Measuring Connectedness of Euro Area Sovereign Risk

Rebekka Gätjen*
Melanie Schienle**

BERLIN

ECONOMIC RISK

SFB 649

*Karslruher Institut für Technologie, Germany
**CASE and Karslruher Institut für Technologie, Germany
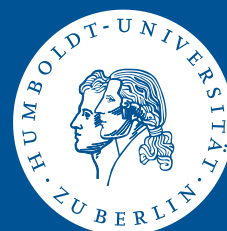
Measuring Connectedness of Euro Area Sovereign Risk *

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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. The resulting relative and absolute connectedness measures find distinct and complementary information from CDS and bond yield data on European area sovereign risk. The detection and use of these second moment differences of CDS and bond data is new to the literature and allows to identify countries that impose risk on the system from those which sustain risk.

Keywords: Sovereign risk measurement, variance decomposition, connectedness, CDS and bond spreads, financial and eurozone crisis

JEL classification codes: C32, C58, F34, G01, G18

1 Introduction

We propose a realized empirical procedure to assess how European sovereigns are interconnected through default risk. 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 have emerged many empirical tools and studies analyzing spillover effects among financial institutions from public market data (see e.g. Engle et al. (2014), Hautsch et al. (2014)), tailored methods and studies for the impact of sovereign interconnections have been rather 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 any form of shocks. We find that Credit Default Swap (CDS) and bond spreads, which both reflect the default risk of the underlying entity, contain complementary information of variance-based connectedness. These differences can be used to obtain a full picture of sovereign interconnectedness.

In this paper, we provide an empirical methodology based on variance decomposition for measuring connectedness between shocks in sovereign CDS and bond yield spreads. We build on a methodology by Diebold and Yilmaz (2014) which we extend to out-of-sample forecast errors. In particular, our contribution is the distinction of estimation and evaluation samples, leading to forecast errors comprising the entire shock as opposed to model-based in-sample forecast errors. These forecast errors are used to compute variance decomposition components which are then aggregated to different measures for connectedness and can be expressed in absolute terms or relative to total risk. Comparable studies examine relative measures only, however a comparison of both relative and absolute measures allows for an in-depth analysis.

The methodology is implemented on CDS and bond yield spreads. They are both known to reflect the creditworthiness of its issuing entity, so a shock in the spread of a country represents a change in its exposure to risk. In levels, CDS and bond spreads are regarded as nearly equivalent and lead to coinciding results when measuring contagion (see Caporin et al. (2013)). However, since our measure is based on variances, we work with both datasets and

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[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.

find that the resulting measures reveal important differences. In contrast to connectedness measures using level data, variance decomposition is a higher moment measure and therefore reflects the dispersion effects of default risk. The results allow to conclude that from the beginning of the crisis onwards, CDS spreads are more powerful for detecting connectedness among sovereigns. Their main disadvantage is that they were not frequently traded before 2008. Therefore, we fall back on bond data for measuring connectedness before that date.

We identify main sources of connectedness by contrasting absolute and relative components. The absolute and relative measures reveal divergences in core or periphery countries and across different periods of the crisis, from which we can deduce whether an individual country or the entire system bears the risk. An analysis of these divergences allows for an extensive overview of the significance of specific countries and the relationships between them.

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. In contrast to this, other papers working with variance decomposition put a focus on the structural model. Alter and Beyer (2014) extend the methodology by Diebold and Yilmaz by using impulse responses instead of forecast error variance decomposition and by adding exogenous variables to the VAR. 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 (see Schmidbauer et al. (2012, 2013)). On the data side, there has been extensive research on the comparison of CDS spread and bond yield spread in levels but, to our knowledge, not on their variances. We find differences in variances and thus compare the resulting spillover measures of CDS and bond spreads to discuss which dataset is more powerful for assessing contagion among sovereigns. Caporin et al. (2013) analyze contagion in the euro area with level 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 bond spreads *or* to CDS spreads. There is a broad scope of literature examining the price discovery process in CDS and bond markets. Many papers find that price discovery is country dependent (Bowe et al. (2009), Longstaff et al. (2011), Delatte et al. (2012), Fontana and Scheicher (2010), among others). A few more recent papers find evidence for a lead in CDS spreads (Palladini and Portes (2011), Gyntelberg et al. (2013), among others). The determinants of CDS and bond spreads or their dynamics are examined

2

in several papers (Beirne and Fratzscher (2012), Heinz and Sun (2014), among others). Arce et al. (2013) study the determinants of the difference in the spreads. Nevertheless, these studies only concern data in levels and not in variances.

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 being under distress. See for instance Adrian and Brunnermeier (2011) proposing the CoVaR, Acharya et al. (2012) introducing the concept of systemic expected shortfall (SES) or Engle et al. (2014) who utilize a Dynamic Conditional Correlation (DCC) model.

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 presents robustness checks of the model. Section 6 concludes.

2 Data

Default risk is commonly measured by CDS spreads and bond yield spreads. We dispose of 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). The CDS are of five years maturity and denominated in US Dollars. 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 DeMarzo and Duffie (1999), Longstaff et al. (2005), Fontana and Scheicher (2010), among others). Sovereign bond spread data is obtained from Datastream. The sample covers the same set of countries as the CDS data and runs from 03.01.2005 to 02.05.2014. Like the CDS spreads, the bond spreads are of five years maturity.[2] A sovereign bond yield depends on the creditworthiness of the national government issuing the bond, furthermore its spread relative to the Euro-swap yield[3] provides a measure of the domestic effect only. Figure 3 in the Appendix shows the levels of CDS spreads and bond yield spreads in comparison.

Tests for stationarity suggest that the data is difference-stationary. We apply the Aug-

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[2] We use bond yields of 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).)

