Measuring Dynamic Spillovers in Networks: Sovereign Contagion, Regulation Effects and Market Sectors

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1 Introduction

In the recent subprime mortgage crisis and sovereign debt crisis, effective threats to and the loss of confidence in the stability of the financial system have increased, which is also denoted as a rise of systemic risk (see, e.g., Billio et al., 2012). Systemically important institutions were first categorized only as “too big to fail”. This was insufficient during the crisis and required an extension by “too interconnected to fail’ (Zhou, 2010), reflecting the importance of interconnectedness for safeguarding financial and economic stability. However, respective data on interdependencies are not publicly available or incomplete. Thus, there is a need for econometric techniques that can handle incomplete and complex, large datasets to detect interconnections and to quantify spillovers between entities.

While there have been various econometric approaches to measure spillovers, in this thesis quantitative measures are developed and evaluated that shed light on important and so far disregarded aspects. In this work, measures are introduced which reveal changes in spillovers faster and more precisely than existing techniques and thus provide more accurate forecasts, in particular in crisis situations. Moreover, methods are provided to distinguish relevant changes in spillovers from others, thus allowing investors and supervisors to focus on statistically significant effects in large networks. Novel insights are given concerning credit risk spillovers between European sovereigns during the recent crisis. It is shown that regulatory changes in the credit default swap (CDS) market effectively reduced systemic risk, whereas policy interventions had a smaller and less sustainable impact. In addition, it is demonstrated that the two data sources commonly used to measure default risk, CDS and bond yields, contain complementary information for measuring connectedness and generate true added value when considered simultaneously. In a spillover analysis of U.S. stocks, not only the commonly evaluated financial sectors are included, but all market segments in the U.S. economy, revealing the increased spillovers especially between financial sectors and the real economy during the recent crisis.

In particular, the contributions of this thesis are as follows. In Chapter 2, a method is introduced for measuring default risk connectedness of euro zone sovereign states using CDS and bond data. The connectedness measure is based on an out-of-sample variance decomposition of model forecast errors. Due to its predictive nature, it can respond more quickly to crisis occurrences than common in-sample techniques. Sovereign default risk connectedness is determined with both CDS and bond data for a more comprehensive picture of the system. In this chapter, evidence is provided that several observable factors drive the difference between CDS and bonds, but both data sources still contain specific information for connectedness spillovers. Generally, countries are identified that impose risk on the system and the respective spillover channels. The empirical analysis covers the years 2009-2014, such that recovery paths of countries exiting EU and IMF financial assistance schemes and responses to the ECB's unconventional policy measures can be analyzed.

In Chapter 3, the impact of changes in regulations and policy interventions on systemic risk among European sovereigns, measured by volatility spillovers in respective credit risk markets, is studied. A unique intraday CDS dataset allows for precise measurement of the effectiveness of these events. In particular, it allows to construct confidence intervals using a bootstrap methodology in order to discern interventions which entail significant changes in connectedness. It is shown that it was only regulatory changes, namely the ban of trading naked sovereign CDS in 2012 as well as the new ISDA regulations in 2014, which were most effective in reducing systemic risk. In comparison, the effect of policy interventions was minor and generally not sustainable. In particular, it is demonstrated that policy measures only had a significant impact when implemented for the first time and when targeting more than one country. It is clearly shown that these findings are not determined by simple liquidity effects. In contrast to existing studies with bonds, evidence for a balanced network is provided, with no fragmentation and no single source of contagion for the channels of volatility spillovers among sovereigns.

In Chapter 4, dynamic spillovers between U.S. stock market sectors are estimated. Time-variation in the underlying dynamics is accounted for by measuring spillovers with impulse responses based on time-varying parameter vector autoregressions (TVP-VARs). Spillovers are computed based on the two common approaches for TVP-VARs: the Kalman filter and the Markov-Chain-Monte-Carlo (MCMC) algorithm. The results show that while the Kalman filter allows for higher dimensional models and requires by far less computation time, the Gibbs sampler provides more precise estimates which capture changes in spillovers more quickly. An empirical application to 49 market sectors reveals that not only financial sectors, but also the real economy and in particular the commodity industries play an equally important role for understanding interaction effects.

