Measuring Connectedness of Euro Area Sovereign Risk

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Abstract

We introduce a methodology for measuring default risk connectedness that is based on an out-of-sample variance decomposition of model forecast errors. The out-of-sample nature of the procedure leads to "realized" measures which, in practice, respond more quickly to crisis occurrences than those based on in-sample methods. Resulting connectedness measures differ systematically when based on CDS or asset swaps in particular during crisis periods. This gap can partly be explained by observable factors, indicating that CDS carry more information with respect to these factors. The analysis of relative and absolute connectedness allows to identify countries that impose risk on the system from those which bear risk.

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1 Introduction

We propose a realized empirical procedure for assessing how European sovereigns are interconnected through default risk in terms of variance spillover effects (as in Diebold and Yilmaz (2014)). Measuring changes in comovements, our method can also be regarded as assessing a specific form of contagion (see e.g. Rodriguez (2007) or Forbes and Rigobon (2002)).[1] Contagious interconnection effects among banks and sovereigns have been central drivers of the recent financial and European sovereign crisis. While there already exist many empirical tools and studies analyzing spillover effects among financial institutions (see e.g. Engle et al. (2014), Hautsch et al. (2014)), tailored methods and studies for the impact of sovereign interconnections have been rare. We therefore introduce an empirical measure of connectedness among sovereigns, which is based on a parsimonious time series approach via variance decomposition. It is an easy-to-apply, one-step procedure, which excells through its directness and transparency and incorporates various sources of uncertainty. We find that Credit Default Swap (CDS) and asset swap spreads, which both reflect the default risk of the underlying entity, contain different information of variance-based connectedness, whereas CDS spreads are favored for our purpose since they include addtional information from 2010 onwards regarding observable factors such as liquidity.

Technically, we provide an empirical methodology based on variance decomposition for measuring connectedness between shocks in sovereigns. We build on a methodology by Diebold and Yilmaz (2014) which we extend to out-of-sample forecast errors. In particular, we separate estimation and evaluation samples and study forecast errors which comprise various aspects of shocks as opposed to model-based in-sample forecast errors. The variance-covariance structure of these forecast errors is decomposed into components revealing the interconnectedness of the cross-sectional entities. We show that these components are related to correlation coefficients, which allows for an alternative perspective on connectedness. The variance decomposition components are reported as complementary measures for connectedness in absolute terms or relative to total risk. Related studies exclusively focus on relative measures, however a comparison of both relative and absolute measures allows for an in-depth analysis.

We apply our method to CDS spreads and asset swap spreads of bonds. Asset swap spreads provide a better comparison to CDS spreads than bond yield spreads, because they

[1]There are numerous definitions of specific forms of financial contagion in the literature. We study the predicted impact of an idiosyncratic shock in default risk of one country on the default risk of other countries.

are free of interest rate risk. CDS and asset swap spreads are regarded as nearly equivalent and lead to coinciding results when measuring contagion purely in returns disregarding second moment aspects as in Caporin et al. (2013) due to the theoretic no-arbitrage condition (Duffie (1999)). Nevertheless, there are important differences across the two datasets for variance decomposition results. From the beginning of the sovereign crisis onwards, CDS spreads show an overall higher level of connectedness than asset swap spreads. We find that these differences can be explained by liquidity, financing costs and crisis-related events, thus motivating the use of CDS spreads for a comprehensive measure of connectedness, especially during financially turbulent times. We empirically investigate CDS spreads of nine European countries (Belgium, France, Germany, Ireland, Italy, Netherlands, Portugal, Spain, United Kingdom) and identify main sources of connectedness by contrasting absolute and relative components. Absolute and relative measures reveal substantial differences in core or periphery countries and across different periods of the crisis. An analysis of these differences yields a detailed overview of the significance of specific countries and the relationships between them. It also allows to deduce whether risk is mainly born by an individual country or the system.

On the model side, Diebold and Yilmaz (2009, 2014) are the first to use variance decomposition in order to measure connectedness. We modify this model by including realized shocks, which captures additional connectedness effects. To the contrary, other papers working with variance decomposition focus on the structural model. Alter and Beyer (2014) extend Diebold and Yilmaz' methodology by using impulse responses instead of forecast error variance decomposition and by adding exogenous variables to the VAR which we found insignificant for our purpose. Heinz and Sun (2014) employ variance decomposition of a VECM. Claeys and Vašíček (2012) augment the VAR by a common factor. The three papers mentioned above all analyze connectedness of European sovereigns. Variance decomposition is also utilized to measure connectedness between other entities, as for instance stock markets (Schmidbauer et al. (2012, 2013)) or futures markets (Antonakakis et al. (2014)).

On the data side, there has been extensive research on the comparison of CDS and bonds in first moments of returns but, to our knowledge, not on their variances. Caporin et al. (2013) analyze contagion in the euro area with return data of both CDS and bond yield spreads. This is special because mostly, when studying contagion in European sovereigns, a method is applied *either* to bonds *or* to CDS. There is a broad scope of literature examining the price discovery process in CDS and bond markets (Longstaff et al. (2011), Delatte et al. (2012), Fontana and Scheicher (2010), Palladini and Portes (2011), Gyntelberg et al. (2013), among others). Several papers have studied determinants of CDS and asset swap spreads or their dynamics in first moments. For example, Arce et al. (2013) find that the difference between the two spreads can be explained by "market frictions like counterparty risk, market illiquidity and funding costs". Fontana and Scheicher (2010) identify that the reason for a higher level in CDS spreads during the crisis could be flight to liquidity and limits to arbitrage. According to Heinz and Sun (2014), the decline in CDS in the second half of 2012 is due to a drop in risk aversion. Calice et al. (2015) identify "CDS market liquidity, local stock returns, and overall risk aversion" as major determinants of the CDS term premium and Santis (2014) finds that flight to liquidity is a decisive factor explaining bond yield spreads.

Furthermore, our paper contributes to the literature of spillover measures. As mentioned before, our work is closely related to that of Diebold and Yilmaz (2014), Alter and Beyer (2014) and Heinz and Sun (2014), who model the entities of a network as a VAR and use the shocks thereof to measure connectedness. Several papers measure systemic risk by investigating the situation of one entity conditional on the entire system or market being under distress. See for instance Adrian and Brunnermeier (2011) proposing the CoVaR or Engle et al. (2014) who utilize a Dynamic Conditional Correlation (DCC) model. Acharya et al. (2012) introduce the concept of Systemic Expected Shortfall (SES) and Brownlees and Engle (2012) develop the Marginal Expected Shortfall (MES). Hautsch et al. (2015) propose the realized systemic risk beta using tail risk exposures. A further approach for measuring connectedness is using principal component analysis and Granger-causality tests as Billio et al. (2012). Ricci and Veredas (2015) propose a metric that is based on a tail interquantile range and Schwaab et al. (2011) estimate measures for systemic risk using a mixed-measurement dynamic factor model approach.

The remainder of the paper is organized as follows. Section 2 describes the data. In section 3, we explain the methodology. The empirical results are discussed in section 4. Section 5 concludes.

2 Data

Default risk is commonly measured by CDS spreads and asset swap spreads of bonds. We employ CDS spreads of nine European countries, including both core and periphery countries: Belgium (BE), France (FR), Germany (DE), Ireland (IE), Italy (IT), Netherlands (NL), Portugal (PT), Spain (ES) and the United Kingdom (GB)[2]. The CDS are of five years maturity and denominated in US Dollars[3]. The data is obtained from Bloomberg and covers the time period from 02.02.2009 until 02.05.2014. A CDS transfers the risk of default from the buyer to the seller of the swap. In return, the buyer pays the seller the CDS spread (see Duffie (1999), Longstaff et al. (2005), Fontana and Scheicher (2010), among others). Sovereign asset swap spreads are obtained from Thomson Reuters. The sample covers the same set of countries and time period as the CDS data. Like the CDS spreads, the asset swap spreads are for bonds of five years maturity.[4] The reference rate of the asset swap is the three month Euribor and the underlying bonds are denominated in Euro[5]. An asset swap transfers a fixed security, here a sovereign bond, against a floating market rate. This rate minus a reference rate such as the Euribor reflects the creditworthiness of the government issuing the bond, stripped of the interest rate risk. Therefore, the asset swap spread serves as a suitable comparison to CDS spreads (see also Gyntelberg et al. (2013)) and should be prefered above bond yield spreads, which include interest rate risk. Figure 7 in the Appendix shows the levels of CDS spreads and asset swap spreads in comparison.

Tests for stationarity suggest that the data is difference-stationary. We apply the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test to each 200-day subsample of the rolling window. We then compute the percentage of times the H_0 of the ADF are rejected and the percentage of times the H_0 of the KPSS cannot be rejected at 5%, which corresponds to the percentage of 200-day series that appear to be stationary. Regarding CDS data and according to KPSS, 1.8% of the level series are stationary and 93.11% of the return series are stationary on average. Using returns of CDS spreads is common in the literature (cf. Cont and Kan (2011), Alter and Beyer (2014), among others). As expected, the statistical properties of asset swap spreads are similar to those of CDS spreads. The results of the KPSS test indicate that 3.6% of the level data and 99.1% of the differenced data are stationary. Countrywise summary statistics of spreads and spread returns, as well as the results of the unit root tests, are provided in Table 2 in Appendix A.1.

[2]We include the United Kingdom as a major financial player in the European Union. Empirical results in Section 4.2.4 show important connectedness effects with other Euro countries. Greece is excluded from our study because trading of Greek sovereign bonds ceased after the disclosure of its budget deficit on 20.10.2009.