[3] The Euro-swap is a commonly used proxy for the risk-free rate

mented Dickey-Fuller (ADF) test and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test to each 200-day subsample of the rolling window.[4] 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 94.7% of the log-return series are stationary on average. Using log-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 bond 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 3 in Appendix A.1.

3 Model

Variance decomposition allows to quantify the effect of a shock in one variable on the forecast error variance of another variable. 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 log-returns of sovereign CDS spreads and returns of bond 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 $\mathbf{y_t} = (y_{1t}, y_{2t}, \ldots, y_{Kt})'$ denotes a $(K \times 1)$ vector of countries and is covariance-stationary with moving average representation $\mathbf{y}_t = \sum_{i=0}^{\infty} \Phi_i \mathbf{u_{t-i}}$. A_i represents the $(K \times K)$ matrices of the autoregressive coefficients for $i = 1, 2, \ldots, p$. The $(K \times 1)$ vector $\mathbf{u_t}$ of error terms is assumed to be a white noise process with $E(\mathbf{u_t}) = \mathbf{0}$, $E(\mathbf{u_t}\mathbf{u_t}') = \Sigma_u$ and $E(\mathbf{u_t}\mathbf{u_s}') = 0$ for $t \neq s$. We conduct a dynamic analysis using a rolling window approach. Thanks to this, structural breaks and time-dependent coefficients are incorporated into the model.

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

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

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[4]This leads to 1147 (2235) subsamples which are tested for CDS (bond) data.

4

where $\hat{\mathbf{y}}_{\mathbf{t}}(H)$ is the linear minimum MSE predictor at time t for forecast horizon H obtained from the estimated coefficients $\hat{A}_i$ of the process[5]. Please note that $\hat{\mathbf{y}}_{\mathbf{t}}(H)$ contains data and estimates computed only from inside the estimation sample, while $\mathbf{y}_{\mathbf{t+H}}$ is taken from outside the estimation sample. Therefore, the resulting forecast error $\mathbf{y}_{\mathbf{t+H}} - \hat{\mathbf{y}}_{\mathbf{t}}(H)$ 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

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

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 $\mathbf{y}_{\mathbf{t+H}} - \hat{\mathbf{y}}_{\mathbf{t}}(H)$ 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 $\mathbf{y}_{\mathbf{t+H}} - \mathbf{y}_{\mathbf{t}}(H) = \sum_{h=0}^{H-1} \Phi_h \mathbf{u}_{\mathbf{t+H-h}}$, which allows to rewrite the MSE as follows:

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

where $\mathbf{y}_{\mathbf{t}}(H)$ is the optimal predictor[6] 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 the entire shock. 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

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

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

processes. However, it is not possible to decompose the approximate MSE because it is an asymmetric sum.

As shown in the Appendix A.2, from the H-step in-sample MSE we derive the ij-th generalized variance decomposition component for a forecast error H periods ahead, given by

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

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).[7]

So far, we have seen the standard model-based variance decomposition as applied in the literature and based on the in-sample MSE. We now introduce variance decomposition based on the out-of-sample MSE. For this purpose 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 the 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

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

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).

4 Results

4.1 Dynamic Specification

Our presented results are robust with respect to the choices of rolling window sizes and the dynamic model fit. 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)).

There are two different window sizes for the estimation of the realized variance decomposition: the number of observations used to estimate the underlying model which we denote by T_e, and the sample size used to estimate the realized forecast error variance based on the results obtained from the first rolling window denoted by T_s. The realized connectedness measure is robust with respect to the window size T_e, which allows us to be flexible with regard to that parameter[8]. In addition, there is no significant difference between the quality of the estimates using different window sizes[9] according to Akaike information criterion (AIC), Bayes information criterion (BIC), and realized MSE. 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[10]. 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, especially in 2012.[11] The choice of the sample size T_s used to estimate the realized MSE is made based on the minor variance and leads to an optimal window size of $T_s = 200$.

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[8]This is not the case for the model-based measure.

[9]We compared 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.

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

[11]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 proveided upon request.

We find that the model most adopted to our needs is a first order differenced VAR with one lag, i.e. a VAR(1) of spread returns. 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. Lag order is chosen via AIC, which leads to a lag order one for all three models. The exogenous variable included in the VARX for bond spreads is the change of the Euribor. The number of cointegration relationships of the VECM is adapted for each estimation window.

Since the systemic risk measure we apply is based on forecast error variance, we choose the model with the greatest forecasting power, which can be measured by the minimum MSE[12]. Additionally to the MSE, we compare models with respect to AIC, BIC and log- likelihood. The results are summarized in Table 1. For more details we refer to Section 5.

	CDS spreads		Bond spreads		
	VAR	VECM	VAR	VARX	VECM
AIC	20.55	20.82	-60.2	-59.34	-59.99
BIC	22.97	23.52	-57.81	-57.71	-56.98
logLik	-4350	-4377	3651	3478	3638

Table 1: 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. For the CDS dataset, we estimate VARs and VECMs and for the bond yield dataset we additionally estimate VARs with an exogenous variable (VARX). Entries report the average values of AIC, BIC and log-Likelihood across all estimation windows.

4.2 Results on Sovereign Connectedness

4.2.1 Reported Measures

Since the decomposed variance contributions of one variable i do not necessarily add up to one when using generalized variance decomposition, 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 $m = \{IN, OUT\}$. This relative measure expresses the percentage of i's MSE that is explained by shocks in j. The comparison of both absolute and relative measures allows us to investigate how much country j contributes to the other countries i while controlling for the total contributions to each country i. It is noteworthy that the original matrix $S^{OUT}(H)$

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[12]As the measure is based on out-of-sample forecast errors, we also use the out-of-sample MSE to measure forecasting power.

is symmetric by construction and $S^{IN}(H)$ is close to a symmetric matrix. By normalizing the elements s_{ij}^m, the resulting matrices $\widetilde{S^m}$ no longer yield symmetry.

