period

Co-crash prob.	Mean	Std. Dev.	num. of obs.	Min	25^{th} pct.	Median	75^{th} pct.	Max
Pre-crisis period	11.17	8.83	18,528	0	5.23	9.35	14.60	101.66
only significant co-crash probabilities*	11.88	7.56	12,792	0	6.89	10.48	15.27	70.12
During-crisis period	10.10	8.85	18,528	0	4.43	8.52	13.66	77.86
only significant co-crash probabilities*	15.53	7.09	1,656	0	10.88	14.78	19.39	52.23
Both periods	10.63	8.86	37,056	0	4.81	8.95	14.10	101.66
only significant co-crash probabilities*	12.30	7.60	14,448	0	7.16	10.96	15.89	70.12

Notes: Co-crash probabilities are reported in basis points. "*" indicates that only statistics are reported for co-crash probabilities between two institutions that share a common "credit-risk link". For these co-crash probabilities, the tail index is not significantly different from one at the 1%-level. The number of observations reflect the number of co-crash probabilities estimates for any possible combination of two institutions in the sample. Since 193 institutions are investigated, the total number of co-crash probabilities per period amounts to $193(193-1)/2 = 18,528$. The "pre-crisis" and "during-crisis" period are separated by August 9, 2007.

TABLE IV

Within and between connectivity for regions and sectors

	Pre-crisis period		During-crisis period	
	Within	Between	Within	Between
Areas				
U.S.	0.594	0.608	0.176	0.062
Europe	0.850	0.700	0.115	0.066
European Union	0.845	0.703	0.112	0.068
Euro area	0.848	0.729	0.124	0.069
O.D.	0.721	0.602	0.207	0.061
E.M.	0.955	0.715	0.367	0.119
Sectors				
Banks	0.791	0.654	0.130	0.060
Financial services	1.000	0.610	0.500	0.071
Insurance	0.763	0.664	0.205	0.067
Investment	0.510	0.541	0.306	0.075
Lease	0.500	0.597	0.500	0.024
PEIT	1.000	0.432	1.000	0.104
REIT	0.401	0.484	0.179	0.043
Subsidiaries	0.667	0.674	0.278	0.039

Notes: *Within connectivity* is measured as the ratio of significant links within a region over all possible links within that region. *Between connectivity* is measured as the proportion of significant links between institutions of a region and any institution of any other region over all possible links in which one institution is from that region. Significance refers to whether the null of dependence between percentage changes in CDS spreads could not be rejected at the one percent level.

TABLE V

Decomposition of co-crash probabilities, regression analysis

Dependent variables: Dummy for significant links in column 1, 3 and 5;
Co-crash probability between institutions (in basis points) in column 2, 4 and 6.