[3]In Section 4.2.2, we control for exchange rate risk among others and find that its effect is negligible.

[4]We use five years maturity in order to make them comparable to CDS spreads, even though bonds of ten years maturity are more liquidly traded, see also Caporin et al. (2013).)

[5]Libor and British Pound for United Kingdom, respectively.

3 Model

Variance decomposition allows to quantify the effect of a shock in one variable on the forecast error variance of another variable. We modify this concept by introducing out-of-sample forecast errors. Diebold and Yilmaz (2014) show how variance decomposition may be utilized for measuring connectedness between different entities of a network.

In order to compute the variance decomposition components, we first model returns of sovereign CDS spreads and returns of asset swap spreads as a vector autoregressive model (VAR):

$$\mathbf{y}_t = \sum_{i=1}^{p} A_i \mathbf{y}_{t-i} + \mathbf{u}_t, \quad t = 1, 2, \ldots, T_e, \tag{1}$$

where the $(K \times 1)$ vector $\mathbf{u}_t$ of error terms is assumed to be a white noise process with $E(\mathbf{u}_t) = \mathbf{0}$, $E(\mathbf{u}_t \mathbf{u}_t') = \Sigma_u$ with elements σ_{ij} and $E(\mathbf{u}_t \mathbf{u}_s') = 0$ for $t \neq s$. $\mathbf{y}_t = (y_{1t}, y_{2t}, \ldots, y_{Kt})'$ denotes a $(K \times 1)$ vector of countries and is covariance-stationary with moving average representation $\mathbf{y}_t = \sum\limits_{i=0}^{\infty} \Phi_i \mathbf{u}_{t-i}$. A_i represents the $(K \times K)$ matrices of the autoregressive coefficients for $i = 1, 2, \ldots, p$. We conduct a dynamic analysis using a rolling window approach using a window width T_e to estimate the VAR. This parsimonious model gives enough flexibility for the approach to stay valid even when structural breaks and additional time dependencies occur.

Given the estimates of the VAR coefficients, we estimate the H-step forecast error variance or mean squared error (MSE), defined as:

$$\Sigma_y^{OUT}(H) := MSE\big[\hat{\mathbf{y}}_t(H)\big] = E\Big[\big(\mathbf{y}_{t+H} - \hat{\mathbf{y}}_t(H)\big)\big(\mathbf{y}_{t+H} - \hat{\mathbf{y}}_t(H)\big)'\Big] \tag{2}$$

where $\hat{\mathbf{y}}_t(H)$ is the linear minimum MSE predictor at time t for forecast horizon H obtained from the estimated coefficients $\hat{A}_i$ of the process[6]. Please note that $\hat{\mathbf{y}}_t(H)$ contains data and estimates computed only from inside the estimation sample, while $\mathbf{y}_{t+H}$ is taken from outside the estimation sample. Therefore, the resulting forecast error $\mathbf{y}_{t+H} - \hat{\mathbf{y}}_t(H)$ is an out-of-sample forecast error and we call $\Sigma_y^{OUT}(H)$ from Equation (2) out-of-sample MSE. A standard estimator for $\Sigma_y^{OUT}(H)$ is given by

$$\hat{\Sigma}_y^{OUT}(H) = \frac{1}{T_s} \sum_{t=1}^{T_s} \big(\mathbf{y}_{t+H} - \hat{\mathbf{y}}_t(H)\big)\big(\mathbf{y}_{t+H} - \hat{\mathbf{y}}_t(H)\big)'. \tag{3}$$

[6] $\hat{\mathbf{y}}_t(H) = \sum_{i=1}^{p} \hat{A}_i \hat{\mathbf{y}}_t(H-i)$

where T_s is the sample size used for estimating $\Sigma_y^{OUT}(H)$. We compute $\hat{\Sigma}_y^{OUT}(H)$ for a second rolling window of width T_s based on the forecast errors $\mathbf{y}_{t+H} - \hat{\mathbf{y}}_t(H)$ obtained from the first rolling window of width T_e.

In contrast to the approach above, for the generalized variance decomposition approach utilized by Diebold and Yilmaz (2014) the MSE is rewritten as a sum of matrices. The forecast error is replaced by the moving average (MA) representation formula given by $\mathbf{y}_{t+H} - \mathbf{y}_t(H) = \sum_{h=0}^{H-1} \Phi_h \mathbf{u}_{t+H-h}$, which allows to rewrite the MSE as follows:

$$\begin{aligned}\Sigma_y^{IN}(H) := MSE\big[\mathbf{y}_t(H)\big] &= E\Big[\big(\mathbf{y}_{t+H} - \mathbf{y}_t(H)\big)\big(\mathbf{y}_{t+H} - \mathbf{y}_t(H)\big)'\Big] \\ &= \sum_{h=0}^{H-1} \big(\Phi_h \Sigma_u \Phi_h'\big), \end{aligned} \tag{4}$$

where $\mathbf{y}_t(H)$ is the theoretical optimal predictor for known Φ_i[7] and Φ_h is the h-th coefficient of the MA-representation. This formula is computed with observations only from inside the estimation sample, namely the residual covariance matrix Σ_u and the MA coefficients Φ_h, so it is an in-sample forecast error variance. An estimate is obtained using respective estimates $\hat{\Sigma}_u$ and $\hat{\Phi}_h$.

While the out-of-sample MSE is computed from the VAR-estimates $\hat{A}_i$ directly, the in-sample MSE requires that these are additionally transformed to the MA-representation. The shocks computed from the MA-representation are solely based on the expectations of the underlying model. In contrast to that, the out-of-sample forecast errors are contingent on one sample for estimation and another for generating the forecast errors and therefore represent various aspects of the shock. In other words, the out-of-sample MSE can be time-varying along different forecast horizons H and between different estimation windows in contrast to the in-sample quantity.[8]

From the H-step in-sample MSE we derive the ij-th generalized variance decomposition component for a forecast error H periods ahead[9], given by

$$s_{ij}^{IN}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \Phi_h \Sigma_u e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Phi_h \Sigma_u \Phi_h' e_i)}, \tag{5}$$

[7] In MA-representation: $\mathbf{y}_t(H) = \sum_{i=H}^{\infty} \Phi_i \mathbf{u}_{t+H-i}$.

[8] Another possibility for representing forecast error variances that are more realistic than the in-sample MSE is the asymptotic approximation of the MSE for estimated processes. However, it is not possible to decompose the approximate MSE because it is an asymmetric sum.

[9] This is shown in the Appendix A.2.

where σ_{jj} is the (j, j) element of Σ_u and e_i is a selection vector with unity as its i-th element and zeros elsewhere. The elements $s_{ij}^{IN}(H)$ for $i, j = 1, ...K$ are summarized in the connectedness matrix $S^{IN}(H) = ((s_{ij}^{IN}(H)))_{ij}$. The numerator of $s_{ij}^{IN}(H)$ is the contribution of shocks in variable j to the H-step forecast error variance of variable i. The denominator is the forecast error variance of variable i. The formula above results from the generalized variance decomposition framework as applied by Diebold and Yilmaz (2014) and the papers using their approach, which was proposed by Koop et al. (1996) and developed by Pesaran and Shin (1998).[10]

We now introduce how to decompose the out-of-sample MSE $\Sigma_y^{OUT}(H)$ in contrast to the standard in-sample variance decomposition. Therefore, we use a variance decomposition component of a one step ahead forecast. For $H = 1$ the MSE from Equation (4) consists only of one matrix $\Sigma_y^{IN}(1) = \Sigma_u$, as opposed to MSEs for $H > 1$ which are represented by sums of matrices. Since $\Phi_0 = I_K$, it is easy to see that for a one-step ahead forecast, Equation (5) simplifies to the following:

$$s_{ij}^{IN}(1) = \frac{\sigma_{jj}^{-1}(e_i'\Sigma_u e_j)^2}{(e_i'\Sigma_u e_i)} = \frac{\sigma_{ij}^2}{\sigma_{ii}\sigma_{jj}}. \tag{6}$$

This shows that variance decomposition components actually have great similarity to the correlation coefficients of forecast error variances. For a one-step ahead forecast, the variance decomposition component between i and j equals the square of the correlation between the forecast errors of i and j. Since it is of higher order than correlation the resulting measure reflects more extreme parts of connectedness.

Equation (6) represents a formula for a variance decomposition component based on an MSE constructed of one single matrix. Since the out-of-sample MSE is one single matrix for any H, we can replace Σ_u in Equation (6) by $\Sigma_y^{OUT}(H)$ and obtain the ij-th variance decomposition component of an out-of-sample forecast error H steps ahead:

$$s_{ij}^{OUT}(H) = \frac{(e_i'\Sigma_y^{OUT}(H)e_j)^2}{(e_i'\Sigma_y^{OUT}(H)e_i)(e_j'\Sigma_y^{OUT}(H)e_j)}. \tag{7}$$

As for in-sample variance decomposition, this is the fraction of variable i's H-step forecast error variance due to shocks in variable j and the individual components are represented in the connectedness matrix $S^{OUT}(H) = ((s_{ij}^{OUT}(H)))_{ij}$. We call this realized connectedness as opposed to standard model-based connectedness as in Equation (5).

[10]Generalized variance decomposition assumes errors to be normally distributed.