Chapter 2 is joint work with Melanie Schienle and has been published in the International Journal of Forecasting. Chapter 3 is joint work with Melanie Schienle and Jörg Urban and has been submitted to the Journal of Banking and Finance. Chapter 4 is single authored.

2 Measuring Connectedness of Euro Area Sovereign Risk

2.1 Introduction

We propose an out-of-sample empirical procedure for assessing how European sovereign states are interconnected through default risk in terms of variance spill-over effects similar to that of 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 spill-over effects, e.g. Diebold and Yilmaz (2014), Billio et al. (2012), or Engle et al. (2014) and Hautsch et al. (2014) among others, our novel measure is tailored for forecasting with a parsimonious time series approach via variance decomposition. The procedure is easy to apply and based on the forecast error variance, which more adequately reveals the extent and timing of volatility spill-over effects, in particular, around unexpected events. Furthermore, we measure sovereign connectedness with both credit default swap (CDS) and asset swap spreads and find that they contain complementary information of variance-based interconnections.

Technically, we provide an empirical method based on variance decomposition for measuring connectedness between shocks in sovereigns. Our technique captures various aspects of shocks by decomposing out-of-sample forecast errors of a vector autoregression (VAR). Thanks to the out-of-sample approach, the forecast error variance covariance structure can pick up new information more quickly than techniques based on pure in-sample fits such as in Diebold and Yilmaz (2014). The obtained components of the forecast error variance-covariance matrix reveal the interconnectedness among all cross-sectional entities with respect to the volatility channel. We jointly assess connectedness relative to country risk, but also in absolute terms for a more comprehensive picture of the situation. This complements other empirical studies (Alter and Beyer, 2014, e.g.) which discard important information with just relative measures only until mid 2012.

We empirically investigate CDS spreads of eight Eurozone countries (Belgium, France,

[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.

Germany, Ireland, Italy, Netherlands, Portugal, Spain) from the beginning of 2009 until February 2014. The sample thus covers the sovereign crisis and beyond, in particular not only including country-specific bailout events for Ireland, Portugal and Greece but also Draghi's speech "whatever it takes..." in July 2012 and the ECB's announcement of unconventional monetary policy measures from 2012 onwards. Our sample allows to take into account the aftermath of the sovereign debt crisis.

We employ both CDS spreads and asset swap (ASW) spreads of bonds for assessing sovereign risk from connectedness. We use asset swaps instead of bond yields as they are free of interest rate risk and thus provide a better comparison to CDS. When measuring contagion purely in returns disregarding connectedness aspects, CDS and bond data lead to similar results (see e.g. Caporin et al., 2013). In variance decomposition results, however, there are important differences across the two types of data. From the beginning of the sovereign crisis onwards, the overall level of connectedness of CDS spreads is substantially higher than that of asset swap spreads. Also, the evolution of country-wise spill-overs on the system reveals different roles of the core countries, Germany, France, Netherlands or Belgium in comparison to the remaining four periphery countries. The latter are captured quite differently for CDS and ASW data and thus reveal different economic and market aspects of the countries. This is also confirmed by contrasting absolute and relative connectedness components which gives information about the share of volatility of a country contributed to the system relative to idiosyncratic volatility. In particular, both sources of data shed different light on the recovery paths of Portugal and Ireland during the crisis in comparison to Spain and Italy where the EU and the IMF did not intervene. Moreover, in terms of effective volatility risk spill-over channels, detected ASW connections can help to focus on the most relevant effects of the dense CDS network which prevail until after the announcement of the OMT. We find that most of the differences in connectedness of ASW and CDS can be explained by bond liquidity, risk aversion and crisis-related events. Although CDS account for risk-related factors driving connectedness, bonds are important for determining a country's risk level compared to other countries. Thus, both datasets should be used to obtain a comprehensive picture of connectedness in the system.