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 2:

(i) The entries C_{ij} in the table are the *pairwise directional connectedness* from j to i.

(ii) Two different kinds of *total directional connectedness* measures are obtained by summing up the off-diagonal ($i \neq j$) elements of columns or rows: *transmitted* and *recieved*. The sum of all off-diagonal elements of column j corresponds to the forecast-error variance that is *transmitted* to all other variables through shocks arising in variable j.

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

Similarly, the sum of row i represents the total effects that variable i *recieves* by others.

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

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

$$TC = \frac{1}{K} \sum_{i,j=1,i\neq j}^{K} C_{ij} \tag{12}$$

In the following, we will use these aggregated measures to represent the dynamics of connect-

edness across the rolling window.

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

Table 2: Connectedness Table

Row variables represent the variables of which the MSE is decomposed into effects of shocks in the column variables, i.e. column variables are risk transmitters while row variables are risk recievers.

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. Figure 4 in the Appendix depicts a comparison of realized and model-based measures.

4.2.2 CDS versus Bond Spreads

CDS spreads and bond yield spreads have generally been used interchangeably in the literature to measure default risk. Although in levels the two datasets reflect the same information on risk, in variances we find important structural differences. A method using variances instead of levels measures the extreme values of risk because higher order moments measure dispersion effects[13].

Figure 1 shows two plots in which bond spreads and CDS spreads are compared. The left hand side plot shows the norm[14] of the realized MSE with different scales for bond spreads and CDS spreads. The plot indicates that the variance of bond spreads is much higher whereas the dynamics of the two MSEs are quite similar. Contrary to that, we find large differences between the total connectedness measures of bond and CDS spreads which are depicted on the right hand side plot of Figure 1. The plotted lines are completely different in shape and no relationship between the two measures is recognizable, indicating that the information contained in the two types of datasets is complementary. The total connectedness based on

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[13]See also Park (2013) who introduces a volatility of the VIX index to measure tail risk.

[14]We utilize the Frobenius norm which, for a $m \times n$ matrix $\mathbf{x}$, equals $\sqrt{\sum_{i=1}^{m} \sum_{j=1}^{n} x_{ij}^2}$.

bond yield spreads drops during 2009-2010 and remains at a low level after 2010, which is at odds with other empirical findings. This implies that variance decomposition measures of bond spreads appear to detect less connectedness relative to variance decomposition measures of CDS spreads. We have seen that variance decomposition components are similar to correlation in Section 3. Since the measures based on CDS spreads are significantly higher than those of bond spreads, we conclude that CDS spreads contain more correlation among countries. This result is not due to the speculation contained in CDS, which we deduce from the fact that the CDS-based measure is higher than the bond-based measure even after the ban of uncovered CDS[15].
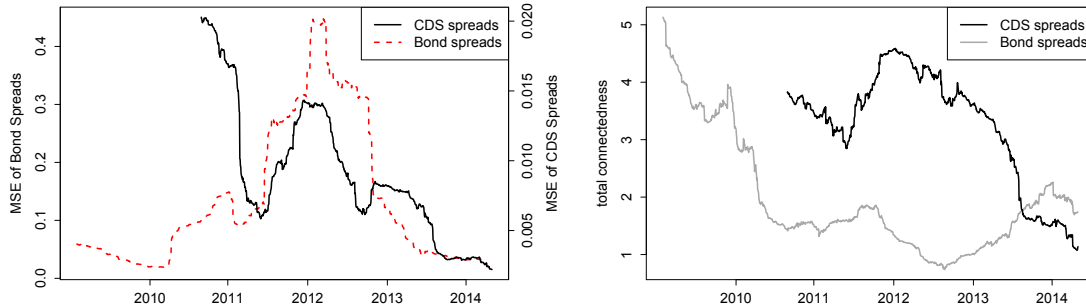
(a) Normed MSE of CDS and Bond Spreads   (b) Total Connectedness of CDS and Bond Spreads

Figure 1: Variance Measures using CDS and Bond Spreads

Figure 1a presents the Frobenius norm of the MSE and Figure 1b presents the total connectedness measure, computed with CDS and bond spreads. Both are computed with out-of-sample forecast errors and averaged across one, two and five forecast periods ahead. Total connectedness is calculated from absolute measures. In both figures, the black line is obtained from CDS spreads. The values resulting from bond spreads are depicted by the red dotted line in Figure 1a and by the solid gray line in Figure 1b. In Figure 1a, the scale for the normed MSE of CDS spreads is on the right axis, the scale for the normed MSE of bond spreads is on the left axis. The sample period for bond spreads is from 03.01.2005 until 02.05.2014, which leads to realized connectedness measures from 21.07.2006 until 02.05.2014. The sample for CDS spreads 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.

The major advantage of bond yields is that their data is available many years before the beginning of the crisis, which allows to investigate the behaviour of connectedness before and at the beginning of the financial crisis in 2008. Such results are important as a benchmark to measure results for the crisis times. CDS, in contrast, have been frequently traded only from 2008 onwards and are too illiquid to be used before that date. Therefore, we need to rely on bond spread data to obtain connectedness measures for a comprehensive overview.

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[15]The EU-regulation on short selling of CDS was decided 14.03.2012 and came into effect 01.11.2012. Measures based on CDS or bond spreads do not reach a resembling level until mid 2013.