4 Results

4.1 Dynamic Specification

Our presented results are robust over a wide range of choices of rolling window sizes and the dynamic model fit. We aim for a parsimonious model fit while maximizing forecasting power, which is our main goal of interest. We compare the normed MSE[11] of different models for each rolling window and define an optimal number of lags. We find that the model most suited to our needs is a first order differenced VAR with one lag, i.e. a VAR(1) of spread returns. Dynamic effects are incorporated by the use of rolling windows. We exclude heteroscedastic effects from the model in order to retain all effects in the resulting connectedness measure and in favor of a parsimonious model. Two other models besides the VAR(1) were considered: a vector error correction model (VECM), which takes cointegration relationships into account, and a vector autoregressive model with exogenous variables (VARX), in order to filter out the common trend.

Rolling window size is chosen with respect to robustness across all windows of the model selected by AIC. More precisely, we choose the number of observations used to estimate the underlying model, denoted by T_e, such that the optimal model choice remains stable for consecutive estimation windows. We find that a window size of 200, which corresponds to 9 months, is optimal with respect to robustness across all windows of the model choice selected by AIC[12]. The realized connectedness measure is robust with respect to the window size T_e in a range between 130 and 400, which allows us to be flexible with regard to that parameter. We compare window sizes of $T_e = \{130, 200, 260, 400\}$ which corresponds to six months, nine months, one year and one and a half years, respectively. In addition, there is no significant difference between the quality of the estimates using different window sizes according to Akaike information criterion (AIC), Bayes information criterion (BIC), and realized MSE. Even though these are few observations for the estimation of a nine-dimensional VAR, model selection actually becomes less robust when including more observations. This is due to the sudden jumps and changes in the data during the crisis.[13] For the computation of the out-of-sample forecast error variance based on the results from the first rolling window of size T_e, a second rolling window is needed, which we denote by T_s. We set T_s equal to the first rolling

[11]Correlation in the forecast error is negligable, thus the properties of optimal forecasts hold for MSE (Patton and Timmermann (2007)).

[12]Results of robustness checks are provided upon request.

[13]From a statistical viewpoint, a larger window size leads to a higher level of stationarity (on average) and the estimated coefficients are more significant (on average) as reported by the t- and F-test; results are provided upon request.

window width $T_e = 200$, which leads to a minor variance compared with other window sizes between 130 and 400.

Considering these optimal parameters, we evaluate a parsimonious model fit. Even though we find cointegration relationships in the data as indicated by the Johansen test for cointegration, the first-differenced VAR outperforms a VECM during the crisis, see also De Santis (2012). The difference of forecasting power is illustrated in Figure 8 in the Appendix which shows the norm of the out-of-sample MSE [14] of a VAR and that of a VECM for CDS and asset swap spreads. The advantage of the VAR over the VECM is explained as follows: A VECM captures the long term relations between the variables. Clearly, these become less important during the crisis because agents become more short-sighted.[15]

The number of lags is chosen according to the AIC, which indicates an optimal lag-order of one ($p = 1$). This is true for all estimations of the rolling window with exception of two days in 2010. In the case of modeling high-dimensional financial data, a low VAR order makes sense for two reasons. First, financial institutions react quickly to changes in the market. Therefore, it is unlikely that high lags have any significance for the estimated variable. Second, the number of lags should not be too high because the complexity, and thus the time needed for the computation of a high-dimensional VAR augments rapidly as the number of lags increases.

There is no improvement in the forecasting power of the VAR by including exogeneous variables, see also Avino and Nneji (2014)[16]. We consider the following exogenous variables to control for common changes among the CDS spreads: change in Euribor reflects financing conditions, VIX as a proxy for investor's fear and iTraxx Europe representing aggregate credit market development. As illustrated in Figure 9 in the Appendix, the MSE of the VARX persistently exceeds that of the VAR.

In addition to the MSE, we compare models with respect to AIC, BIC and log- likelihood. The results are summarized in Table 4 in the Appendix. We find that the optimal window size with respect to robustness across the rolling window equals 200. The model fit with the highest forecasting power is a vector autoregressive model of order one (VAR(1)).

[14] As before, we use the Frobenius norm. We compute the cumulated average of MSEs based on $H = 1$, $H = 3$ and $H = 5$ forecast periods ahead.

[15] This confirms the finding by De Santis (2012) that cointegration models for European Monetary Union (EMU) government bond spread dynamics break down in the period from September 2008 until August 2011.

[16] Avino and Nneji (2014) find that the prediction of CDS spreads by an AR(1) is not improved by adding exogenous variables.

4.1.1 Reported Measures

It is common practice to normalize the elements of $S^m(H)$ by row:

$$\widetilde{s_{ij}^m} = \frac{s_{ij}^m}{\sum_{j=1}^K s_{ij}^m}, \tag{8}$$

with $m \in \{IN, OUT\}$, such that the row sums of the resulting matrix $\widetilde{S^m}$ are equal to unity. The normalized components $\widetilde{s_{ij}^m}$ can be considered as relative connectedness measures since they express how much one variable j is connected with another variable i, relatively to how much all other variables are connected with i. Thus, we control for the fact that some entities are more connected than others. By comparing absolute and relative measures we can conclude whether default risk is born by a specific entity or the entire system. It is noteworthy that the original matrix $S^{OUT}(H)$ is symmetric by construction and $S^{IN}(H)$ is close to a symmetric matrix[17]. This is why interpretations concerning directedness as in Diebold and Yilmaz (2014) of the connectedness measures should be treated with caution. By normalizing the elements s_{ij}^m, the resulting matrices $\widetilde{S^m}$ no longer yield symmetry.[18]

A cumulated average of components leads to a more robust measure. Considering that the variance decomposition coefficients $s_{ij}^m(H)$ vary insignificantly in function of the forecast periods H, all connectedness measures are computed by averaging variance decomposition components of one, two and five forecast steps ahead:

$$C_{ij}^m = \frac{1}{3}(s_{ij}^m(1) + s_{ij}^m(2) + s_{ij}^m(5)). \tag{9}$$

Similarly, Alter and Beyer (2014) also work with cumulated average variance decomposition components, arguing for the inclusion of feedback effects and the possibility to measure long-run effects of shocks.

As Diebold and Yilmaz (2014), we use the connectedness measure on three different aggregation levels, which can be clearly summarized in the connectedness table which is shown in Table 1:

(i) The entries C_{ij} in the table are the *individual connectedness* between j and i.

(ii) The sum of all off-diagonal elements of column j corresponds to the connectedness of

[17] Matrix A is close to symmetric if $||A - A^T|| \leq \varepsilon$ for ε small.

[18] Due to the symmetry property, normalizing by column sums would be equivalent to normalizing by row sums.

entity j with all other entities of the system and is called *entity–wise connectedness*.[19]

$$EC_j = \sum_{i=1, i \neq j}^{K} C_{ij} \tag{10}$$

(iii) Finally, the sum of all off-diagonal elements, which is equivalent to the sum of all *entity–wise*- measures, expresses the *total connectedness* of the system.

$$TC = \frac{1}{K} \sum_{i,j=1, i \neq j}^{K} C_{ij} \tag{11}$$

In the following, we will use these aggregated measures to represent the dynamics of connectedness across the rolling window following Diebold and Yilmaz (2014).

	y_1	y_2	$\cdots$	y_K	
y_1	C_{11}	C_{12}	$\cdots$	C_{1K}	
y_2	C_{21}	C_{22}	$\cdots$	C_{2K}	
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	
y_K	C_{K1}	C_{K2}	$\cdots$	C_{KK}	
	$\sum_{i=1}^{K} C_{i1}$ $i \neq 1$	$\sum_{i=1}^{K} C_{i2}$ $i \neq 2$	$\cdots$	$\sum_{i=1}^{K} C_{iK}$ $i \neq K$	$\frac{1}{K} \sum_{i,j=1}^{K} C_{ij}$ $i \neq j$

Table 1: Connectedness Table

4.2 Results on Sovereign Connectedness

4.2.1 Advantages of the Realized Measure

We compare the novel realized MSE and connectedness measure with those resulting from the standard method in order to illustrate empirically where the difference between the two measures lie.

Figure 1 shows realized and model-based measures in black and gray respectively, as well as the ratio between them, depicted by the dashed blue line. The left hand side Figure 1a depicts the normed MSEs[20] while the right hand side Figure 1b represents total connectedness measures. Vertical lines represent important events during the crisis.[21] In both Figures 1a

[19] If we would have normalized the elements by column sums instead of row sums in equation (8), we would take row sums here.

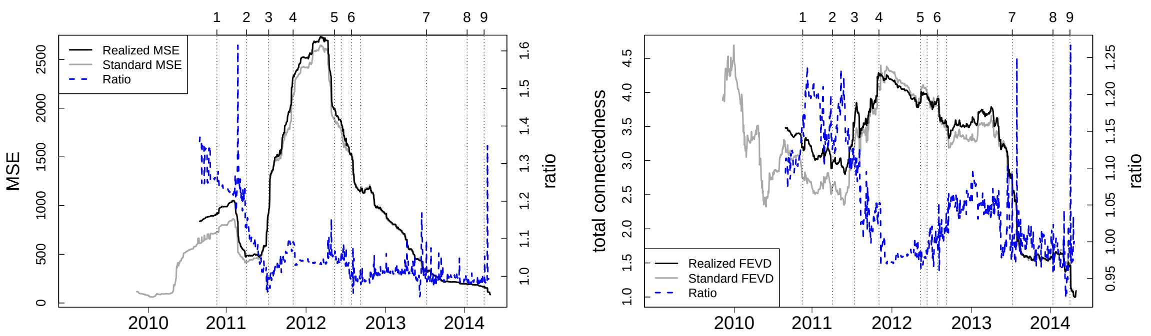
[20] We employ the Frobenius norm which, for a $m \times n$ matrix $\mathbf{x}$, equals $\sqrt{\sum_{i=1}^{m} \sum_{j=1}^{n} x_{ij}^2}$. All norms are equivalent in finite dimensions, thus reported results are qualitatively not specific to the employed norm and in size equal up to a constant.