As far as the model is concerned, Diebold and Yilmaz (2009, 2014) are the first to use variance decomposition for measuring connectedness. We extend their methodology by including out-of-sample shocks in order to capture all connectedness effects of volatility type more quickly and thereby enhancing measurement quality. There are various extensions of Diebold and Yilmaz (2009). These are complementary to our work with a focus on out-of-sample forecast error variance and the joint analysis of CDS and bonds: Alter and Beyer (2014), Heinz and Sun (2014) and Claeys and Vašíček (2012) analyze connectedness of European sovereigns, while Schmidbauer et al. (2012, 2013) and Antonakakis et al. (2014) measure connectedness between other entities.

For the data, there has been extensive research on the comparison of CDS and bonds in levels (such as e.g., Longstaff et al., 2011; Delatte et al., 2012; Fontana and Scheicher, 2016; Palladini and Portes, 2011; Gyntelberg et al., 2013b; among others) but not on their volatility (the only exceptions are Caporin et al. (2013) and Lange et al. (2016)). To our knowledge, we are the first to compare a second moment measure such as variance decomposition for these two sources of credit quality of a country. This also complements many empirical papers studying contagion in European sovereigns which generally focus on just one type of data, either bonds or CDS. There is also a broad scope of literature examining the price discovery process in CDS and bond markets (such as e.g., Ehrmann and Fratzscher, 2017; Heinz and Sun, 2014). For the differences in the dynamics of levels of CDS and asset swap spreads, several papers have determined important factors such as market frictions like counterparty risk, market illiquidity and funding costs (Arce et al., 2013), but also flight to liquidity effects at the height of the crisis and limits to arbitrage (Fontana and Scheicher, 2016; De Santis, 2014) as well as changes in risk attitude (Calice et al., 2015). We find that for volatility spill-overs, these factors also play an important role, but both measures still contain peculiar information for interconnectedness of European sovereigns.

Furthermore, our paper contributes to the literature on systemic risk and contagion. Several papers measure systemic risk by investigating the situation of one entity conditional on the entire system or market being under distress. For example, Adrian and Brunnermeier (2016) propose the CoVaR and Engle et al. (2014) 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. (2014, 2015) propose the realized systemic risk beta using tail risk exposures. Another approach for measuring connectedness uses principal component analysis and Granger-causality tests (Billio et al., 2012; Kalbaska and Gatkowski, 2012). Further approaches include principal component analysis (Arghyrou and Kontonikas, 2012) and impulse responses in a Markov-switching framework (Guidolin and Pedio, 2017). 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. Giudici and Spelta (2016) and Bianchi et al. (2015) use graphical models to evaluate systemic risk.

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

2.2 Model

2.2.1 Forecast Error Variance Decomposition

In the following, we assess spill-over effects between countries by fitting an appropriate dynamic specification for the system first, and then studying the variance decomposition of the remaining errors. Variance decompositions generally allow to quantify the effect of a shock in one variable on the variance of another one. In contrast to Diebold and Yilmaz (2014), we base our analysis on out-of-sample forecast errors instead of in-sample errors which are generated in a rolling window approach.

Thus, we first model returns as a vector autoregressive model (VAR)-type process with the following baseline specification:

$$\mathbf{y}_t = \sum_{i=1}^{p} A_i \mathbf{y}_{t-i} + \mathbf{u}_t, \quad t = 1, 2, \ldots, T_e, \tag{2.1}$$

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 containing data of K 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 $i = 1, 2, \ldots, p$. In order to obtain forecast errors over time, we fit the dynamic specification in rolling windows with a window width T_e for the estimation period of the VAR. In Section 2.4.1, we provide empirical evidence that for the relatively short window sizes in practice, a VAR-type model specification is sufficient to capture the dynamics of CDS and asset swap returns. On the basis of the estimated VAR coefficients, we can estimate the H-step forecast error variance or mean squared error (MSE), defined as:

$$\Sigma_y^{OUT}(H) := MSE[\hat{\mathbf{y}}_t(H)] = E\Big[\big(\mathbf{y}_{t+H} - \hat{\mathbf{y}}_t(H)\big)\big(\mathbf{y}_{t+H} - \hat{\mathbf{y}}_t(H)\big)'\Big] \tag{2.2}$$