	Pooled sample		*Pre-crisis period*		*During-crisis period*	
	Probit[A]	Sig. only	Probit[A]	Sig. only	Probit[A]	Sig. only
Dummy	(1)	(2)	(3)	(4)	(5)	(6)
Group 1: Relative to "Within country/within sector" ties						
Within country/	-0.217***	-1.066	-0.185***	4.711***	-0.071***	-16.235
between sectors	[0.012]	[0.653]	[0.025]	[1.030]	[0.004]	[13.079]
Between countries/	-0.225***	-0.974	-0.131***	2.090***	-0.111***	-15.634
within sector	[0.018]	[0.622]	[0.030]	[0.730]	[0.009]	[14.015]
Between countries/	-0.333***	-0.078	-0.236***	7.074***	-0.175***	-23.061
between sector	[0.018]	[0.823]	[0.028]	[1.256]	[0.011]	[20.484]
Group 2: Relative to "Within U.S." ties						
Within Europe	0.222***	-2.477***	0.265***	-13.499***	0.014	-0.602
	[0.022]	[0.571]	[0.017]	[1.686]	[0.011]	[1.675]
Within O.D.	0.162***	0.556	0.136***	-5.349***	0.056***	7.945
	[0.027]	[0.638]	[0.020]	[1.058]	[0.019]	[5.185]
Within E.M.	0.435***	5.819***	0.276***	-7.467***	0.199***	18.635
	[0.036]	[1.482]	[0.012]	[2.700]	[0.049]	[13.688]
Between U.S.	-0.025**	-0.964***	-0.024	0.741**	0.000	-0.603
and other regions	[0.012]	[0.245]	[0.015]	[0.363]	[0.007]	[0.626]
Between Europe	0.116***	-2.086***	0.175***	-8.908***	-0.009	-3.941***
and other regions	[0.012]	[0.357]	[0.015]	[1.067]	[0.007]	[1.356]
Between O.D.	-0.027**	-0.925***	-0.016	0.601*	-0.009	-3.658**
and other regions	[0.012]	[0.262]	[0.015]	[0.352]	[0.007]	[1.428]
Between E.M.	0.113***	2.680***	0.100***	-0.491	0.056***	8.303
and other regions	[0.014]	[0.344]	[0.014]	[0.567]	[0.010]	[5.878]
Other variables						
Crisis dummy	-0.622***	4.457**				
	[0.004]	[1.877]				
Inverse Mill's		-1.131		-27.823***		25.397
Ratio		[1.439]		[3.980]		[21.968]
Constant	n.a.	14.769***	n.a.	28.528***	n.a.	-12.191
	n.a.	[0.465]	n.a.	[1.980]	n.a.	[25.097]
Observations	37,056	14,448	18,528	12,792	18,528	1,656
(Pseudo) $R^{2,A}$	0.348	0.078	0.068	0.063	0.066	0.052
Log likelihood	-16.144.498	-49.203.379	-10.688.468	-43.606.165	-5.210.305	-5.543.895

Notes: Heteroscedastic robust standard errors reported in brackets. '***', '**' and '*' denote respectively significantly different from zero at the 1%, 5% and 10% level. The inverse Mill's ratio represents the selection effect arising from the selection of only significant linkages. Dummy group 1 is relative to the "within country/within sector" dummy; dummy group 2 is relative to the "within U.S." dummy. Since 193 institutions are investigated, the total number of co-crash probabilities per period amounts to $193(193-1)/2 = 18,528$. [A]The dependent variable in the probit analysis reported in columns 1, 3, and 5 is a dummy that takes on the value of one when the co-crash probability constitutes a significant credit link between two institutions. For these co-crash probabilities the tail index is found not to be significantly different from 1 at the 1%-level. The pseudo R^2 is reported for these columns.

TABLE VI

Dates of first time rescue measures for financial institutions

Name	First time fin. support received	Capital injection	Asset support	Total cap. injections	Total asset support
ABN Amro	07/31/09		x		1
Aegon N.V.	10/28/08	x		1	
AIG	11/11/08	x	x	3	1
Allied Irish Bank	12/12/08	x		2	
Alpha Bank	01/12/09	x		2	
American Express	01/09/09	x		1	
Anglo Irish Bank	05/29/09	x		3	
Banca Monte Paschi	12/30/09	x		1	
Bank of America	10/28/08	x		3	
Bank of Ireland	01/08/09	x		1	
Banque Pop. France	06/30/09	x		1	
Bayrische Landesbank	10/21/08	x		2	
BNP	10/20/08	x		2	
Caisse d' Epargne	10/20/08	x		1	
Capital One Fin. Corp.	11/14/08	x		1	
Citigroup	10/28/08	x		1	
Commerzbank	11/03/08	x		2	
Credit Agricole	10/20/08	x		1	
Danske Bank	05/05/09	x		1	
Dexia	09/30/08	x		1	
EBS Building Society	04/02/10		x		1
EFG Eurobank	01/12/09	x		1	
Erste Bank	02/27/09	x		1	
Fannie Mae	03/02/09	x		7	
Fortis Group	10/03/08	x		3	
Freddie Mac	11/14/08	x		5	
Goldman Sachs Group	10/28/08	x		1	
HSH Nord Bank	05/20/09	x		1	
Hypo Real Estate	03/30/09	x		6	
IKB	07/27/07	x		4	
ING Groep	10/20/08	x		1	
Irish Nationalwide	04/02/10	x	x		1
JPMorgan Chase	10/28/08	x		1	
KBC Group	10/27/08	x		2	
Landesbank Baden-Wurtemb.	11/21/08	x		1	
Lloyds Bank	01/19/09	x		2	
Morgan Stanley	10/28/08	x		1	
National Bank of Canada	01/21/09	x		1	
Natixis	05/14/09	x		1	
Nordea Bank	03/12/09	x		1	
Northern Rock	10/28/09	x		1	
Pireus Bank	01/23/09	x		1	
RBS	10/13/08	x		2	
SNS Bank	11/13/08	x		1	
Societe Generale	10/20/08	x		2	
Sparkasse Koln-Bonn	01/01/09	x		2	
Suntrust Banks	11/14/08	x		2	
UBS	10/16/08	x	x	1	1
US Bank Corp.	11/14/08	x		1	
Wells Fargo	10/28/08	x		1	
Westdt. Landesbank	02/01/08		x		3