[21] A detailed timeline with their exact specification can be found in the Appendix in Table 3.

and 1b, the ratio jumps at the same points in time, although not to the same extent. This is not surprising since total connectedness is derived from the MSE.

Out-of-sample MSE and connectedness are higher than their in-sample counterparts at the beginning of our sample and converge when the sovereign debt crisis becomes acute after the stress test results are published (15.07.2011, event number 3). A possible explanation is that information flow between economic agents is more dense or more exact during the high-time of the crisis.

The realized (out-of-sample) measure is higher than the model-based (in-sample) measure when unexpected crisis-related events occur. This is true for both absolute as well as relative measures. Yet, apart from these events, the dynamics are relatively similar. Accordingly, the use of realized measures is of advantage for obtaining more realistic results for unexpected key events.



(a) Normed MSE

(b) Total Connectedness

Figure 1: Realized and Model-Based Measures

Figure 1a depicts norm of out-of-sample and in-sample MSE while Figure 1b shows absolute total connectedness measures, computed using CDS data. Realized (out-of-sample) connectedness is presented by the black line and standard (in-sample) connectedness by the gray line. The dashed blue line represents the ratio between them. Important events are marked with vertical lines. The sample period is from 02.02.2009 until 02.05.2014, which leads to realized connectedness measures from 25.08.2010 until 02.05.2014 and standard connectedness measures from 09.11.2009 until 02.05.2014.

4.2.2 CDS versus Asset Swap Spreads of Bonds

CDS spreads and asset swap or bond yield spreads have generally been used interchangeably in the literature to measure default risk. Although the theoretic no-arbitrage condition (see Duffie (1999), among others) would imply that the two datasets reflect the same information on credit risk, we find important structural differences, especially during the crisis. Figure 2 illustrates total connectedness of CDS and asset swap spreads. Variance decomposition measures of asset swap spreads appear to systematically detect less connectedness relative to variance decomposition measures of CDS spreads. This can be explained by the fact that bonds of affected countries are rarely traded during the crisis, so they cannot reflect any connectedness. CDS, on the other hand, represent an insurance against default and since it is well-known that stable European countries pay for the default of their neighbours, CDS spreads will react in all countries when crisis-related events occur. Since CDS spreads incorporate more information compared to asset swap spreads, they are preferred when measuring connectedness.

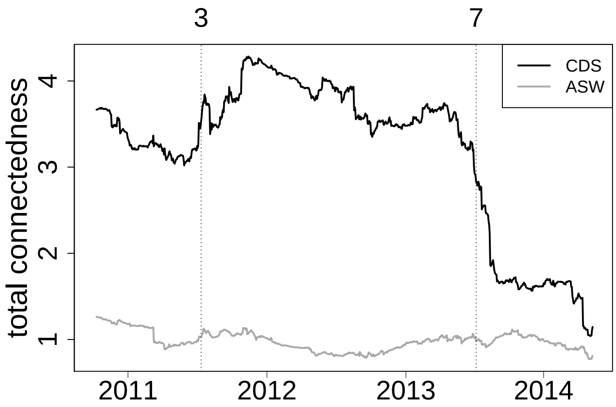


Figure 2: Total Connectedness of CDS and Asset Swap Spreads

Total connectedness measures for CDS and asset swap spreads are calculated from absolute measures. Both are computed with out-of-sample forecast errors and averaged across one, two and five forecast periods ahead. The black line is obtained from CDS spreads and the values resulting from asset swap spreads are depicted by a gray line. The vertical lines marked 3 and 7 (see timeline in the Appendix for details) designate the borders of the subperiods used in the panel regression. The sample covers the period from 02.02.2009 until 02.05.2014, which leads to realized connectedness measures from 25.08.2010 until 02.05.2014.

We investigate the driving determinants of the difference between connectedness measures of CDS and asset swap spreads, which we call difference in connectedness hereafter, by estimating a fixed effects panel model with robust standard errors[22]. In order to control for heterogeneity across time and countries[23], the model is estimated for three seperate periods and a dummy variable that equals one for Ireland, Italy, Portugal and Spain is added.[24] The three estimation periods correspond to the most turbulent period of the crisis and the time

[22]Standard errors take account of serial correlation and cross-sectional correlation, as proposed by Driscoll and Kraay (1998).
[23]See Figure 11 in the Appendix for an illustration.
[24]See also Fontana and Scheicher (2010).

periods before and after these dates.[25]

We regress the difference in connectedness on the bid-ask spread of CDS, the Euribor-Eurepo three month spread and the Euro Currency Volatility Index (EVZ). All employed determinants are level stationary according to the LR-bar test for multiple cointegration (Larsson et al., 2001). The bid-ask spread is a proxy for liquidity and is expected to have a positive impact on the difference in connectedness. The Euribor-Eurepo spread represents arbitrage costs and the general refinancing situation: When the repo rate is lower than the Euribor, it is costly to implement a positive basis trade. A positive basis trade would drive CDS and asset swap spreads closer to each other, thus a high Euribor-Eurepo spread (standing for high arbitrage and refinancing cost) would be positively related to the difference in connectedness. Uncertainty about future variation of the Euro-USD rate is expressed by the EVZ. A higher variation would imply more risk for a dealer providing USD-denominated CDS spreads of European entities, hence the basis would increase.

The regression results are summarized in Table 5 in the Appendix and are discussed in anti-chronological order. All estimates are significant, with the exception of the estimate for the EVZ for core countries in periods one and three. The other estimates for the EVZ are significant, but its effect is of minor importance compared to the other regressors in all time periods. In the third estimation period, the most turbulent phase of the crisis has come to an end. Both the bid-ask spread and the Euribor-Eurepo spread have a strong and positive impact on the difference in connectedness of core countries and to a lesser extent for periphery countries. Arbitrage and financing costs are extremely low, so it is easy to conduct basis trades that drive CDS and asset swap spreads together. In periphery countries that are not yet recovered from the crisis, CDS liquidity is still very low, which is why the relation between the difference in connectedness and liquidity and financing costs is less important in these countries. The results of the second estimation period are noteworthy. The effect of the Euribor-Eurepo spread is almost at zero and the parameter for the bid-ask spread is negative, although smaller than in the other periods. During the high-time of the crisis, other crisis-related effects have a stronger impact such that liquidity no longer plays a leading role for the difference in connectedness. This is confirmed by the fact that idiosyncratic effects account for 70% when estimating a random effects model. The first period is at the beginning of the sovereign debt crisis. Market conditions are irregular, but not as turbulent as in period two. This is reflected in lower values for the estimates of the bid-ask spread and the Euribor-

[25]The dates correspond to events number 3 and 7 in the timeline and are discussed in more detail the following Section 4.2.3. The dates are marked in Figure 3.

Eurepo spread compared to the third estimation period.

To summarize, CDS spreads are more representative for measuring connectedness comprehensively because they are more liquidly traded from the beginning of the European sovereign debt crisis onwards. In extremely turbulent times such as the second estimation period, CDS spreads reflect more connectedness than asset swap spreads.

4.2.3 Absolute versus Relative Connectedness Measures

We study the directional impact transmitted from one country to others, both in absolute and relative terms measured by connectedness s_{ij}^{OUT} and normed connectedness $\widetilde{s_{ij}^{OUT}}$ (see Section 4.1.1 for the definitions). Both measures are required for a comprehensive picture on the impact of one specific country and the total interconnectedness between all of them. Uniquely examining a relative measure is not sufficient considering that from one time point to another, the absolute connectedness of a specific country but also the total level of absolute connectedness among all countries in the system can change. If e.g. at one time point, the absolute transmitted effect of a country is larger than its percentual effect in connectedness, this means that risk spillovers of this country are less important relative to the connectedness of other countries with the rest of the system. Note that for this analysis, the two measures are compared among each other and not in absolute terms. Figure 3 shows the connectedness impact of each country to all others in absolute and relative terms.

In stable European countries like Germany, the Netherlands or United Kingdom, the dynamics of absolute and relative measures are similar, providing evidence that they have not contributed to the total risk in an exceptional manner. For "periphery" European countries as for example Ireland, Italy or Spain, however, the dynamics of the two measures vary considerably. Relative transmitted connectedness is normalized by the total transmitted shocks, so a rise can originate from an increase in absolute individual connectedness or from a decline in total connectedness. A comparison of the two measures reveals the connectedness situation of a specific country as well as of the entire system.

It is of particular interest to study how risk interconnectedness evolves in reaction to characteristic events during the crisis. We distinguish between country specific events which appear in blue for the directly involved country and the most important European-wide events in solid black. Country-specific events for the not directly involved countries are marked with dotted lines.