where $\hat{\mathbf{y}}_t(H)$ is the linear minimum MSE predictor at time t with forecast horizon H obtained from the estimated coefficients $\hat{A}_i$ of the process[2]. Note that $\hat{\mathbf{y}}_t(H)$ is computed only with data from within the estimation sample which does not contain $\mathbf{y}_{t+H}$. Therefore, $\mathbf{y}_{t+H} - \hat{\mathbf{y}}_t(H)$ is an out-of-sample forecast error and we call $\Sigma_y^{OUT}(H)$ in Equation (2.2) out-of-sample MSE. A standard estimator for $\Sigma_y^{OUT}(H)$ is given by

$$\hat{\Sigma}_y^{OUT}(H) = \frac{1}{T_s} \sum_{t=1}^{T_s} \big(\mathbf{y}_{t+H} - \hat{\mathbf{y}}_t(H)\big)\big(\mathbf{y}_{t+H} - \hat{\mathbf{y}}_t(H)\big)'. \tag{2.3}$$

where T_s is the sample size used for estimating $\Sigma_y^{OUT}(H)$. This is in contrast to the approach by Diebold and Yilmaz (2014) who base their variance decomposition on an in-sample MSE. They replace the forecast error by the moving average (MA) representation

[2] $\hat{\mathbf{y}}_t(H) = \sum_{i=1}^{p} \hat{A}_i \hat{\mathbf{y}}_t(H-i)$. For a detailed representation, see Lütkepohl (2005).

formula given by $\mathbf{y}_{t+H} - \mathbf{y}_t(H) = \sum_{h=0}^{H-1} \Phi_h \mathbf{u}_{t+H-h}$, which then yields:

$$\Sigma_y^{IN}(H) := MSE[\mathbf{y}_t(H)] = E\Big[\big(\mathbf{y}_{t+H} - \mathbf{y}_t(H)\big)\big(\mathbf{y}_{t+H} - \mathbf{y}_t(H)\big)'\Big] \\ = \sum_{h=0}^{H-1} (\Phi_h \Sigma_u \Phi_h'), \tag{2.4}$$

where $\mathbf{y}_t(H)$ is the theoretical optimal predictor for known Φ_i[3] and Φ_h is the h-th coefficient of the MA-representation. This formula is computed with observations only within the estimation sample, namely the residual covariance matrix Σ_u and the MA coefficients Φ_h. Hence, it is an in-sample forecast error variance. An estimate is obtained using respective estimates $\hat{\Sigma}_u$ and $\hat{\Phi}_h$.

The out-of-sample MSE is directly computed from the VAR-estimates $\hat{A}_i$, whereas the in-sample MSE requires transforming the latter into the MA-representation. In-sample forecast errors use the same sample for estimating the MA-representation and for forecasting. Measures of spill-over effects, however, are mostly intended to deliver a basis for future decisions. In this sense, risk measures derived from the out-of-sample MSE provide a more reliable basis for practical forecasting purposes. Out-of-sample forecast errors separate the estimation sample from the prediction and therefore contain all aspects of potential shocks of predictions. The formulas show that the out-of-sample MSE contains additional variation that is not contained in the in-sample MSE due to unknown future shocks. We show empirically in Section 2.4.2 that this plays an important role when unexpected events occur. [4]

From the H-step in-sample MSE we derive the ij-th generalized variance decomposition component for a forecast error H periods ahead[5], given by

$$s_{ij}^{IN}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \Phi_h \Sigma_u e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Phi_h \Sigma_u \Phi_h' e_i)}, \tag{2.5}$$

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.

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

[4]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.

[5]Generalized variance decomposition was proposed by Koop et al. (1996) and Pesaran and Shin (1998). The derivation is shown in the 3.6.5.

For our out-of-sample measure, we decompose the out-of-sample MSE $\Sigma_y^{OUT}(H)$ in contrast to the standard in-sample variance decomposition. For the special case of a one step ahead forecast, i.e. $H = 1$, the MSE in Equation (3.6) 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 in this special case, Equation (3.7) simplifies to $s_{ij}^{IN}(1) = \frac{\sigma_{jj}^{-1}(e_i'\Sigma_u e_j)^2}{(e_i'\Sigma_u e_i)} = \frac{\sigma_{ij}^2}{\sigma_{ii}\sigma_{jj}}$. This shows that variance decomposition components actually are related to squared correlation coefficients of forecast error variances. Generally, for the ij-th variance decomposition component of an out-of-sample forecast error H steps ahead, we replace Σ_u in $s_{ij}^{IN}(1)$ by $\Sigma_y^{OUT}(H)$:

$$s_{ij}^{OUT}(H) = \frac{(e_i'\Sigma_y^{OUT}(H)e_j)^2}{(e_i'\Sigma_y^{OUT}(H)e_i)(e_j'\Sigma_y^{OUT}(H)e_j)}. \tag{2.6}$$

