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 based on joint extreme movements in credit default swap spreads. Estimated pairwise co-crash probabilities identify significant connections among 193 financial institutions. We calculate network centrality measures to identify systemically important financial institutions and test if bailouts stabilized network neighbors. 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. Network centrality indicators identify many institutions that failed during the 2007/2008 crisis. Excess equity returns in response to bank bailouts are negative and significantly lower for connected banks.

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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, 2013). Such policies bode ill for market discipline and moral hazard. Any financial institution considered too big or too connected to fail has strong incentives to misbehave. Freixas and Rochet (2013) 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.

We first identify financial institutions that are too connected too fail. Using Extreme Value Theory (EVT), we 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 four different sectors and 37 different countries between January 2004 and January 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 market participants' perceptions of credit risk. We identify SIFIs based on significant pairwise CCPs with bootstrap methods and investigate first the change of CCP levels and connections before and during the crisis as well as across countries and sectors. CDS-based CCPs are agnostic because they do not require frequently lacking information on structural links between financial firms, for instance interbank credit, equity entanglement, joint asset exposures, and the like. Given the absence of structural links, we consider Granger-causality of underlying CDS spread changes to shed some light on the anatomy of credit-risk connectivity across different sectors and regions.

We ask next if our measure of connectivity helps to predict government support measures for financial institutions and whether the latter were effective in stabilizing the financial system. We generate measures of network centrality based on significant CCPs to identify very connected institutions and test if network centrality helps to predict government bailouts during the crisis of 2007/2008, which are defined as capital injections and asset support measures issued by governments to rescue distressed banks (Stolz and Wedow, 2010). Subsequently, we test whether bailouts of distressed banks caused cumulative abnormal returns (CARs) among connected and non-connected peers. 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.[1] Numerous empirical studies assess the contagion potential of interbank markets.[2] But given the proprietary nature 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.[3]

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

[2]Upper and Worms (2004) (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).

[3]For instance, Angelini et al. (2009) find that only after the 2007/2008 financial crisis interbank interest rates depend on the creditworthiness of the counterparty. Another challenge in empirical work are that interbank exposures are often imputed from large credit exposures, suffering from selection bias

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[4] that is undesirable from a societal perspective.

Some 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. 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. Adrian and Brunnermeier (2011) calculate VaR for the financial system with and without considering the institution in question, the so-called Co-VaR measure, and estimate marginal values applying quantile regressions.[5]

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 sys-

and low reporting frequency.

[4]Through common real asset exposures (Acharya, 2009) or joint liquidation risk (Wagner, 2010, 2011).

[5]Other systemic risk metrics mushroom, see e.g., Lehar (2005) or Huang et al. (2009).

temic 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 banks' 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).[6]

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 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. Granger-causality tests of CDS-spread changes that underly CCP estimates in-

[6]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.

dicate also that the share of pairs of financial institutions that do not affect another increases from 20% during the crisis to 24%. Likewise, the share of firm pairs that exhibit bidirectional Granger causality plummets from 19% to 34%. Overall, the network is characterized by cutting links during the crisis. "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). Probit regressions confirm that higher pre-crisis network centrality of a financial firm increase the likelihood of a government bailout after controlling for the idiosyncratic risk and size of the firm. Average cumulative abnormal equity returns around government bailouts of banks are overall negative for both connected and unconnected peers, especially other banks. This negative effect is significantly larger for connected banks and economically substantial, namely around 6.1% negative CARs.

This paper is organized as follows. Section II. introduces the data and methods to estimate the tail dependence index and discusses CCP and CDS Granger-causality results. 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.[7]

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

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 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).[8] 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.[9]

[8]See http://www.dtcc.com/products/derivserv/data/index.php.

[9]According to DTCC, the majority of CDS contracts are denominated in USD (62%) and EUR (35%).

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.[10]

B. *Tail dependence index estimation*

Because news about the credit worthiness of counter parties are well reflected in CDS spreads, they are meaningful indicators of credit events. 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:

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

[10]See Table XIII for a list of countries per region.

Co-crash probabilities (CCPs) capture the likelihood that the CDS spreads of institutions i and j exceed jointly the 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.[11]

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. 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, one needs to address the biasing impact of the marginal densities on the joint probability estimate. Therefore, we follow the semi-parametric approach of Draisma et al. (2004) and Drees et al. (2004), which 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 estimated dependence between the two series' maxima. Thus, differences in the estimated tail index are only attributed 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

[11]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. We develop a bootstrap technique to test for dependence in subsection D..

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:

$$\begin{aligned} \text{Prob}[X_{i,t} > x_j \cap X_{j,t} > x_i] &= \text{Prob}[\tilde{X}_{i,t} > q \cap \tilde{X}_{j,t} > q] \\ &= \text{Prob}[\min\{\tilde{X}_{i,t}, \tilde{X}_{j,t}\} > q]. \end{aligned} \tag{2}$$

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

$$Z_t := \min\{\tilde{X}_{i,t}, \tilde{X}_{j,t}\}. \tag{3}$$

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. Then Z_t equals the transformed variable $\tilde{X}_{i,t}$ and its density exhibits a unit tail index. 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 use Hill's (1975) ML technique to estimate the tail index η, which is denoted by:

$$\hat{\eta}(k) := \frac{1}{k} \sum_{m=1}^{k} \ln\Big[\frac{Z(n-m+1)}{Z(n-k)}\Big]. \tag{4}$$

A typical problem in calculating Equation (4) is the nontrivial choice of k, i.e. the sample of "large" CDS spread changes in the joint series that is used to predict extreme CDS changes occurring simultaneously. If k is too small, too few observations enter the estimation of the tail index to ensure consistent estimation of the 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 (4), 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.[12] The bias is a linear relation between the estimated tail index and the number of observations included for estimation:

$$\hat{\eta}(k) = \gamma_0 + \gamma_1 k + \varepsilon_k, \quad \forall k \in \{1, ..., n-1\}, \tag{5}$$

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 (4) and the number of observations included for its computation. Like Huisman et al. (2001), we estimate Equation (5) with weighted least squares using $\sqrt{k}$ as weights to obtain unbiased and consistent estimates of $\hat{\gamma}_0$ and $\hat{\gamma}_0$. This procedure assigns less weight 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 (4) 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^*.[13] Substitution into Equation (4) yields the tail dependence index of the two series of percentage changes in CDS spreads.