We observe that during the high-time of the crisis between mid 2011 and mid 2013, all

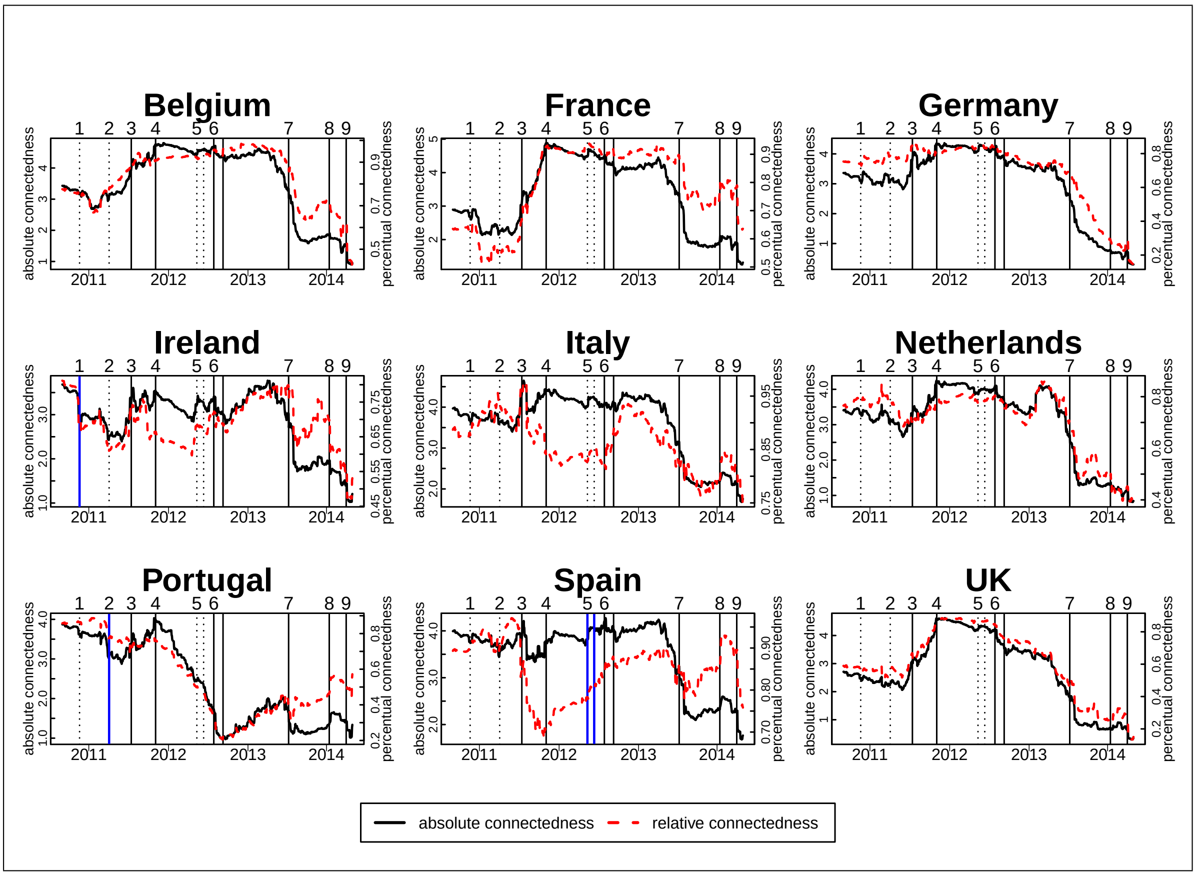


Figure 3: Country-Specific Transmitted Connectedness Using Absolute and Relative Variance Decomposition Components.
This figure presents the transmitted connectedness impact computed with CDS spreads for each country. Absolute connectedness is depicted by a solid black line and its scale is on the left-hand axis. Relative connectedness is depicted by a dashed line and its scale is on the right-hand axis. Important events are marked with vertical lines. A detailed timeline with their exact specification can be found in the Appendix in Table 3. The sample period is as in Figure 2.

countries' connectedness measures are affected by crisis-related incidents, moreover reactions in unstable countries are stronger compared to core countries. Hence, countries which are already less stable appear more recipient to crisis events than stable countries. Moreover, connectedness of all countries is especially high between mid 2011 and mid 2013. Thus we distinguish between events during the most turbulent period of the crisis (3-7) and events outside this period (1, 2, 8, 9). In the following, we group events of similar type and neglect consecutive time ordering in favor of a streamlined presentation.

After July 2013, connectedness measures of all countries are at a low level, indicating a recovery. At the beginning of 2014 we observe jumps of varying magnitude in all countries except Germany, the Netherlands or the United Kingdom. This coheres with the adoption of risk finance guidelines of the European Commission on 15.01.2014, displayed by the line in the plot marked (8). The new guidelines improve SMEs' and midcaps' access to funding and apparently have a greater effect on countries which had been weakened by the crisis. We note analogous results for the last event in the plot marked (9), after which reactions in Germany, the Netherlands and United Kingdom are weaker than those in other countries.

The first two events in the plot designate the dates on which Ireland and Portugal request financial support. Like the dates concerning the bailout of Spain labeled (5), they are indicated in blue for the respective countries. We observe that directly afterwards, absolute contributed risk diminishes more than to relative risk in each of the three countries. These results indicate that the moment a high-risk country seeks financial support, the risk of the entire system remains high or rises, but it is no longer attributed to that specific country. The figure also clearly shows that other not directly involved countries react in response to such a country-specific event. For instance, after Ireland's and Portugal's request for financial support by the Eurozone (events (1) and (2)) entails small jumps in the connectedness measures of the other countries. When the crisis has grown more accute and the Spanish government rescues Bankia (09.05.2012, marked (5)) and later seeks financial assistance for its banking sector (09.06.2012), connectedness of France, Ireland and Italy reacts more strongly compared to reactions after Ireland's and Portugal's bailout.

In a similar manner as Spain's bailout, the subsequent events ensued heterogenous reactions in all countries. The first of the two consecutive lines (26.07.2012, designated (6)) denotes the declaration of unrestricted buying of short-dated bonds by ECB president Draghi. Shortly afterwards (06.09.2012), details of the ECB's bond-buying plan are announced. This causes a drop of the absolute connectedness in all countries, signaling a decline of total risk. From this date onwards we see a rise in relative risk exceeding that of absolute risk, especially in Belgium, France, Germany and at a later point in time also Ireland and the Netherlands. Similar dynamics are observed in Ireland, Portugal and Spain after they request financial support, allowing to conclude that total risk is born by the entire system rather than individual countries after this event.

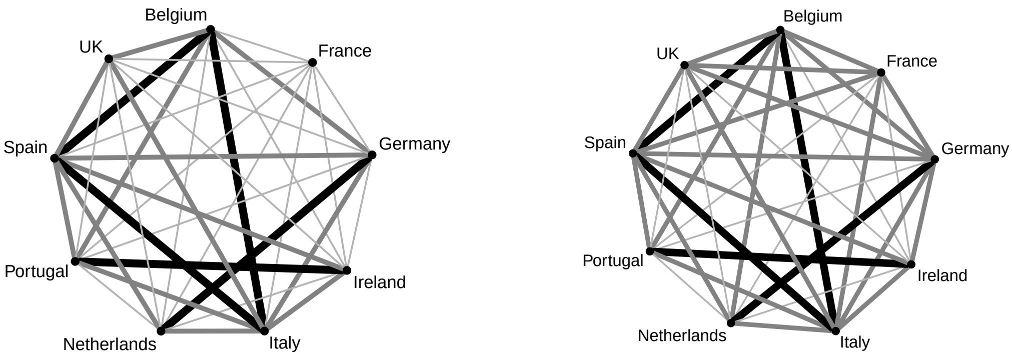
The same observation can be made in the end of 2011, succeeding the announcement of the ECB's second bond purchasing programm and an unexpected lowering of key interest rates (03.11.2011, marked (4)). For all countries except Germany and France, we observe a larger change of absolute connectedness than of relative connectedness. Again, this indicates that from this date onwards, overall risk can largely be attributed to the entire system and to a lesser extent to these respective countries. This effect is especially pronounced in Ireland, Italy, Portugal and Spain. In Italy and Spain, absolute risk remained somewhat constant while relative risk declined, indicating a rise in total risk. In Ireland and Portugal, relative risk prevailed at a constant level while absolute risk increased. Hence, we can conclude that these countries contributed more to total risk compared to other countries. It is noteworthy that for Germany, we observe opposite dynamics. Before the announcement of the bond purchasing program, the change of absolute connectedness is higher than the change of relative connectedness. After the event, their slopes are similar. This gives evidence that after the announcement, Germany bears more of the system's risk than before, which coincides with the fact that Germany, as the most stable European economy, was mainly responsible for sustaining financial stability in the Eurozone.

We furthermore mark two instances as the beginning and ending of the most turbulent period of the crisis, which are denoted in the plot by (3) and (7). Line (3) on 15.07.2011 marks the publication of the ECB stress test results. This is the first event at which we observe a spike in both relative and absolute connectedness measures for all countries, and thus identify it as a kickoff event of the crisis high-time. The event shows that in crisis times connectedness rises when a piece of information inducing tension is expected and relaxes after this information is revealed. We have already noted a decline of connectedness after Draghi's promise to sustain the euro (event (6)). In mid 2013 (04.07.2013, marked (7)), the ECB apprehends that key interest rates would remain at low levels for a prolonged period of time, marking the first time that the ECB commits to hold a certain level of interest rates. Consequently, we state a radical drop of connectedness in almost all countries with exception of Germany, where connectedness declines moderately. This allows to conclude the effectiveness of the ECB's policy provisions.