Notes: The table provides an overview of financial support for financial institutions implemented by financial regulators. Dates are denoted by "dd/mm/yy". "Total Capital injections" and "Total Asset Support" refer to the total amount of capital injections received and asset support received in the period defined by the first time of financial support received until March 10, 2011.

TABLE VII
Cumulative abnormal returns as a result of rescue events

sector	Mean	Std. Dev.	Num of obs.	Mean	Std. Dev.	Num of obs.	Mean sig.- Mean Insig.
Mean response to bank rescue measures							
			Within and between country links				
		No sig. CCPs			*Only sig. CCPs*		
Banks	-0.025	0.202	537	-0.072	0.235	81	-0.047**
Insurance	-0.039	0.167	149	0.039	0.195	15	0.078*
Other	-0.034	0.137	164	0.137	0.025	6	0.171
Total	-0.029	0.185	850	-0.050	0.226	102	-0.021
			Within country links				
		No sig. CCPs			*Only sig. CCPs*		
Banks	0.019	0.290	37	-0.083	0.316	33	-0.102
Insurance	-0.064	0.209	38	0.103	0.437	2	0.167
Other	0.019	0.138	11	0.013	0.093	4	-0.006
Total	-0.018	0.242	86	-0.064	0.304	39	-0.046
			Between country links				
		No sig. CCPs			*Only sig. CCPs*		
Banks	-0.028	0.194	500	-0.065	0.160	48	-0.037
Insurance	-0.031	0.142	111	0.030	0.166	13	0.061
Other	-0.038	0.137	153	0.049	0.027	2	0.087
Total	-0.031	0.177	764	-0.042	0.162	63	-0.011
Mean response to insurance institution rescue measures							
			Within and between country links				
		No sig. CCPs			*Only sig. CCPs*		
Banks	-0.018	0.243	29	0.097	0.306	8	0.115
Insurance	-0.059	0.175	8	-0.068	0.313	3	-0.009
Other	-0.012	0.329	2	-	-	0	-
Total	-0.026	0.229	39	0.052	0.302	11	0.078
			Within country links				
		No sig. CCPs			*Only sig. CCPs*		
Banks	0.059	0.139	5	0.155	0.330	2	0.096
Insurance	-0.165	-	1	-0.038	0.436	2	0.127
Other	-0.012	0.329	2	-	-	0	-
Total	0.013	0.181	8	0.059	0.335	4	0.046
			Between country links				
		No sig. CCPs			*Only sig. CCPs*		
Banks	-0.034	0.259	24	0.077	0.328	6	0.111
Insurance	-0.044	0.183	7	-0.126	0.309	1	-0.082
Other	-	-	0	-	-	0	-
Total	-0.036	0.241	31	0.048	0.309	7	0.084

Notes: Summary statistics are only reported for cumulative abnormal returns that are significant at the 5%-level. *sig. CCPs* refers to the co-crash probabilities that are significant at the 1%-percent level. '***', '**' and '*' indicate significant at the 1%-, 5%- and 10%-level, based on a t-test of mean difference. In estimating the CARs the estimation window consisted of 50 day observations on stock price returns prior to the event window, which is 3 days. The event itself are announcements of bailouts for financial institutions.