[12] Alternatively, one can plot Equation (4) 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.

[13] We do 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 $\hat{\eta}$.

–Table II around here–

Table II summarizes the percentage changes in CDS spreads for the 193 sampled financial institutions in the periods before and after August 9, 2007. That day marks the first major public interventions by central authorities due to the Global Financial Crisis. To alleviate market concerns about widespread exposures of financial institutions to U.S. subprime mortgage lending markets, the ECB provided low-interest credit lines of USD 130 billions. The Federal Reserve followed suit with USD 12 billions in temporary reserves. Therefore, we denote the period until August 9, 2007 as the pre-crisis period, which 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 only use 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 in Table II with those specified, e.g., in Value-at-Risk based approaches to calculate "extreme" events. Related, the percentiles of 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 the optimal sample size to calculate CCPs in light of the consistency-bias tradeoff.

C. Co-crash probability estimation

Draisma et al. (2004) extend Ledford and Tawn (1996) and develop an estimator for the probability of an extreme event as in Equation (1) that allows for both asymptotic dependence and independence between two series. This semi-parametric estimator requires no distributional assumptions about the joint density of the percentage changes in CDS spreads. Constructing this joint probability estimator 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

$$F_i(x) := 1 - \Big(1 + \xi_i \frac{x - b_i}{a_i}\Big)^{-\frac{1}{\xi_i}}. \tag{6}$$

Parameters are estimated with ML techniques and calculated independently for each institution. Parameter estimates are denoted by $\hat{\xi}_i$, scaling parameter $\hat{a}_i$, and location parameter $\hat{b}_i$. Equation (6) is estimated for each individual firm. Thus, heterogeneity with respect to idiosyncratic failure probabilities is preserved.

$\hat{F}_i$ denotes Equation (6) 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:

$$\hat{p}_{i,j} := c_{i,j}^{1/\hat{\eta}_{i,j}} \frac{1}{n_{i,j}} \sum_{t=1}^{n_{i,j}} \mathbf{1}\big\{(X_{i,t}, X_{j,t}) \in \hat{\boldsymbol{F}}_{i,j}^{-1}(\boldsymbol{\iota} - \boldsymbol{D}_{i,j}/c_{i,j})\big\}. \tag{7}$$

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 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 $[0, 1] \times [0, 1]$, the choice of $c_{i,j}$ is limited to $(\max\{\boldsymbol{D}_{i,j}\}, 1]$. We determine $c_{i,j}$ by evaluating $\hat{p}_{ij}$ as a function of $c_{i,j}$, and choose the minimal value of $c_{i,j}$ for which $p_{i,j}$ is sufficiently stable (Draisma et al., 2004).[14]

D. *Significance of CCP connections*

Draisma et al. (2004) investigate the asymptotic properties of the tail index estimate $\hat{\eta}_{i,j}$ as defined by Equation (4) 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 (7). 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 described in subsection 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 $X_{i,t}^b$ and $X_{j,t}^b$ of equal length as the original

[14] The same grid search is adopted as in determining the optimal numbers of observations k^* in the estimation of the tail index.

sample, where b indexes the b^{th} replication.[15] From these bootstrap samples B tail index estimates $\hat{\eta}^b_{i,j}$ are generated 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.

Dependence in large percentage changes of CDS spreads between two institutions is then determined by testing the null of dependence against the alternative of independence. In terms of the tail index value, dependence holds if $\eta = 1$. Independence holds if $\eta < 1$. For $\eta = 1$, i.e. when the extreme percentage changes in CDS spreads between two institutions co-move sufficiently such that the joint crash probability converges to a nonzero value. If the null is not rejected, a credit link between institutions i and j exists. Throughout, the number of bootstrap replications is 10,000, and the confidence level is one percent.

Table III reports descriptive statistics of the estimated co-crash probabilities. Note that we distinguish between all co-crash probabilities and those 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 around here–

Co-crash probabilities are right-skewed. The number of CCPs for which we find dependence is considerably lower during the crisis period relative to the pre-crisis

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

[16] Each institution can share a credit connection with 192 institutions. Counting connections only once results in $\frac{193(193-1)}{2} = 18,528$ potential credit risk connections.

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 crisis period after August 9, 2007.

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. Connectivity within U.S. and European regions plummeted from around 60% and 85% to around 18% and 11%, respectively. European and 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 shows 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. 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 from a regional perspective.

E. Directionality of CDS co-movements

For policy purposes, information about the directionality of co-movements in extreme credit risks is useful. But such inference requires information about structural links between financial institutions, for instance interbank market exposures, which is usually not at all or only for certain subsamples per country and/or sector available. We argue that an important advantage of the the CCP measure in Equation (7) is its agnostic nature that does exactly not require such structural information. However, a limitation is that this joint probability measure reflects the likelihood of extreme CDS spread co-movements of two financial institutions during the period of underlying CDS spread changes. Therefore, it does not permit inference on directionality as such.

We attempt to shed some light on the patterns of directionality across subsamples of sector and regional links by conducting Granger causality tests between each pair of institutions' change rates in CDS spreads. We distinguish four cases: (i) institution i's and j's CDS spread percentage change do not influence another (column *No* in Table V), (ii) institution i's series is caused by institution j's series (column *Caused*), (iii) institution i's series causes institution j's series (column *Causes*), or (iv) whether the effect is bidirectional (column *Mutual*). We estimate the following regressions for all i and j in different subsamples as well as before and during crisis periods:

$$X_{it} = \alpha + \sum_{k=1}^{K} \beta_k X_{i,t-k} + \sum_{k=1}^{K} \gamma_k X_{j,t-k} + u_t, \quad \forall i \neq j, \tag{8}$$

where u_t denotes a residual term. Granger causality prevails if at least one γ_k parameter differs significantly from zero at the five percent significance level. The optimal lag structure, K, is determined by minimizing the Akaike Information Criterion for each regression. Tables V and VI summarize the results for the before and during crisis sample, respectively.