4.2.4 Networks

The following figures show absolute individual connectedness components as an undirected network graph for two points in time, where darker and wider edges signify higher connectedness. As mentioned in Section 4.1.1 we do not consider directed measures because the variance decomposition matrix is symmetric by construction. The figures illustrate our observations from the previous Section 4.2.3, as for example a rise in the system's connectedness when a weakness such as the need for financial assistance is revealed. Compared to the aggregated measures of connectedness, the network graphs allow for a comprehensive overview of inter-country relations.

Figure 4 depicts the network before and after the publication of the stress test results on



(a) Before (08.07.2011)

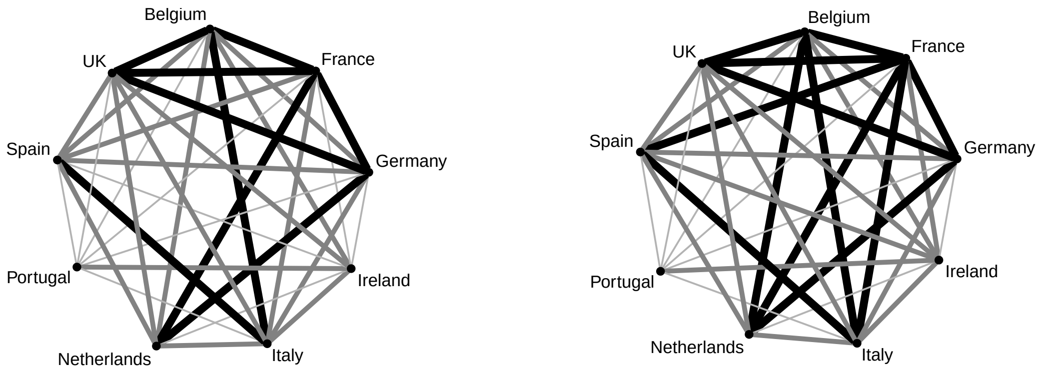
(b) After (19.07.2011)

Figure 4: Connectedness before and after the ECB publishes stress test results (15.07.2011)
The two figures illustrate the connectedness between all entities of the system. Nodes represent countries and edges represent the connectedness between them. Wide, black edges represent stronger connectedness (greater than $0,6$), medium, darkgray edges designate connectedness values between $0,4$ and $0,6$, and thin, lightgray edges show weak connectedness between $0,2$ and $0,4$. Connectedness below $0,2$ is not shown.

15.07.2011, which unexpectedly reported the instability of many European banks. We see that after this information, the countries are more connected. France and Germany, which are regarded as stable countries, reveal higher connectedness with other European countries after this event. More specifically, we mark a greater connectedness of Germany with the United Kingdom, Ireland and France. France is more strongly connected to Spain, Italy, and Belgium. Belgium in turn indicates a higher connectedness with the Netherlands. Thus, the entire system of countries is affected.

This is also the case for country-specific events, for example Spain's vulnerability in May 2012. Figure 5 shows the connectedness measures before and after the Spanish government rescues Bankia. After the disclosure of its instability, Spain is more strongly connected to Ireland and France. In addition, other countries of the system are also marked by higher dependencies, such as France with Ireland and Italy, or the Netherlands and Belgium.

One of the most important monetary interventions by the ECB was Draghi's speech in July 2012, illustrated in Figure 6. The promise that the ECB would do “whatever it takes” to sustain the Euro substantially relaxed the European sovereign debt crisis and reduced connectedness among countries. The network graph shows reduced connectedness between Spain with Belgium, France and Portugal. Moreover, Portugal is less connected with Belgium and Ireland, and Ireland's connectedness with the United Kingdom decreases. France and Germany are the only countries for which we do not observe a change in connectedness components, which is in line with the results from Section 4.2.3.

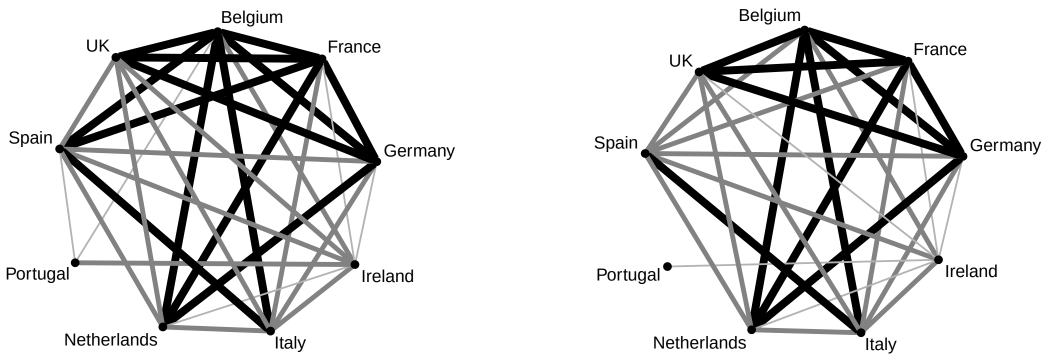


(a) Before (08.05.2012)

(b) After (14.05.2012)

Figure 5: Connectedness before and after the Spanish government rescues Bankia (09.05.2012) Explanation as in Figure 4.

Investigating individual connectedness between countries is only possible for selected points in time. Nevertheless, it allows for a vivid demonstration of how European sovereigns' connectedness reacts to specific events.



(a) Before (25.07.2012)

(b) One Week Later (03.08.2012)

Figure 6: Connectedness before and after Draghi's speech "whatever it takes" (26.07.2012) Explanation as in Figure 4.

5 Conclusion

Interconnectedness was a crucial element of the financial and European sovereign crisis and its propagation. Accordingly, appropriate measures to quantify this interconnectedness are crucial. We have provided a methodology to measure connectedness via the realized forecast error variance decomposition, which allows for a simple and direct computation. In contrast to the standard model-based variance decomposition, this method uses forecast errors observed outside the estimation sample instead of forecast errors deduced from the MA-representation formula and thus incorporates more aspects of uncertainty.

Although CDS and asset swap spreads contain roughly the same information on risk in levels, we find substantial differences related to their variances. CDS data is only available from the end of 2008, thus one has to rely on bond data to study connectedness before and at the beginnning of the crisis. High information content and liquidity in CDS during the crisis motivate utilizing CDS spreads to analyze connectedness in more recent periods.

The comparison of absolute and relative connectedness measures provides insight into the relative risk a country imposes on the network during different time periods. We find that peripheral countries are affected by any crisis-related event while core countries only react during the high-time of the crisis from mid 2011 until mid 2013. There is evidence that a high level of default risk of an affected country remains a purely idiosyncratic issue until financial aid is requested, after which the risk spreads out to the entire system. Ensuing the ECB's policy measures in mid 2012, connectedness measures indicate a recovery of the system.

In further research, we would like to extend this approach to a larger network not only of sovereigns but also of banks. Here, however, econometric dimension reduction techniques, which exceed the scope of this paper, are necessary using for instance LASSO or principal component factorization. Furthermore, the results for CDS and asset swap spreads motivate an in-depth study on the factors driving the difference between them.