TABLE VIII
Countries within regions

U.S.	Europe	O.D.	E.M.
United States (US)	Austria (AT)	Australia (AU)	Argentina (AR)
	Belgium (BE)	Canada (CA)	Brazil (BR)
	Denmark (DK)	Japan (JP)	China (CN)
	France (FR)	Singapore (SG)	Hong Kong (HK)
	Germany (DE)		India (IN)
	Greece (GR)		Indonesia (ID)
	Iceland (IS)		Kazakhstan (KZ)
	Ireland (IE)		Korea (KR)
	Italy (IT)		Malaysia (MY)
	Luxembourg (LU)		Russia (RU)
	Netherlands (NL)		South Africa (ZA)
	Norway (NO)		Taiwan (TW)
	Portugal (PT)		Thailand (TH)
	Spain (ES)		Turkey (TR)
	Sweden (SE)		Ukraine (UA)
	Switzerland (CH)		
	United Kingdom (GB)		

Notes: ISO 3166 country codes reported in parentheses. The region *European Union* in table IV excludes Iceland and Switzerland from the Europe region. In the same table the region *Euro Area* excludes Sweden, Switzerland, and the United Kingdom from the Europe region.

TABLE IX
Descriptive statistics of stock price returns

Sector/Region	Mean	Std. Dev.	Obs.	N. of inst.	Min	25^{th} pct.	Median	75^{th} pct.	Max
Sector									
Banks	-0.053	3.556	123,578	90	-285.538	-0.985	0.000	0.915	141.986
Financial services	-0.165	5.358	1,747	1	-69.315	-1.471	0.000	1.292	46.586
Insurance	-0.050	4.050	31,592	23	-122.273	-1.012	0.000	0.964	71.562
Investment	0.036	2.073	3,324	3	-13.941	-0.925	0.064	1.046	15.729
Lease	-0.025	5.418	1,719	2	-41.552	-1.440	0.000	1.417	68.401
PEI	-0.048	3.835	3,447	2	-47.992	-1.104	0.037	1.061	43.176
REIT	-0.008	3.369	23,960	14	-77.539	-1.139	0.038	1.158	53.785
Subsidiaries	0.062	2.042	1,675	2	-14.351	-0.937	0.000	1.085	13.505
Region									
U.S.	-0.066	4.771	66,517	58	-285.538	-1.081	0	1.010	141.986
Europe	-0.047	2.859	85,961	52	-88.239	-0.979	0	0.925	54.952
O.D.	-0.018	2.834	28,443	18	-280.336	-0.915	0	0.909	69.314
E.M.	0.048	2.798	14,427	9	-36.384	-1.137	0	1.226	49.559
Total	-0.042	3.619	195,348	137	-285.538	-1.012	0	0.971	141.986
Market index									
MSCI world index	0.011	1.131	1,831	1	-7.325	-0.445	.074	0.521	9.096

Notes: Stock price data are obtained from the Bloomberg database. Daily stock price changes are pooled within industries and regions. These changes are calculated by taking the natural logarithm of the daily return in stock price changes, multiplied by 100 percent.'REIT' stands for Real Estate; Investment Trust, 'PEIT' stands for Private Equity Investment Trust; 'O.D.' denotes 'Other; Developed countries' and includes Canada, Japan, Australia, and Singapore. 'E.M.' means 'Emerging Markets' and includes China and Hong Kong, India, Kazakhstan, Korea, Malaysia, and Russia.

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