–Table V and VI around here–

Consider first the bottom row in Table V with a grand total mean CCP of 11.2 basis points (*cf.* Table III). Around 20% of the CDS spread change series do not Granger cause another prior to the crisis (3,752/18,528). However, during the crisis, this share of unrelated CDS series increases to around 24%. Likewise, the share of CDS series exhibiting bi-directional Granger causality declines substantially from 35% to 19% during the crisis. These results indicate that raw CDS spread changes do not point towards a generally higher occurrence of co-movements in credit risk premiums.

The two panels in Tables V and VI present further breakdowns of mean CCP and Granger causality tests for subsamples of different sectoral (upper panel) and regional connections (lower panel) to shed light on the anatomy of CDS series.

Consider first the upper panel. We differentiate four groups of financial institution pairs, namely those where both firms i and j are from the same sector and country, the same country but different sectors, the same sector but different countries, and from both different sectors and countries. The last column in Ta bles V and VI shows that the level of CCPs is highest among financial firms from the same sector and country whereas it is lowest for pairs from different sectors and firms. This result is in line with the intuition that credit connectivity is largest among financial firms that are geographically and functionally closely linked, for instance banks in interbank markets. The comparison of the pre and during crisis results also shows, however, that the average level of CCPs was not significantly different between pairs of financial firms from different sectors in one country and financial firms from one country and one sector.

This result suggests that cross-sectoral ties are of similar importance in terms of credit risk connectivity as measured by CCP as cross-country ties. Interestingly, only the former issue is subject to the ongoing policy debate and regulatory reform, for instance witnessed by the creation of a single banking supervisor for the EMU area, whereas cross-sectoral supervision is largely ignored.

Regarding the four different groups of Granger causality types depicted in the columns, the comparison of Tables V and VI confirms the result for the entire sample. During the crisis the share of pairs exhibiting bidirectional causation of CDS spread changes declined compared with the pre crisis period. The share of pairs without Granger causality increased. This pattern holds for all four connectivity type subsamples that are distinguished in the rows of Group 1.

We distinguish regional subsamples in the bottom panel. Pairs of financial institutions that are both from emerging markets exhibit the highest mean CCP (prior: 22 basis points; during 19 basis points), followed by pairs from other developed economies (14 and 11 basis points), the U.S. (11 and 13 basis points), and Europe (11 and 11 basis points). Highest levels of CCP in emerging markets are in line with higher country risk and less well developed financial systems. But it is also notable that within US CCP levels increased the most during the crisis.

The distinction across columns between the four possible results of Granger causality tests highlights that prior to the crisis the share of pairs with bi-directional Granger causality in CDS series was largest, especially among industrialized regions in general and between Europe and the US in particular. This large share of bi-directional relations collapsed during the crisis. The share of pairs where US financial institutions' CDS spread changes influenced CDS series of European and other developed financial firms remained constant during the crisis (column *Causes* in Tables V and VI). At the same time, US and European CDS series were much more often Granger caused by financial firms from the same region.

Overall, Granger causality tests corroborate the notion that the network of connections collapsed during the crisis and focused in particular on other financial firms that were 'nearby', both in a regional and sectoral sense. Ideally, we could validate results of CCP levels and Granger causality of CDS spread changes across subsamples with structural links that we observe, for example interbank credit relations. But possible data that serves such a purpose are unfortunately not available for our sample.[17] Instead, we turn next to a more formal measurement of connectivity based on significant CCPs and their relation with systemic importance revealed by rescue policies.

III. Connectivity

A. SIFI identification based on network centrality

The previous results showed that both regional and sectorial origin highlight important differences in estimated CCPs and directionality of underlying CDS spread changes. Given the drastic concentration of the network during the crisis, i.e. much fewer significant CCP 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. Significant co-crash probabilities in Equation (7) provide an indicator for the strength with which two institutions are linked. A simple measure for the network centrality of an institution is the ratio of the number of co-crash proba-

[17] It might be possible to gather selected information on structural links for subsamples, e.g. banks from one country. But which structural links to consider beyond obvious candidates (such as interbank exposures as opposed to cross-ownership, social ties of executives, common asset exposures, etc.) to explain financial firms' credit risk co-movements remains an open issue. Another challenge is the proprietary nature of most of such data hosted by regulators and central banks. Therefore, we consider such a validation exercise out of the present paper's scope and leave it for further research.

bilities 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. Degree centrality equals (Jackson, 2010)

$$degree_i = \frac{1}{I-1} \sum_{j \in \{1,\ldots,I | j \neq i\}} l_{i,j}, \tag{9}$$

and ranges from zero to one. Zero indicates that the institution has no direct credit links with other institutions. One implies full connection to all institutions.[18]

To identify systemically important financial institutions, Table VII shows the ranking of the top 40 connected financial firms according to degree centrality based on significant CCPs for both the pre- and during-crisis period.

–Table VII around here–

The resulting ranking is plausible to the extent that a number of banks are listed, both prior to (e.g. IKB, Commerzbank, LB Hessen Thuringia) and during the crisis (Bear Sterns, Fannie Mae, Freddie Mac, Lehman, ABN Amro), which failed and were actually bailed out by government programs. In addition, a number of insurances as well as not so obvious banking firms are connected to many other financial institutions. Regionally, the U.S., but also the U.K. and Germany appear often, which reflects their high sample representation.

But the rank-order correlation between the sample before and during the crisis are only weakly correlated. Spearman's ρ shown in Table VII is only 27.6%. Consequently, this network measure appears to identify SIFIs rather well ex post, but is of only limited use for an Early Warning System. The apparent lack of out-of-sample prediction qualities does not necessarily render the measure of degree centrality useless.

[18]We also used the Bonacich (1972) indicator of network centrality as well as $degree_i$ multiplied with the level of the CCP. The subsequently reported results are qualitatively identical and not reported here to conserve on space.

As noted for instance by Tarashev et al. (2010), a measure of systemic importance is not only needed to calculate forward looking capital charges that reflect a systemic tax. They should also allow the calculation of fair insurance premia for systemic events. In this regard it is important to note that not *all* of the financial firms identified as central to the network of significant CCPs did actually fail. This measure merely indicates, which institutions are central, not necessarily risky. Hence, the suggested ranking provided in Table VII would avoid to systematically levy higher insurance premia on institutions that are bound to fail, thus representing an undesirable pro-cyclical policy tool. With the benefit of hindsight, it seems reasonably suited though to identify institutions considered worthwhile to bail out when they become distressed.