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A Appendix

A.1 Summary Statistics

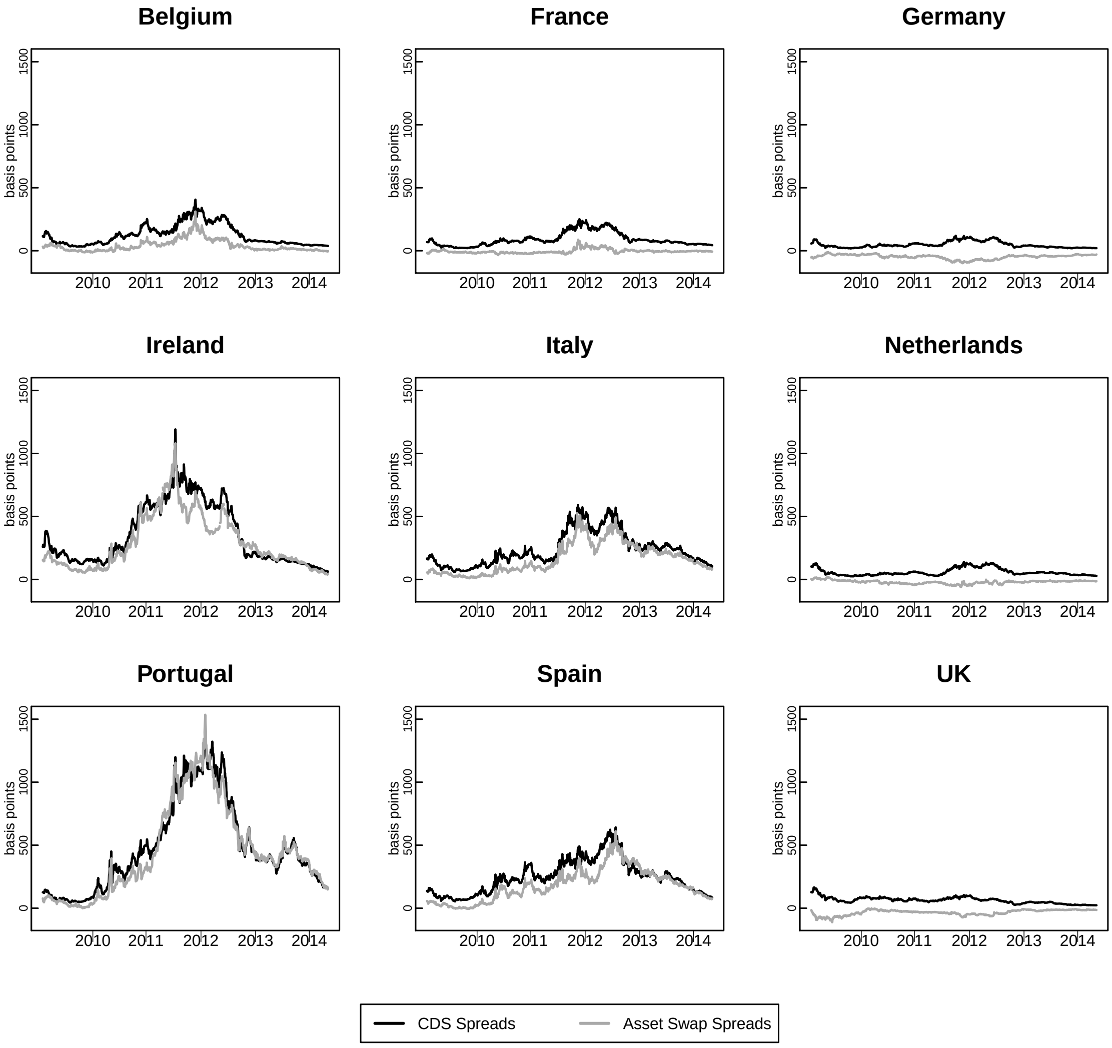


Figure 7: Levels of CDS and Asset Swap Spreads.

This figure shows CDS spreads plotted with black lines and asset swap spreads plotted with gray lines for each country. The left axis represents the levels of spreads denoted in basis points. The sample covers the period from 02.02.2009 until 02.05.2014.

			Belgium	France	Germany	Ireland	Italy	Netherlands	Portugal	Spain	United Kingdom
CDS Spreads	level data	Mean	123.73	90.78	47.43	349.82	239.68	58.69	480.23	249.45	62.41
		Median	87.83	75.44	40.02	223.85	199.83	48.29	395.38	237.16	61.83
		Max	406.12	249.62	119.17	1191.50	591.54	139.84	1526.95	641.98	164.79
		Min	31.93	19.66	18.73	61.08	57.60	24.50	44.52	53.69	22.84
		Std dev	82.95	54.30	24.67	241.41	133.01	28.56	352.23	132.90	25.02
		Skew	-12.97	-62.35	-938.35	3.54	2.40	-550.74	4.19	2.67	-788.22
		Kurt	66.62	422.05	14330.92	9.82	14.60	7138.90	11.29	15.00	11549.81
		ADF	17.3	10.2	10.3	16.0	4.3	10.6	10.8	5.9	13.1
		KPSS	0.9	3.2	2.1	1.0	6.8	1.6	0.6	1.8	0.0
	returns	Mean	-0.06	-0.02	-0.03	-0.15	-0.05	-0.06	0.03	-0.04	-0.08
		Median	-0.05	-0.05	-0.00	-0.08	-0.22	-0.03	0.00	-0.01	-0.01
		Max	35.67	22.76	15.69	107.74	64.08	14.81	141.59	55.29	16.17
		Min	-59.35	-30.03	-14.67	-146.15	-80.83	-15.64	-159.11	-73.89	-15.32
		Std dev	6.19	4.25	2.11	14.62	11.14	2.47	21.09	11.82	2.32
		Skew	-0.54	-0.21	0.19	-0.60	0.09	-0.15	-0.38	-0.50	-0.27
		Kurt	16.75	10.34	10.93	20.26	10.59	9.90	14.35	8.63	11.56
		ADF	100.0	100.0	100.0	100.0	100.0	100.0	99.7	100.0	100.0
		KPSS	91.6	94.7	94.0	93.1	95.8	85.5	92.6	98.1	88.1
Asset Swap Spreads of Bonds	level data	Mean	40.33	-3.78	-47.23	294.04	167.55	-20.04	452.94	183.00	-33.30
		Median	22.80	-6.90	-42.90	210.10	131.24	-18.00	386.11	172.30	-29.00
		Max	311.50	88.30	-10.10	1080.70	526.90	19.70	1535.70	611.80	-0.80
		Min	-14.90	-35.00	-98.90	37.82	8.50	-60.90	-0.50	-4.40	-111.20
		Std dev	48.71	16.48	17.73	213.76	121.07	13.38	360.93	128.77	21.23
		Skew	-89.75	-3327.68	-3767.92	5.14	2.42	-7089.41	4.87	3.13	-1979.68
		Kurt	749.87	81383.37	92189.12	16.57	22.63	219378.36	13.41	20.85	39601.49
		ADF	26.5	22.5	2.8	17.0	3.0	0.6	10.9	8.3	9.7
		KPSS	0.0	15.4	12.5	0.0	0.0	8.8	0.0	1.7	5.5
	returns	Mean	-0.03	0.01	0.02	-0.09	0.02	-0.01	0.07	0.01	0.00
		Median	0.00	0.07	0.05	-0.43	-0.10	-0.10	0.17	0.00	-0.03
		Max	33.10	28.30	8.70	102.80	71.60	15.30	183.40	50.90	20.20
		Min	-47.90	-21.30	-10.30	-109.20	-82.90	-12.50	-165.60	-79.80	-17.30
		Std dev	6.26	3.84	2.20	13.69	10.66	2.64	19.83	10.59	2.64
		Skew	-0.29	0.09	-0.08	-0.43	-0.35	0.18	0.55	-0.93	0.61
		Kurt	13.22	11.53	4.84	15.31	13.82	6.93	23.60	11.47	11.41
		ADF	100.0	100.0	100.0	99.9	100.0	100.0	99.9	100.0	100.0
		KPSS	100.0	99.8	98.1	98.4	99.7	100.0	96.0	98.6	99.4

Table 2: Entries report the descriptive statistics of CDS spreads and asset swap spreads of bonds in levels and returns. Unit root test results show the percentage of times the H_0 of the ADF are rejected and the percentage of times the H_0 of the KPSS cannot be rejected at 5%. The tests have been conducted on a rolling window of width 200, leading to 1087 samples.

A.2 Generalized Variance Decompositon

Koop *et al.* (1996) define the generalized impulse response function of $\mathbf{y_t}$ at horizon H for a shock of size δ and a known history $\mathbf{\Omega}_{t-1}$ as follows:

$$\mathbf{GI}(H, \delta, \mathbf{\Omega}_{t-1}) = E(\mathbf{y}_{t+H}/\mathbf{u_t} = \delta, \mathbf{\Omega}_{t-1}) - E(\mathbf{y}_{t+H}/\mathbf{u_t} = 0, \mathbf{\Omega}_{t-1}) \tag{12}$$

For a shock only on the j-th element of $\mathbf{u_t}$, the function is written as:

$$\mathbf{GI_j}(H, \delta_j, \mathbf{\Omega}_{t-1}) = E(\mathbf{y}_{t+H}/\mathbf{u_{tj}} = \delta_j, \mathbf{\Omega}_{t-1}) - E(\mathbf{y}_{t+H}/\mathbf{\Omega}_{t-1}) \tag{13}$$

In this case, the effects of the other shocks must be integrated out. For $\mathbf{u}_t$ normally distributed we have:

$$E(\mathbf{u_t}/\mathbf{u_{tj}} = \delta_j) = (\sigma_{1j}, \sigma_{2j}, \cdots, \sigma_{nj})' \frac{\delta_j}{\sigma_{jj}} = \Sigma_u e_j \frac{\delta_j}{\sigma_{jj}} \tag{14}$$

Thus, the generalized impulse response is given by

$$\mathbf{GI_j}(H, \delta_j, \mathbf{\Omega}_{t-1}) = \mathbf{\Phi}_H \Sigma_u e_j \frac{\delta_j}{\sigma_{jj}} \tag{15}$$

By setting $\delta_j = \sqrt{\sigma_{jj}}$ one obtains an impulse response function which measures the effect of one standard error shock to the jth variable at time t on the expected values of $\mathbf{y}$ at time $t + H$:

$$\mathbf{GI_j}(H, \delta_j, \mathbf{\Omega}_{t-1}) = \sigma_{jj}^{-1/2} \mathbf{\Phi}_H \Sigma_u e_j \tag{16}$$

As in Pesaran and Shin (1996), this is used to derive the generalized forecast error variance decomposition components $s_{ij}^{IN}(H)$:

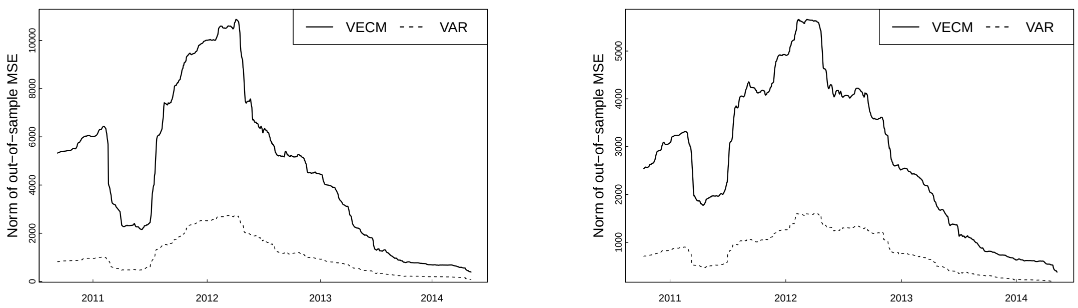
$$s_{ij}^{IN}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \Phi_h \Sigma_u e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Phi_h \Sigma_u \Phi_h' e_i)} \tag{17}$$