Although CDS and bond spreads are on a par in empirical studies on default risk and contagion, some papers argue in favor of CDS spreads. Arce et al. (2013), among others, identify that CDS spreads react more to country-specific risk than bonds. When measuring connectedness among countries, it makes sense to use a dataset that contains the maximum of information concerning specific countries. There is evidence that CDS prices lead bond yield prices (see Delatte et al. (2012), Palladini and Portes (2011), Gyntelberg et al. (2013), among others), hence motivating the use of CDS from 2008 onwards, which is in line with our second moment based findings.

4.2.3 Absolute versus Relative Connectedness Measures

We study the directional impact transmitted from one country to the others, both in absolute and relative terms (see Section 4.2.1 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 a time point, the absolute transmitted effect of a country is larger than its percentage effect in connectedness, this means that risk spillovers of this country are less important relative to the contributions of other countries to the rest of the system. Figure 4 shows the connectedness impact of each country to all others in absolute and relative terms.

In the "core" European countries marked with black titles and frames, 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 in gray, however, the dynamics of the two measures vary considerably. Relative transmitted connectedness is normalized by the total transmitted shocks, so a rise can origin 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.
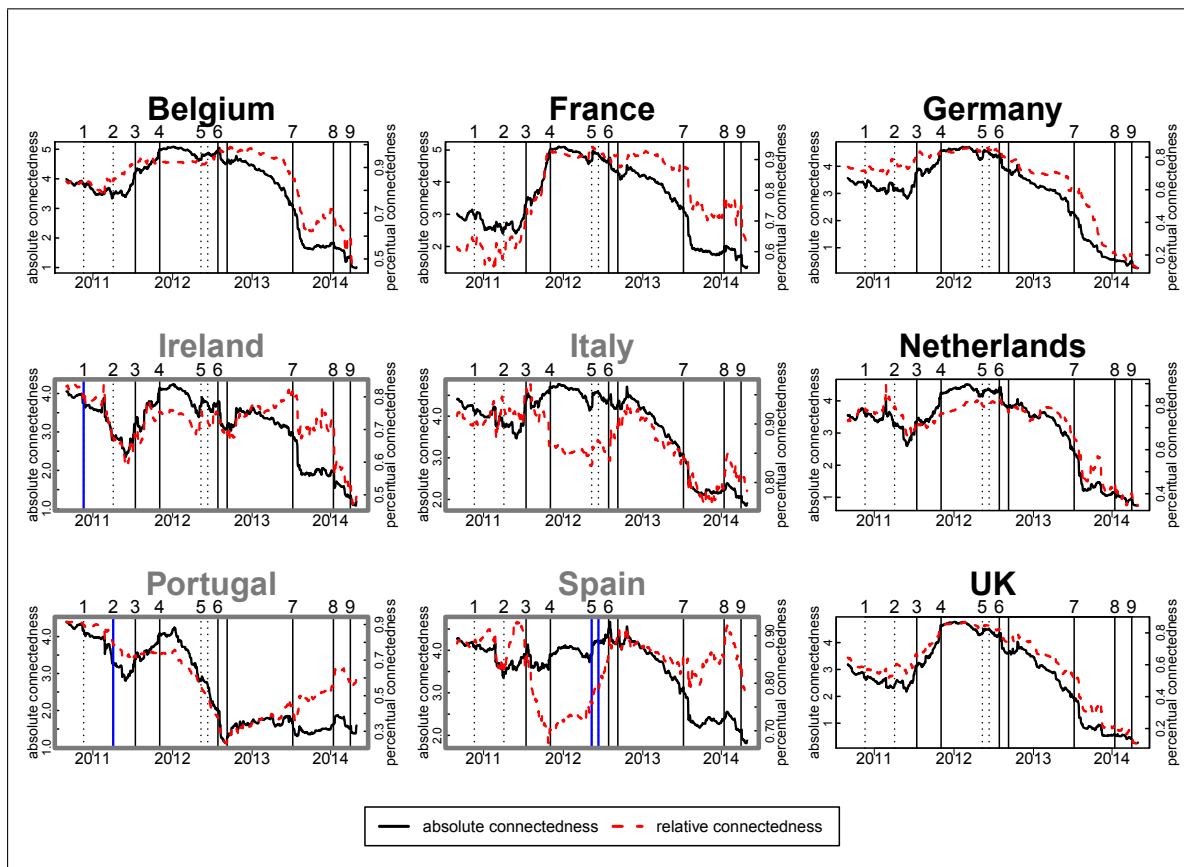
Figure 2: Country-Specific Transmitted Connectedness Using In-Sample and Out-of-Sample Forecast Error Variances.

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 dotted red line and its scale is on the right hand axis. Core countries are indicated by black titles and frames, while periphery countries are represented with gray titles and frames. Important events are marked with vertical lines. A detailed timeline with their exact specification can be found in the Appendix in Table 4. The sample period is as in Figure 1.

We observe that during the high-time of the crisis between mid 2011 and mid 2013, all countries' connectedness measures are affected by crisis-related incidents, moreover reactions in periphery countries are stronger than in core countries. Compared to this, outside of this turbulent period only periphery countries react to such events. Hence, countries which are already less stable appear more recipient to crisis events than stable "core" countries. Thus we distinguish between events during the most turbulent period of the crisis (3-7) and events outside this period (1,2,8,9).