B. Does network centrality explain bailouts?

We test this last notion more formally. Whereas we cannot 'validate' our agnostic CCP-based connectivity measure of systemic importance with structural data, we argue that a bailout of any financial institution reveals the regulators perception of that firm's systemic relevance (see also Dam and Koetter, 2012). 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 network centrality represented by significant CDS co-crash probabilities. 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 fund (*"Bundesanstalt für Finanzmarktstabilisierung"*) and other 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.[19] These data are shown in Table VIII.

– Table VIII around here –

We estimate a simple probit model with the dependent variable equal to one if a financial firm was bailed out and zero otherwise. The first announcement of a rescue measure constitutes the event. In case of successive rescue measures during the sample period, we denote these as one event. In total, we sample 51 institutions, mostly banks, that were rescued during the crisis.

We predict these bailouts with covariates of the financial firm *prior* to the crisis to avoid endogeneity by construction. Next to network centrality based on significant CCPs, we control for the idiosyncratic risk of the financial firm with betas obtained from Datastream as well as firm size, either measured in terms of employees or total assets. Table IX provides descriptive statistics for these variables.

– Table IX around here –

The probit results in Table X show that degree centrality increases the likelihood of a bailout significantly. The insignificant effect of firms' betas indicates that bailouts during the crisis were not geared towards financial firms running particularly higher idiosyncratic risk. Positive size effects, in turn, corroborate the well-known perception that certain financial institutions need to be rescued when troubled because they are too-big-to-fail. In sum, the observed bailout pattern of official authorities seems to be in line with systemic importance considerations of financial institutions in terms of both size and connectivity.

– Table X around here –

[19]More specifically, governmental institutions include federal and local governments. As a consequence 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.

After controlling for firm size, the pseudo-R^2 increases substantially from 1.7% to 14%, which is a reasonable fit for profit models. Too-connected-to-fail considerations appear to be of subordinate importance to regulators' choices whom to rescue compared to too-big-to-fail concerns. It does not imply, however, that connectivity is of lesser importance to explain the *level* of systemic risk. Future research on this matter would be useful to inform policy makers, which weights should be assigned to these two aspects of systemic importance.

IV. Bailout effects

A. Event study method

The widespread use of government bailouts during the financial crisis begs the question, whether and which effects these interventions had on financial markets? Politicians and policy makers frequently motivate bailouts with the need to calm financial markets.[20] This narrative suggests that bailouts should represent positive news about connected peers if weak institutions are supported. Alternatively, investors may infer from revealed distress at one financial institution that connected peers may be in trouble as well, and regard thus a bailout as bad news.

We test if bank bailouts generated cumulative abnormal equity returns (CARs) among non-bailed out competitors with an event study method.[21] To test if bailouts

[20]For example, after the agreement of the Eurozones Finance ministers to provide a 100 billion Euro rescue package to Spanish banks in June 2012, Finland's prime minister Jyrki Katainen contended that Europe succeeded to avoid a major crisis (http://www.guardian.co.uk/business/2012/jun/11/spanish-banking-bailout-market-nerveshttp://www.guardian.co.uk). Though in the context of the European sovereign debt problems, the initial announcement of a systematic bond-buying program to financial industry representatives in London by ECB president Draghi on July 26, 2012 provides further anecdotal evidence on policy makers motives to calm markets, see http://www.examiner.com/article/draghi-promise-turns-into-ecb-disappointmenthere.

[21]Note that we do not investigate here whether bailouts as such had any effect on the bailed out firm itself, which is prone to bias due to the direct purchase of equity at stipulated prices in most bailout programs.

had system-wide effects, we estimate CARs of peers that are significantly connected in terms of CCP separately from CARs for non-connected peers. If our CCP-based measure contains any information about network links as perceived by financial markets, whether it is for structural reasons such as private information on credit links between certain firms or for behavioral reasons such as changes in overall risk aversion towards the financial industry, we expect to find significant differences in CARs between connected and unconnected peers.

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:

$$r_{i,t} = \beta_{0,i} + \beta_{1,i} r_{m,t} + u_{i,t}, \tag{10}$$

where $r_{i,t}$ denotes the return of the institution i on trading day t, $r_{m,t}$ denotes the market return, and $u_{i,t}$ is a random error term. The event study is conducted on the return rates of total return indices of the 137 listed institutions in our sample of 193 institutions. The market return is measured using the MSCI world index. Summary statistics on the data are presented in Table XI.

– Table XI here –

The least squares estimates obtained from estimating Equation (10) are denoted by $\hat{\beta}_{0,i}$ and $\hat{\beta}_{1,i}$. Abnormal returns are calculated as $AR_{i,t} := r_{i,t} - \hat{\beta}_{0,i} + \hat{\beta}_{1,i} r_{m,t}$, and quantify the extent with which bailout of a connected peer impacted on institution i's total return rate. We test if this impact is statistically significant using the method suggested by Kolari and Pynnönen (2010), which accounts for correlations in stock returns between financial institutions. Economically, accounting for cross-sectional dependance is especially important during a financial crisis, where stock prices of financial firms may generally require higher risk premia due to increased uncertainty among investors irrespective of fundamentals and potential herding behavior. Econometrically, ignoring cross sectional return correlation may entail to overstate test statistics considerably, thus leading to over rejection of the null of no impact. Appendix A describes the method in detail.

B. Bailout effects

Table XII reports the average CARs that are significantly different from zero (upper panel) and those that are not (bottom panel).[22] Vertically, each panel reports descriptive statistics for CARs of peers that are not significantly CCP-connected (left) versus peers from four different sectors (banks, insurances, trusts, others) that exhibit a significant CCP connection with the bailed out bank.

–Table XII around here–

The comparison of observations in the upper and lower panel shows that in around 32% (=(476+50)/(476+50+1,017+112)) of all possible cases bailouts generated significant CARs among both connected and unconnected peers. This share is roughly equal when considering connected (31%) and unconnected (32%) peers separately. This result indicates that our agnostic approach to identify links among financial institutions on the basis of CCPs instead of constructing structural network ties based on observables coincides to a fair degree with market perceptions on which financial firm is tied to another. As such, CCPs seem to contain useful information about the connectivity

[22]Most bailouts (49) pertain to banks, only two insurance companies were rescued. We consider here only CARs in response to bank bailouts.

of financial firms.