A.3 Timeline

21.11.2010	(1) Ireland seeks financial support; EU-IMF package for Ireland is agreed: 07.12.2010
06.04.2011	(2) Portugal asks for support by the Eurozone; aid to Portugal is approved: 17.05.2011
15.07.2011	(3) Stress test results are published
03.11.2011	(4) ECB announces details of second covered bond purchase programme (decision to launch CBPP2: 06.10.2011) and unexpectedly reduces the key interest rates after fear of recession. In reaction, stocks rise.
09.05.2012	(5) Spanish government rescues Bankia, which is entirely nationalized later.
09.06.2012	Announcement that Spain will seek financial assistance for its banking sector; financial aid is granted: 20.07.2012
26.07.2012	(6) Draghi promises the ECB would do "whatever it takes" to sustain the euro; his speech marks the turning point of the crisis.
06.09.2012	Details of ECB's new bond-buying plan are announced. Subsequently, stock markets rallied and bond yields of Spain and Italy decreased.
04.07.2013	(7) ECB reveals that key interest rates would remain at present or lower levels for an extended period of time. It is the first time that the ECB makes a commitment regarding interest rates.
15.01.2014	(8) European Commission adapts Risk Finance Guidlines 4.
03.04.2014	(9) ECB states that it is disposed to apply unconventional measures such as bond purchasess or quantitative easing. In response, yields of periphery countries fall.

Table 3: Timeline of important events during the European debt crisis.

A.4 Forecasting Power of Different Models

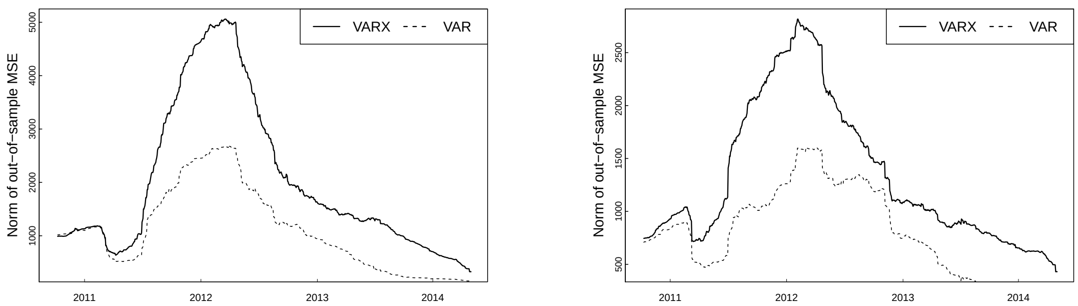


(a) using CDS data (b) using bond data

Figure 8: MSE of VECM and VAR

This figure shows the normed MSE of a VAR(1) and a VECM across all rolling windows, using CDS data in figure 8a and bond data in figure 8b. The solid line represents the normed MSE of a VECM. The number of cointegration relationships of the VECM is adapted for each estimation window. The dotted line represents the normed MSE of a VAR(1). The sample covers the period from 25.08.2010 until 02.05.2014.

The number of cointegration relationships of the VECM is adapted for each estimation window.



(a) using CDS data (b) using bond data

Figure 9: MSE of VARX and VAR

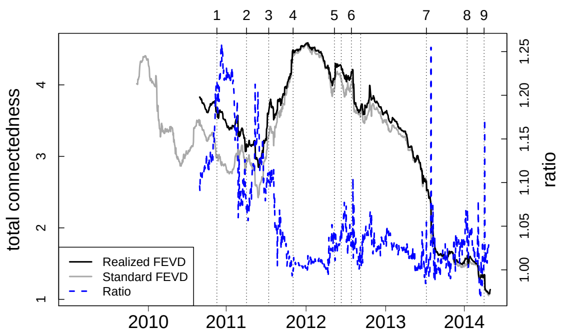
This figure shows the normed MSE of a VAR(1) and a VECM across all rolling windows, using CDS data in figure 9a and bond data in figure 9b. The solid line represents the normed MSE of a VARX including change of Euribor, VIX and iTraxx Europe as exogenous variables. VIX and iTraxx Europe are included as first differenes in order to ensure stationarity. In each estimation window, the variables are jointly significant for at least seven out of nine equations of the VARX according to the F-test. The dotted line represents the normed MSE of a VAR(1). The sample covers the period from 25.08.2010 until 02.05.2014.

	CDS spreads			Bond spreads		
	VAR	VECM	VARX	VAR	VECM	VARX
AIC	20.55	20.82	20.24	26.51	26.93	25.86
BIC	22.97	23.52	22.69	28.61	29.93	27.89
logLik	-4350	-4377	-7485	-5818	-4956	-5687

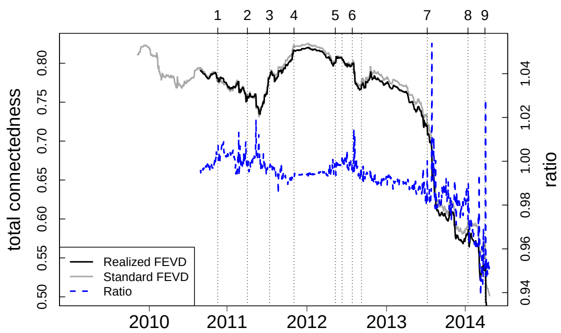
Table 4: AIC, BIC and log-Likelihood of a selection of models

For each rolling window in our samples we compute the AIC, BIC and log-Likelihood of different estimated models. Entries report the average values of AIC, BIC and log-Likelihood across all estimation windows.

A.5 Realized and Model-Based Measures



(a) using absolute measures

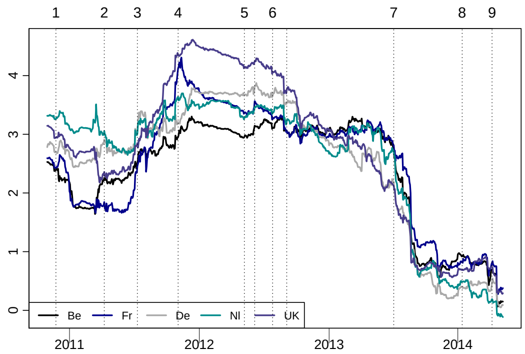


(b) using relative measures

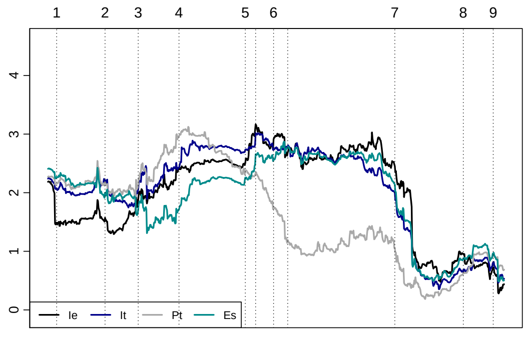
Figure 10: Out-of-Sample and In-Sample Connectedness

This figure depicts the realized and model-based connectedness, as well as the ratio between them. The black line represents the realized measure, the gray line is obtained with the model-based method and the blue dashed line shows the ratio between them. The sample covers the period from 02.02.2009 until 02.05.2014, which leads to realized connectedness measures from 25.08.2010 until 02.05.2014 and model-based connectedness measures from 10.11.2009 until 02.05.2014. A selection of important events are marked with vertical lines. A detailed timeline with their exact specification is depicted in Appendix A.3.

A.6 Plots and Regression Results of difference in connectedness



(a) core countries



(b) periphery countries

Figure 11: Basis of Connectedness Measures

Figure 11a presents the difference in connectedness of Belgium (Be), France (Fr), Germany (De), the Netherlands (Nl) and the United Kingdom (UK). Figure 11b shows the difference in connectedness of Ireland (Ie), Italy (It), Portugal (Pt) and Spain (Es). Gray vertical lines mark crisis related events as in Figure 1. Vertical yellow lines mark the announcement and the entry into force of the ban of uncovered CDS, respectively. The sample covers the period from 25.08.2010 until 02.05.2014.

	Period 1		Period 2		Period 3	
Variable	Estimate	Std. Dev.	Estimate	Std. Dev.	Estimate	Std. Dev.
Bid-ask	14.29	(1.71)***	-5.27	(1.34)***	31.18	(2.56)***
Euribor-Eurepo	-10.18	(1.92)***	0.60	(0.12)***	60.55	(9.71)***
EVZ	0.08	0.06	0.08	(0.01)***	-0.46	0.32
D*bid-ask	13.02	(4.61)**	-15.01	(2.16)***	-26.05	(3.24)***
D*Euribor-Eurepo	13.26	(2.31)***	0.54	(0.09)***	-24.62	(2.76)***
D*EVZ	-0.13	(0.04)**	-0.17	(0.01)***	-0.46	(0.11)***
Adj. R-squared	0.26		0.39		0.56	

Table 5: Results from panel regression

Results from panel regression of the difference in connectedness including fixed effects and robust standard errors, using 840 observations of nine countries. Since the difference in connectedness is computed on a 200 day rolling window, we use rolling window estimates of the same width for the regressors. Period 1 covers the time between 20.10.2010 and 15.07.2011 (event 3) , the second period is from 15.07.2011 to 04.07.2012 (event 7) and the last period ends on 12.05.2014. *D* represents a dummy variable that equals unity for Ireland, Italy, Portugal and Spain.