After July 2013, connectedness measures of all counries are at a low level, indicating a recovery. At the beginning of 2014 we observe spikes in all periphery countries and to a lesser extent in the relative connectedness of Belgium and France. We observe no peculiarity in 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 severely weekened by the crisis. We note analogous results for the last event in the plot marked (9) as well as at the very beginning of the European crisis, namely the first two events marked by (1) and (2) in the plot. Similarly to the event in January 2014 marked (8), reactions in periphery countries after events (1), (2) and (9) are stronger than those in core 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 compared 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 in response to such a country-specific event, other not directly involved periphery countries react similarly to the affected country. For instance, the connectedness dynamics of Portugal and Spain is similar to that of Ireland after the latter requests support by the Eurozone (21.11.2010, marked (1)). Likewise, Portugal's request for financial support (06.04.2011, marked (2)) entails strong reactions in Italy and Spain, but not in any of the core countries. This is different 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). Contrary to the beginning of the Euro crisis in the cases of Ireland and Portugal, here the absolute connectedness measures of all countries rise.

In a similar manner as Spain's bailout, the subsequent events ensued heterogenous reactions in the other 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 state a rise in relative risk compared to 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.

14

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, we observe a larger change of absolute connectedness than for 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 the four periphery countries. 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 augmented. 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 programm, the change of absolute connectedness is greater 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 risk of the system 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). The line 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 all connectedness measures for all countries, relative as well as absolute, 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 presume the effectiveness of the ECB's policy provisions.

5 Robustness

In this section, we evaluate a parsimonious model fit with respect to forecasting power and robustness across all rolling windows. More precisely, we compare the normed MSE of different

models for each rolling window and define an optimal number of lags.

Even though we find cointegration relationships in the data as indicated by the Johansen test for cointegration[16], the first-differenced VAR outperforms a vector error correction model (VECM) during the crisis, see also De Santis (2012)[17]. The difference of forecasting power is illustrated in Figure 6 in the Appendix which shows the norm[18] of the out-of-sample MSE [19] of a VAR and that of a VECM for CDS and bond 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.

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[20]. 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)[21]. We consider several exogenous variables that are generally used in the literature to control for common changes among the CDS spreads (as in Alter and Beyer (2014) or Caporin et al. (2013)): Eonia, VIX, Euribor-Eoniaswap spread (measure for interbank risk premium), change in Euribor, EuroStoxx 50 (stock index), iTraxx Europe (CDS index of 125 European investment grade companies), iTraxx Crossover (CDS index of 50 European sub-investment grade companies). When testing their significance individually we find that none of them are significant for CDS spreads and only the change of the Euribor is significant for bond yield spreads. The difference between the MSE of a VAR and a VAR including exogenous variables lies merely between -0.005 and 0.005, which can be seen in Figure 5 in the Appendix.

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[16]Results are provided upon request.

[17]De Santis (2012): Cointegration models for EMU government bond spread dynamics break down in the period from September 08 until August 11.

[18]As before, we use the Frobenius norm.

[19]As for the connectedness measure, we compute the cumulated average of days $H = 1$, $H = 3$ and $H = 5$.

[20]For 10.05.2010 and 11.05.2010, an optimal lag-order of two is selected. This is respected in the estimation of the VARs of these windows.

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

6 Conclusion

Interconnectedness was a crucial element of the financial and European sovereign crisis and its propagation. Accordingly, appropriate measures to quantify this interconnectedness are inalienable. We have provided a methodology to measure connectedness via realized forecast error variance decomposition, which allows for a simple and direct computation. In contrast to 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 reflects the entire shock.

Although CDS and bond yield spreads contain the same information on risk in levels, we find substantial differences in variances, which suggests that the two datasets include complementary information and should both be considered. CDS data is only available from the end of 2008 onwards, thus one has to rely on bond yield data to study connectedness before and at the beginnning of the crisis. High correlation between CDS spreads and their sensitiviy to country-specific risk motivate utilizing CDS spreads to analyze connectedness in more recent periods.

The comparison of absolute and relative connectedness measures provides insight into the relative weight of the risk a country imposes on the network across different time periods. We find that "unstable" countries are affected by any crisis-related event while "stable" 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 impaired country remains a purely country-specific 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.

References

Acharya, V. V., L. H. Pedersen, T. Philippon, and M. P. Richardson (2012): "Measuring Systemic Risk," CEPR Discussion Papers 8824, C.E.P.R. Discussion Papers.

Adrian, T. and M. K. Brunnermeier (2011): "CoVaR," Staff Reports 348, Federal Reserve Bank of New York.

Alter, A. and A. Beyer (2014): "The dynamics of spillover effects during the European sovereign debt crisis," Working Paper Series 1558, European Central Bank.

Arce, O., S. Mayordomo, and J. I. Pea (2013): "Credit-risk valuation in the sovereign CDS and bonds markets: Evidence from the euro area crisis," *Journal of International Money and Finance*, 35, 124–145.

Avino, D. and O. Nneji (2014): "Are CDS spreads predictable? An analysis of linear and non-linear forecasting models," *International Review of Financial Analysis*, 34, 262–274.

Beirne, J. and M. Fratzscher (2012): "The Pricing of Sovereign Risk and Contagion during the European Sovereign Debt Crisis," Tech. Rep. 9249, C.E.P.R. Discussion Papers.

Bowe, M., A. Klimavicienne, and A. Taylo (2009): "Information Transmission and Price Discovery in Emerging Sovereign Credit Risk Markets," Tech. rep., Midwest Finance Association annual conference.

Caporin, M., L. Pelizzon, F. Ravazzolo, and R. Rigobon (2013): "Measuring sovereign contagion in Europe," Working Paper 2012/05, Norges Bank.

Claeys, P. and B. Vašíček (2012): "Measuring Sovereign Bond Spillover in Europe and the Impact of Rating News," Working Papers 2012/07, Czech National Bank, Research Department.

Cont, R. and Y. H. Kan (2011): "Dynamic hedging of portfolio credit derivatives," Postprint, HAL.