On average, CARs are negative for both connected and unconnected peers. Across all four financial sub-sectors, bailouts of distressed firms caused negative CARs on the order of 4.9% among other financial firms identified as connected by our CCP measure. This discount is substantial and significantly larger compared with the 0.9% discount for unconnected peers. This result therefore corroborates the conclusion that CCP-connectivity reflects to some extent market perceptions on existing links between financial firms through which credit risk might spread. Moreover, the negative CARs support the notion that financial market participants regard bailouts in general as bad news for other financial firms, especially those they consider connected with the rescue subject.

The separation of the four different sub-sectors highlights that these effects are driven by CARs of banks. Within the banking industry, negative CARs are even larger compared to the overall average and the gap between connected and unconnected peers is both bigger and significant, too (-6.1% versus -0.3%). Insurances mimic this result, however, the difference between insurances that are connected and unconnected do not differ significantly from zero. CCP connectivity therefore adds no further information for this sub-sector. Equity returns of significantly connected investment trusts, in turn, exhibit positive CARs in response to bank bailouts on the order of 1.8%. Unconnected trusts exhibit, in turn, significantly negative CARs on the order of 3.9%.

Hence, rescue policies in one sub-sector, banking, seem to exert rather diverse effects in other arenas of the financial industry. Intra-sector links appear to matter a lot regarding the magnitude of (negative) CARs whereas trusts that are significantly linked benefit in contrast to unconnected trusts from government interventions. This disparity in equity return reaction may indicate the competitive distortions caused by any intervention, which for our sample seem to benefit trusts that are closely linked to a rescued bank.

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 during the financial crisis and significant mean CCPs increase from around 12 to 16 basis points. Credit risk connectivity is the highest among firms from the same sub-sector and country as shown by mean CCP levels for this subsample. At the same time, mean CCP levels do not differ significantly for pairs of firms that are from different countries (but the same sector) and those that are from different sectors (but the same country). This result indicates that while much of the public policy debate centers on coordinating prudential supervision of banks across countries, it might be equally important to coordinate such policies across sub-sectors in the financial industry, i.e. insurances, trusts, and other financial institutions.

Second, we attempt to shed some light on the directionality in CDS-spread co-movement by considering Granger causality tests. CDS spread change series that underly the CCP measure indicate that the share of financial pair firms not exhibiting any Granger causality rises from 20% to 24%. At the same time, pairs exhibiting bi-directional causality plummets from 35% to 19% of all possible pairs. In line with a drastically reduced number of significant CCP ties found before, these results indicate that financial firms may have attempted to insulate themselves from another in times of increased uncertainty during the crisis.

Third, 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. Considering more than just the banking sector is therefore not irrelevant for supranational financial stability policy. Probit analyses further show that measures of degree centrality prior to the crisis increase the likelihood of a bank bailout during the crisis. Hence, CCP-based network centrality measures seem to reflect at least regulators assessment of systemic relevance as revealed by the decision to rescue certain banks rather than to letting them fail.

Finally, we find that in around a third of all possible cases for both connected and unconnected peers, bailouts generated significant cumulative abnormal equity returns (CARs). We conclude from this result that our CCP-based connectivity indicator reflects to a reasonable degree market participants perspective on ties in the financial industry. After accounting for cross-sectional dependance, 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 significantly larger negative CARs compared to unconnected competitors. This result indicates that financial market participants appear to regard a bailout as bad news for other financial institutions considered connected. Negative CARs cast doubt on the effectiveness of bailout programs to achieve the frequently mentioned objective to calm financial markets.

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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 (10) 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

$$s = \sqrt{\frac{1}{I-1}\sum_{i=1}^{I}(A_i - \bar{A})^2}, \tag{11}$$

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 (10) by least squares. Kolari and Pynnönen (2010) note that Equation (11) 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	104.2	264.7	203,144	122	3.3	13.6	39.1	113.0	20,457.7
Insurance	249.3	732.1	62,386	35	4.8	23.8	51.4	154.8	26,990.1
Investment Trusts	203.0	446.5	33,511	19	5.7	36.8	66.2	190.4	7,856.9
Other institutions	254.0	499.9	27,738	17	6.4	28.7	74.2	306.0	10,046.8
Region									
U.S.	230.4	642.4	99,400	58	4.8	26.4	53.3	170.3	26,990.1
Europe	105.5	236.0	154,097	88	3.3	13.1	39.0	118.1	10,046.8
O.D.	143.6	407.1	54,308	32	3.9	15.2	45.7	110.5	14,496.2
E.M.	190.3	406.1	18,974	15	10.9	34.4	77.9	189.8	20,457.7
Total	154.8	438.1	326,779	193	3.3	17.3	48.1	132.1	26,990.1

Notes: Daily CDS spreads are reported in basis points, pooled within sectors and regions and are obtained from the Markit Group databases. With respect to the sectors: ‘Investment Trusts’ consists of real estate investment trusts, and private equity investment trusts. ‘Other institutions’ consist of financial services institutions, investment and lease firms, and subsidiary firms. For the regions: "U.S." stands for United States. "Europe" for the developed countries in europe. "O.D" stands for developed countries other than the U.S. and the countries in Europe. "E.M" stands for "emerging markets". The specific countries within these four groups are listed in table XIII.

TABLE II
Descriptive statistics: CDS percentage changes and critical 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 (4). 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	11.21	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	10.07	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	10.64	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" is until and "during-crisis" period starts after August 9, 2007.