De Santis, R. A. (2012): "The Euro area sovereign debt crisis: safe haven, credit rating agencies and the spread of the fever from Greece, Ireland and Portugal," Working Paper Series 1419, European Central Bank.

DELATTE, A.-L., M. GEX, AND A. LOPEZ-VILLAVICENCIO (2012): "Has the CDS market influenced the borrowing cost of European countries during the sovereign crisis?" *Journal of International Money and Finance*, 31, 481–497.

DEMARZO, P. AND D. DUFFIE (1999): "A Liquidity-Based Model of Security Design," *Econometrica*, 67, 65–100.

DIEBOLD, F. AND K. YILMAZ (2009): "Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets," *Economic Journal*, 119, 158–171.

DIEBOLD, F. X. AND K. YILMAZ (2014): "On the network topology of variance decompositions: Measuring the connectedness of financial firms," *Journal of Econometrics*, 182, 119–134.

ENGLE, R., E. JONDEAU, AND M. ROCKINGER (2014): "Systemic Risk in Europe," *Review of Finance*, "to appear".

FONTANA, A. AND M. SCHEICHER (2010): "An analysis of euro area sovereign CDS and their relation with government bonds," Working Paper Series 1271, European Central Bank.

FORBES, K. J. AND R. RIGOBON (2002): "No Contagion, Only Interdependence: Measuring Stock Market Comovements," *Journal of Finance*, 57, 2223–2261.

GYNTELBERG, J., P. HRDAHL, K. TERS, AND J. URBAN (2013): "Intraday dynamics of euro area sovereign CDS and bonds," BIS Working Papers 423, Bank for International Settlements.

HAUTSCH, N., J. SCHAUMBURG, AND M. SCHIENLE (2014): "Forecasting systemic impact in financial networks," *International Journal of Forecasting*, 30, 781–794.

HEINZ, F. F. AND Y. SUN (2014): "Sovereign CDS Spreads in Europe: The Role of Global Risk Aversion, Economic Fundamentals, Liquidity, and Spillovers," IMF Working Papers 14/17, International Monetary Fund.

KOOP, G., M. H. PESARAN, AND S. M. POTTER (1996): "Impulse response analysis in nonlinear multivariate models," *Journal of Econometrics*, 74, 119–147.

LONGSTAFF, F. A., S. MITHAL, AND E. NEIS (2005): "Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit Default Swap Market," *Journal of Finance*, 60, 2213–2253.

LONGSTAFF, F. A., J. PAN, L. H. PEDERSEN, AND K. J. SINGLETON (2011): "How Sovereign Is Sovereign Credit Risk?" *American Economic Journal: Macroeconomics*, 3, 75–103.

PALLADINI, G. AND R. PORTES (2011): "Sovereign CDS and Bond Pricing Dynamics in the Euro-area," NBER Working Papers 17586, National Bureau of Economic Research, Inc.

PARK, Y.-H. (2013): "Volatility of volatility and tail risk premiums," Finance and Economics Discussion Series 2013-54, Board of Governors of the Federal Reserve System (U.S.).

PESARAN, H. H. AND Y. SHIN (1998): "Generalized impulse response analysis in linear multivariate models," *Economics Letters*, 58, 17–29.

RODRIGUEZ, J. C. (2007): "Measuring financial contagion: A Copula approach," *Journal of Empirical Finance*, 14, 401–423.

SCHMIDBAUER, H., A. RÖSCH, AND E. ULUCEVIZ (2012): "Connectedness Cycles in Equity Markets: A Wavelet Approach," Tech. rep., EcoMod.

A Appendix

A.1 Summary Statistics
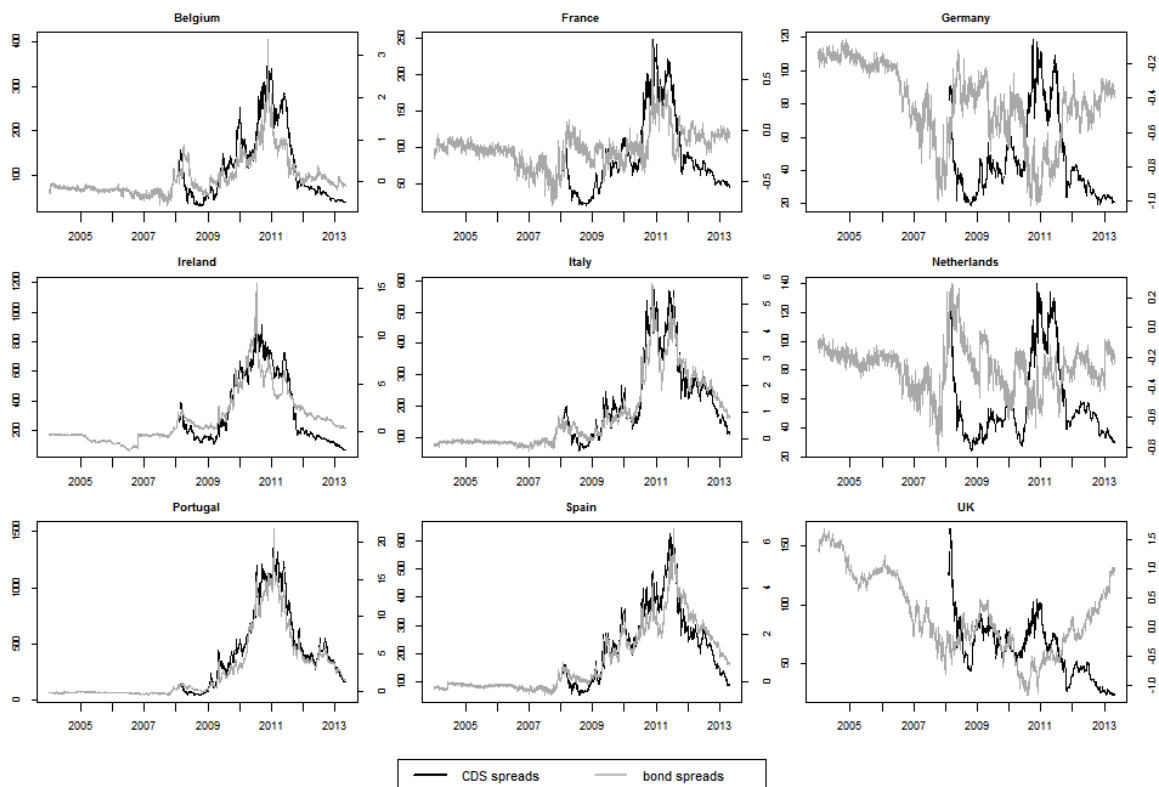
Figure 3: Levels of CDS and Bond Yield Spreads.