TABLE IV

Within and between connectivity for regions and sectors

	Pre crisis period		During crisis period	
	Within	Between	Within	Between
Regions				
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
Insurance	0.763	0.664	0.205	0.071
Investment Trusts	0.385	0.484	0.180	0.045
Other	0.529	0.610	0.114	0.058

Notes: *Within connectivity* is measured as the ratio of significant links within a region over 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 possible links in which one institution is from that region. Significance in this context refers to whether the null of dependence between percentage changes in CDS spreads could not be rejected at the one percent level. With respect to the sectors: 'Investment Trusts' consists of real estate investment trusts, and private equity investment trusts. 'Other institutions' consist of financial services institutions, investment and lease firms, and subsidiary firms. Definitions of the regions are presented in table XIII

TABLE V

Pre crisis co-crash probabilities across link types

	Granger causality									
	No		Caused		Causes		Mutual		Total	
	Mean CCP	SE Obs.	Mean CCP	SE Obs.	Mean CCP	SE Obs.	Mean CCP	SE Obs.	Mean CCP	SE Obs.
Group 1: Country and sectoral ties										
Within country/within sector (n=809)	12.48	(0.98)	13.50	(0.90)	13.99	(0.74)	13.86	(0.54)	13.63	(0.37)
		115		175		204		315		809
Within country/between sector (n=1,479)	9.06	(0.57)	11.17	(0.46)	10.48	(0.41)	11.49	(0.37)	10.63	(0.22)
		287		318		471		403		1,479
Between country/within sector (n=7,474)	11.65	(0.38)	10.59	(0.23)	10.88	(0.27)	11.46	(0.14)	11.20	(0.11)
		1,245		1,389		1,674		3,166		7,474
Between country/between sector (n=8,766)	11.48	(0.28)	10.59	(0.25)	10.07	(0.21)	11.95	(0.18)	11.10	(0.11)
		2,105		1,833		2,138		2,690		8,766
Group 2: within and between regional ties										
U.S. - U.S. (n=1,653)	9.35	(0.55)	11.53	(0.50)	11.29	(0.39)	12.88	(0.39)	11.42	(0.23)
		303		361		547		442		1,653
U.S. - Europe (n=5,104)	8.62	(0.30)	9.30	(0.25)	8.73	(0.22)	11.22	(0.18)	9.73	(0.11)
		874		965		1,400		1,865		5,104
U.S - O.D. (n=1,856)	8.61	(0.46)	9.20	(0.53)	8.41	(0.54)	11.72	(0.44)	9.58	(0.24)
		542		422		376		516		1,856
U.S. - E.M. (n=870)	18.89	(1.01)	13.97	(0.91)	15.18	(0.78)	14.15	(0.68)	15.67	(0.44)
		236		196		223		215		870
Europe - Europe (n=3,828)	10.20	(0.54)	11.05	(0.33)	10.44	(0.26)	11.00	(0.18)	10.77	(0.14)
		500		648		879		1,801		3,828
Europe - O.D. (n=2,816)	9.95	(0.40)	9.00	(0.34)	9.68	(0.51)	11.08	(0.29)	10.10	(0.19)
		655		610		523		1,028		2,816
Europe - E.M. (n=1,320)	16.23	(0.73)	14.52	(0.69)	13.09	(0.55)	13.34	(0.39)	14.09	(0.28)
		275		275		305		465		1,320
O.D. - O.D. (n=496)	14.06	(0.96)	12.39	(1.03)	12.89	(1.11)	18.17	(1.59)	14.33	(0.60)
		177		124		85		110		496
O.D. - E.M. (n=480)	25.14	(1.71)	16.86	(1.21)	21.93	(1.70)	18.02	(0.99)	21.03	(0.80)
		161		99		111		109		480
E.M. - E.M. (n=105)	21.03	(2.49)	26.21	(3.14)	24.02	(2.96)	15.64	(1.31)	22.05	(1.49)
		29		15		38		23		105
Total (n=18,528)	11.38	(0.21)	10.78	(0.16)	10.60	(0.15)	11.78	(0.11)	11.21	(0.07)
		3,752		3,715		4,487		6,574		18,528

Notes: Table reports the mean value of co-crash probabilities and corresponding standard error across link types between financial institutions during the pre crisis period. A further distinction across link types is made by testing for Granger causality in the underlying daily CDS spreads' growth rates of a link. *No* indicates that no evidence is found indicating Granger causality either way and *Mutual* indicates that Granger causality is found for both ways. *Caused* and *Causes* do not allow for distinguishing between CCP levels, due to the joint probability's symmetrical nature between two given series, but may provide information on how Granger causality runs between countries, sectors and regions. Since 193 institutions are investigated, the total number of co-crash probabilities per period amounts to $193(193-1)/2 = 18,528$.

TABLE VI

During crisis co-crash probabilities across link types

	Granger causality									
	No		Caused		Causes		Mutual		Total	
	Mean CCP	S.e. Obs.	Mean CCP	S.e. Obs.	Mean CCP	S.e. Obs.	Mean CCP	S.e. Obs.	Mean CCP	S.e. Obs.
Group 1: Country and sectoral ties										
Within country/within sector (n=809)	12.77	(1.05)	13.54	(0.72)	14.01	(0.99)	13.63	(0.45)	13.50	(0.40)
		197		208		184		220		809
Within country/between sector (n=1,479)	14.38	(0.69)	10.67	(0.50)	11.66	(0.54)	10.56	(0.46)	11.90	(0.29)
		374		391		401		313		1,479
Between country/within sector (n=7,474)	11.31	(0.32)	10.41	(0.20)	11.32	(0.25)	9.66	(0.19)	10.70	(0.12)
		1,688		2,523		1,841		1,422		7,474
Between country/between sector (n=8,766)	9.56	(0.24)	8.51	(0.16)	8.91	(0.18)	8.70	(0.19)	8.91	(0.10)
		2,182		2,886		2,124		1,574		8,766
Group 2: within and between regional ties										
U.S. - U.S. (n=1,653)	14.77	(0.69)	11.28	(0.54)	12.70	(0.61)	11.50	(0.44)	12.67	(0.30)
		445		414		441		353		1,653
U.S. - Europe (n=5,104)	9.49	(0.30)	8.79	(0.22)	10.48	(0.26)	7.86	(0.23)	9.30	(0.13)
		1,357		1,399		1,477		871		5,104
U.S - O.D. (n=1,856)	9.40	(0.84)	9.24	(0.43)	9.00	(0.55)	8.29	(0.43)	9.04	(0.27)
		260		819		445		332		1,856
U.S. - E.M. (n=870)	16.94	(0.96)	13.19	(0.75)	11.76	(0.79)	10.12	(0.68)	13.27	(0.42)
		220		256		214		180		870
Europe - Europe (n=3,828)	8.75	(0.27)	9.78	(0.21)	9.65	(0.25)	9.98	(0.22)	9.55	(0.12)
		903		1,087		920		918		3,828
Europe - O.D. (n=2,816)	6.43	(0.42)	7.52	(0.19)	7.90	(0.32)	9.54	(0.35)	7.71	(0.15)
		551		1,272		535		458		2,816
Europe - E.M. (n=1,320)	13.31	(0.58)	13.12	(0.50)	13.10	(0.62)	10.84	(0.46)	12.74	(0.28)
		356		455		260		249		1,320
O.D. - O.D. (n=496)	12.08	(1.22)	10.91	(0.72)	10.58	(0.83)	11.33	(0.77)	11.24	(0.48)
		143		151		120		82		496
O.D. - E.M. (n=480)	22.08	(1.55)	11.51	(0.83)	11.55	(0.93)	9.14	(1.08)	15.16	(0.73)
		186		131		111		52		480
E.M. - E.M. (n=105)	19.86	(1.93)	18.95	(1.51)	17.78	(1.22)	19.77	(1.88)	19.13	(0.89)
		20		24		27		34		105
Total (n=18,528)	10.78	(0.19)	9.63	(0.12)	10.34	(0.15)	9.57	(0.13)	10.07	(0.07)
		4,441		6,008		4,550		3,529		18,528