This figure shows CDS spreads plotted with black lines and bond spreads plotted with gray lines for each country. The left axis represents the levels of CDS spreads denoted in basis points, the right axis represents the levels of bond yield spreads denoted in percent. The sample period for bond spreads is from 03.01.2005 until 02.05.2014 and the sample for CDS spreads 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	124	91	47	351	239	59	479	250	63
	Median	88	75	40	226	200	48	395	238	62
	Max	406	250	119	1192	592	140	1527	642	165
	Min	32	20	19	65	58	24	45	54	23
	Std dev	83	54	25	241	133	29	352	133	25
	Skew	-13	-62	-948	3.6	2.4	-548	4.2	2.7	-814
	Kurt	66	418	14497	9.9	15	7082	11	15	12031
	ADF	15.1	9.8	10.1	15.6	4.6	11.0	10.3	5.1	12.5
	KPSS	0.0	3.3	1.7	1.3	7.0	1.3	1.2	0.5	0.0
	log-returns									
	Mean	-0.0008	-0.00031	-0.00076	-0.001	-0.0003	-0.00091	0.00021	-0.00031	-0.0013
	Median	-0.00073	-0.00074	-0.000012	-0.00042	-0.0011	-0.00032	0	-0.000002	-0.000016
	Max	0.17	0.2	0.25	0.27	0.2	0.15	0.21	0.25	0.15
	Min	-0.19	-0.19	-0.27	-0.33	-0.44	-0.22	-0.47	-0.37	-0.18
	Std dev	0.038	0.04	0.039	0.035	0.041	0.035	0.042	0.044	0.032
	Skew	-0.091	0.076	0.037	-0.14	-0.55	-0.18	-0.58	-0.43	-0.28
	Kurt	6.3	5.9	8.9	15	15	7	18	9.4	7
	ADF	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
	KPSS	98.5	96.3	95.3	95.4	96.0	85.9	94.4	99.7	90.8
Bond Yield Spreads	**level data**									
	Mean	0.11	-0.16	-0.43	1.4	0.9	-0.27	2.9	0.93	0.22
	Median	-0.05	-0.17	-0.42	0.57	0.31	-0.25	0.53	0.2	0.11
	Max	3.4	0.9	-0.058	16	5.8	0.29	22	6.6	1.7
	Min	-0.57	-0.73	-1	-1.9	-0.41	-0.83	-0.5	-0.61	-1.2
	Std dev	0.48	0.18	0.22	2.7	1.3	0.15	4.4	1.4	0.67
	Skew	-25	-640	-508	2.5	1.9	-1221	3.4	1.7	-9.1
	Kurt	159	9587	6691	8.8	9.6	22182	10	7.9	45
	ADF	13.2	14.4	1.0	12.7	3.4	3.7	6.4	5.5	11.0
	KPSS	1.9	11.7	5.2	2.2	4.5	4.1	0.4	1.2	1.2
	returns									
	Mean	0.000059	0.000064	-0.000086	0.00027	0.00043	-0.000049	0.00072	0.00042	-0.00013
	Median	0	-0.001	0	-0.002	0	0	0	0	-0.002
	Max	0.65	0.32	0.24	1.7	0.9	0.42	3.5	0.62	0.33
	Min	-0.61	-0.31	-0.3	-1.7	-0.96	-0.29	-2.4	-1.2	-0.23
	Std dev	0.065	0.057	0.049	0.16	0.097	0.055	0.23	0.098	0.055
	Skew	0.21	0.14	-0.069	0.063	-0.15	0.22	2.4	-1.3	0.31
	Kurt	16	6.2	6.1	29	18	7.4	69	21	5.5
	ADF	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
	KPSS	99.8	100.0	100.0	93.4	100.0	100.0	98.4	99.9	100.0

Table 3: Entries report the descriptive statistics of CDS spreads and bond yield spreads in levels and log-returns or levels and level returns, respectively. 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 20, leading to 1148 samples for CDS spreads and 2236 samples for bond spreads.