Notes: Table reports the mean value of co-crash probabilities and corresponding standard error across link types between financial institutions during the during crisis period. A further distinction across link types is made by testing for Granger causality in the underlying daily CDS spreads' growth rates of a link. *No* indicates that no evidence is found indicating Granger causality either way and *Mutual* indicates that Granger causality is found for both ways. *Caused* and *Causes* do not allow for distinguishing between CCP levels, due to the joint probability's symmetrical nature between two given series, but may provide information on how Granger causality runs between countries, sectors and regions. Since 193 institutions are investigated, the total number of co-crash probabilities per period amounts to $193(193-1)/2 = 18,528$.

TABLE VII

Institutions ranked by degree centrality

Spearman correlation of degree centrality for the two periods: 0.2760***

Pre-crisis period				*During-crisis period*			
Name	Country	sector	Degree centrality (%)	Name	Country	sector	Degree centrality (%)
Norinchukin	JP	Banks	97.4	Bear Stearns	US	Banks	50.0
SEB	SE	Banks	96.9	Shinhan Bank	KR	Banks	40.6
Comm. Bank of Australia	AS	Banks	96.9	Dresdner Bank	DE	Banks	32.8
DZ Bank Zentral	DE	Banks	94.8	Washington Mutual	US	Banks	28.6
St. George Bank	AS	Banks	94.3	L. Banki Islands	IS	Banks	27.6
Anglo Irish Bank	IE	Banks	94.3	Bayersche Hypo Ver.	DE	Banks	27.1
Public Bank Berhad	MY	Banks	93.8	Unicredito	IT	Banks	26.6
Royal Suna Alliance Insur.	GB	Insur.	93.8	Glitnir Banki	IS	Banks	24.5
HBOS	GB	Banks	93.8	Sun Trust Bank	US	Banks	24.0
IKB	DE	Banks	93.2	Kaupthing	IS	Banks	23.4
Mizuho Bank	JP	Banks	93.2	Comm. Bank of Australia	AS	Banks	22.4
Standard Chartered Hold.	GB	Banks	92.7	Freddie Mac	US	Banks	22.4
Banco Sabadell	ES	Banks	92.2	Wachovia Corp.	US	Banks	22.4
Assicurazioni Generali	IT	Insur.	91.1	ABN Amro	NL	Banks	20.8
ANZ Banking Group	AS	Banks	91.1	Fannie Mae	US	Banks	20.8
Wind Acquisition Finance	LU	Subsi.	91.1	China Dev. Bank	CN	Banks	20.8
Credit Agricole	FR	Banks	90.6	Metlife	US	Insur.	20.3
United Overseas Bank	SG	Banks	90.6	Deutsche Bank	DE	Banks	20.3
HSH Nord Bank	DE	Banks	90.6	HSBC Bank	GB	Banks	19.8
Aegon	NL	Insur.	90.1	ANZ Banking Group	AS	Banks	19.8
Aviva	GB	Insur.	89.6	Swiss Reinsurance	CH	Insur.	19.3
HSBC Bank	GB	Banks	89.6	Liberty Mutual Group	US	Insur.	18.8
West Pac Banking	AS	Banks	89.6	West Pac Banking	AS	Banks	17.2
Raiffeisenbank Zentral	AT	Banks	89.1	HBOS	GB	Banks	17.2
BBVA Group	ES	Banks	89.1	GPT Corp.	AS	Invest.	17.2
Commerzbank	DE	Banks	89.1	KBC Group	BE	Banks	17.2
Prudential	GB	Insur.	89.1	State Bank of India	IN	Banks	17.2
Banca Monte Paschi Sienna	IT	Banks	89.1	Abbey National	GB	Banks	16.7
Banco Santander	ES	Banks	89.1	Societe Generale	FR	Banks	16.1
L. Bank Hessen-Thueringen	DE	Banks	88.5	Stan. Chartered Bank	GB	Banks	15.6
Glitnir Banki	IS	Banks	88.5	Barclays Bank	GB	Banks	15.6
Banco Espirto Santo	PT	Banks	88.5	Nat. Australia Bank	AS	Banks	15.1
State Bank of India	IN	Banks	88.0	Lehman Brothers	US	Banks	15.1
Caja Ahorros Valencia	ES	Banks	88.0	Prudential Financial	US	Insur.	14.6
Banco Commer. Portuguesa	PT	Banks	88.0	ING Bank	NL	Banks	14.6
Swiss Reinsurance	CH	Insur.	88.0	ING Verzekeringen	NL	Insur.	14.6
Unicredito	IT	Banks	88.0	Bank of Tokyo Mitsubishi	JP	Banks	14.1
HSBC holding	GB	Banks	88.0	Credit Suisse Group	CH	Banks	14.1
Credit Lyonnais	FR	Banks	87.5	Assicurazioni Generali	IT	Insur.	14.1
Munich Re	DE	Insur.	87.5	Aegon	NL	Insur.	14.1

Notes: Pre-crisis is the period of January 1, 2004 until August 9, 2007 and the During-crisis period ranges from August 9, 2007 to January 11, 2011. Institutions are sorted in descending order by their degree centrality measure. Degree centrality is calculated by dividing the number of significant co-crash probabilities associated with an institution through the number of institutions in the sample minus one, 192. The two character country codes correspond to the ISO 3166 country codes. '***' denotes a significantly different from zero Spearman rank order coefficient at the 1%-level (Bonferroni adjusted).

TABLE VIII

Dates of first time rescue measures for financial institutions

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

Table provides overview of financial support for financial institutions implemented by financial regulators. Dates are denoted by "mm/dd/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 IX
Descriptive statistics for pre crisis variables

	Mean	Std. Dev.	Obs.	Min	25^{th} pct.	Median	75^{th} pct.	Max
Variables in probit model								
Degree Centrality (in %)	43.5	34.4	193	0.5	10.4	29.2	79.7	98.4
Firm's Beta	0.3	0.2	137	-0.1	0.1	0.3	0.4	1.1
Employees (th. of people)	35.7	53.2	137	0.2	3.4	13.7	46.5	295.1
Total Assets (millions of U.S. dollars)	3854040.8	2.0e+07	137	159.7	39,104.6	170,315.2	810,588.8	1.4e+08

Table reports summary statistics statistics on the regressor variables used in the estimated probit model, see table VII . Data is obtained from Thomson Reuter's datastream and covers the pre-crisis period.

TABLE X
During crisis rescue measures explained by pre crisis centrality

Dependent variable:
Received gov. support during the crisis

	(1)	(2)	(3)
Degree Centrality	0.003**	0.006**	0.006*
	[0.001]	[0.003]	[0.003]
Firm's Beta		-0.413	-0.404
		[0.288]	[0.274]
Employees		0.003**	
(th. of people)		[0.001]	
Total Assets			0.080***
(millions of U.S. dollars)			[0.028]
Observations	193	137	137
log-likelihood	-92.675	-43.476	-43.464
Pseudo R^2	0.017	0.138	0.138

Notes: Table reports the marginal effects of a probit regression of whether an institution received financial support from central regulators in the during crisis period, 1, or not, 0. The regressors are obtained in the pre crisis period. Heteroscedastic robust standard errors reported in brackets. '***', '**' and '*' denote respectively significantly different from zero at the 1%, 5% and 10% level.

TABLE XI
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	-0.06	3.67	109,324	90	-285.54	-0.98	0.00	0.91	141.99
Insurance	-0.06	4.23	28,113	23	-122.27	-1.04	0.00	0.98	71.56
Investment Trusts	-0.01	3.34	23,987	16	-77.54	-1.14	0.04	1.15	53.79
Other	-0.01	3.25	6,755	8	-69.31	-1.04	0.00	1.10	46.59
Region									
U.S.	-0.07	4.77	66,517	58	-285.54	-1.08	0.00	1.01	141.99
Europe	-0.05	2.86	85,961	52	-88.24	-0.98	0.00	0.93	54.95
O.D.	-0.02	2.83	28,443	18	-280.34	-0.92	0.00	0.91	69.31
E.M.	0.05	2.80	14,427	9	-36.39	-1.14	0.00	1.22	49.56
Total	-0.04	3.62	195,348	137	-285.54	-1.01	0.00	0.97	141.99
Market index									
MSCI world index	0.01	1.13	1,83	1	-7.33	-0.45	0.07	0.52	9.10

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.

TABLE XII
Cumulative abnormal returns as a result of rescue events

sector	Mean	Std. Dev.	Num of obs.	Mean	Std. Dev.	Num of obs.	Mean sig. CCP- Mean Insig. CCP
Mean response to bank rescue measures							
				Significant Cars only			
		No sig. CCPs			*Only sig. CCPs*		
Banks	-0.003	0.194	291	-0.061	0.154	38	-0.058**
Insurance	-0.024	0.137	83	-0.014	0.169	10	0.010
Investment trusts	-0.039	0.117	73	0.048	0.018	2	0.087**
Other	0.042	0.116	29	n.a.	n.a.	0	n.a.
Total	-0.009	0.168	476	-0.047	0.152	50	-0.038*
				Insignificant Cars only			
		No sig. CCPs			*Only sig. CCPs*		
Banks	-0.019	0.068	601	-0.032	0.094	93	-0.013
Insurance	-0.001	0.082	182	-0.003	0.052	13	-0.002
Investment trusts	-0.020	0.084	172	0.014	0.021	2	0.034
Other	-0.018	0.069	62	-0.062	0.065	4	-0.044
Total	-0.016	0.073	1,017	-0.029	0.087	112	-0.013

Notes: Summary statistics are reported for cumulative abnormal returns that are found to be significantly different from zero at the 5 percent level and those that are not. *sig. CCPs* refers to the co-crash probabilities that are found to be significantly larger than zero at the one percent level. '***', '**' and '*' indicate significantly different from zero at the respective levels of 1, 5 and 10 percent; based on a *t*-test of mean difference. This t-test is performed on unrounded statistics. 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 XIII
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)	Hong Kong (HK)	China (CN)
	France (FR)	Japan (JP)	India (IN)
	Germany (DE)	Singapore (SG)	Indonesia (ID)
	Greece (GR)		Kazakhstan (KZ)
	Iceland (IS)		Korea (KR)
	Ireland (IE)		Malaysia (MY)
	Italy (IT)		Russia (RU)
	Luxembourg (LU)		South Africa (ZA)
	Netherlands (NL)		Taiwan (TW)
	Norway (NO)		Thailand (TH)
	Portugal (PT)		Turkey (TR)
	Spain (ES)		Ukraine (UA)
	Sweden (SE)		
	Switzerland (CH)		
	United Kingdom (GB)		

Notes: ISO 3166 country codes reported in parentheses. In the classification of "Other Developed" and "Emerging Markets" we follow the MSCI country classification. The region *European Union* in table III excludes Iceland, Norway and Switzerland from the Europe region. In the same table the region *Euro Area* excludes Sweden and the United Kingdom as well from the Europe region.