A.2 Generalized Variance Decompositon

Koop *et al.* (1996) define the generalized impulse response function of $\mathbf{y_t}$ at horizon H as follows:

$$\mathbf{GI}(H, \delta, \boldsymbol{\Omega}_{t-1}) = E(\mathbf{y}_{t+H}/\mathbf{u_t} = \delta, \boldsymbol{\Omega}_{t-1}) - E(\mathbf{y}_{t+H}/\mathbf{u_t} = 0, \boldsymbol{\Omega}_{t-1}) \tag{13}$$

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

$$\mathbf{GI_j}(H, \delta_j, \boldsymbol{\Omega}_{t-1}) = E(\mathbf{y}_{t+H}/\mathbf{u_{tj}} = \delta_j, \boldsymbol{\Omega}_{t-1}) - E(\mathbf{y}_{t+H}/\boldsymbol{\Omega}_{t-1}) \tag{14}$$

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

$$E(\mathbf{u_t}/\mathbf{u_{tj}} = \delta_j) = (\sigma_{1j}, \sigma_{2j}, \cdots, \sigma_{nj})' \frac{\delta_j}{\sigma_{jj}} = \Sigma_u e_j \frac{\delta_j}{\sigma_{jj}} \tag{15}$$

Thus, the generalized impulse response is given by

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

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 $t + H$:

$$\mathbf{GI_j}(H, \delta_j, \boldsymbol{\Omega}_{t-1}) = \sigma_{jj}^{-1/2} \boldsymbol{\Phi}_H \Sigma_u e_j \tag{17}$$

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

$$s_{ij}^{IN}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \Phi_h \Sigma_u e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Phi_h \Sigma_u \Phi_h' e_i)} \tag{18}$$

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 4: Timeline of important events during the crisis.

A.4 Realized and Model-Based Measures

(a) using absolute measures   (b) using relative measures
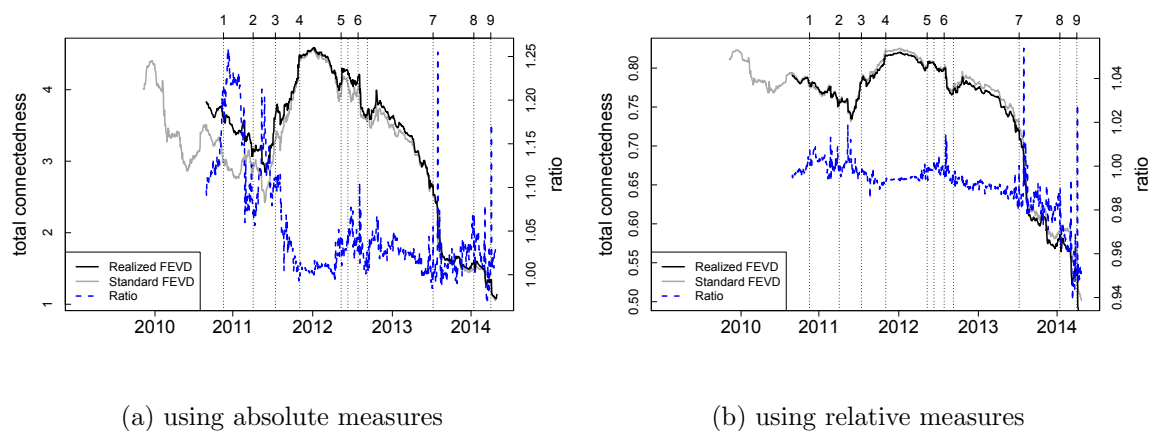
Figure 4: Out-of-Sample and In-Sample Connectedness

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.5 Forecasting Power of Different Models

Difference of MSE of VAR and VARX
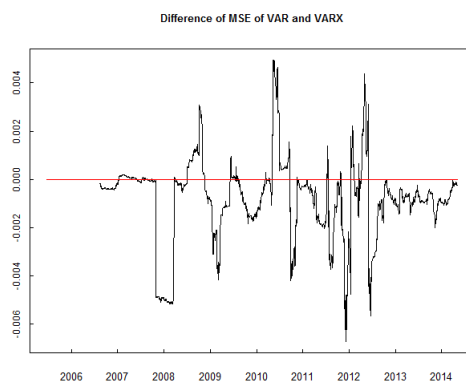
Figure 5: This figure depicts the difference between the normed MSE of a VAR(1) and a VAR(1) with exogenous variables across all rolling windows using bond data. The sample period is from 03.01.2005 until 02.05.2014, which leads to realized MSEs from 21.07.2006 until 02.05.2014.
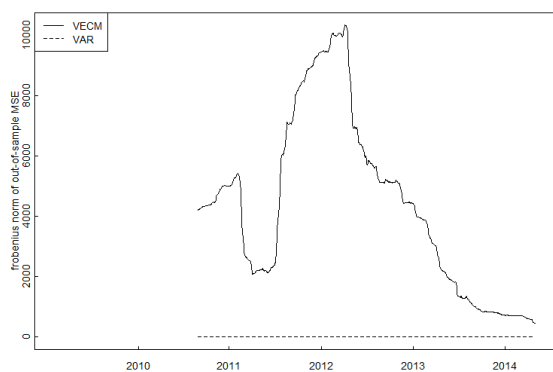
(a) using CDS data
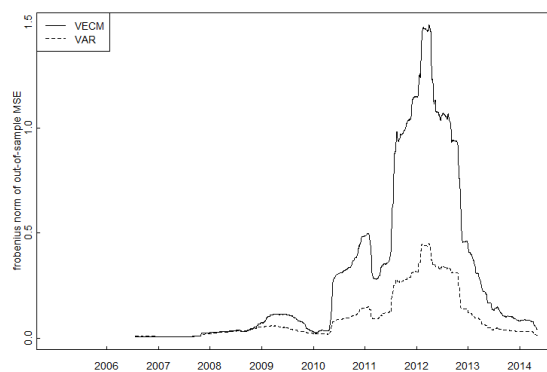
(b) using bond data

Figure 6: This figure shows the normed MSE of a VAR(1) and a VECM across all rolling windows, using CDS data in figure 6a and bond data in figure 6b. The solid line represents the normed MSE of a VECM with adapting the number of cointegration relationships for each rolling window. The dotted line represents the normed MSE of a VAR(1). The sample periods are as in Figure 1.

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