Analogously to the 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 $S^{OUT}(H) = ((s_{ij}^{OUT}(H)))_{ij}$. Since the in-sample measure has been used in the literature we also call it standard connectedness.

2.2.2 Measures of Connectedness

We now derive the connectedness C_{ij} marking the volatility spill-over of country j to i from the corresponding variance decomposition elements s_{ij}^{OUT} in (2.6). In particular, we set

$$C_{ij}^{OUT} = \frac{1}{3}(s_{ij}^{OUT}(1) + s_{ij}^{OUT}(2) + s_{ij}^{OUT}(5)) \tag{2.7}$$

to obtain an average over the respective one, two and five step-ahead forecast variance decomposition components. In this way, C_{ij}^{OUT} accounts for both, short and longer term effects of shocks and includes potential feedback effects (see also, e.g. Diebold and Yilmaz (2015) and Alter and Beyer (2014)). We take the standard case as a benchmark and define C_{ij}^{IN} analogously to (2.7). As in Diebold and Yilmaz (2014), individual connectedness C_{ij}^m for $m \in \{OUT, IN\}$ can be gathered for all i and j in Table 2.1 which then serves as the adjacency matrix determining the underlying network structure. In particular, each element C_{ij}^m marks the directed effect of country j on i depicted as the directed edge between the two nodes in the corresponding network graph. We obtain dynamic networks over time by recalculating them for each rolling window. From this granular network structure we obtain the following network statistics which we use to compare the shapes of different networks over time.[6] In particular, country-wise aggregation determines the local importance of a node. We define outgoing connectedness OC_j^m as a general real-valued version of the degree (see e.g. Barrat et al. (2004)) of node

[6] Other network measures such as clustering coefficients and eigenvector centrality require some nodes to be unconnected and thus are not applicable in this setting.

Table 2.1: Connectedness table

The connectedness table depicts connectedness measures on three different aggregation levels; m is omitted for readability.

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

j as

$$OC_j^m = \sum_{i=1, i \neq j}^{K} C_{ij}^m \ . \tag{2.8}$$

Outgoing connectedness summarizes all individual connectedness that entity j transfers to any other node in the system. Correspondingly, ingoing connectedness IC_i^m aggregates all connectedness received by i from others by summing row-wise in Table 2.1 :

$$IC_i^m = \sum_{j=1, i \neq j}^{K} C_{ij}^m \ . \tag{2.9}$$

The overall global shape of a network is reflected by its network density[7]. Thus we define total connectedness in line with Diebold and Yilmaz (2014) by aggregating the values of all outgoing and ingoing edges in the network as:

$$TC^m = \frac{1}{K} \sum_{i,j=1, i \neq j}^{K} C_{ij}^m \ . \tag{2.10}$$

For a more expedient interpretation as weights, the elements of the variance decomposition $S^m(H)$ are normalized row-wise before connectedness measures are calculated. In particular, we use

$$\widetilde{s_{ij}^m} = \frac{s_{ij}^m}{\sum_{l=1}^{K} s_{il}^m}, \tag{2.11}$$

[7]Weighted density is computed by $\frac{1}{K(K-1)} \sum_{i,j=1, i \neq j}^{K} C_{ij}$.

where the row sums of the resulting matrix $\widetilde{S^m}$ are equal to unity. We denote all measures based on these normalized $\widetilde{s_{ij}^m}$ as relative connectedness measures since the impact of j on i is scaled by the total effect of all other $l \neq i$ on i. Thus we define as in (2.7):

$$\widetilde{C}_{ij}^{OUT} = \frac{1}{3}(\widetilde{s_{ij}^{OUT}}(1) + \widetilde{s_{ij}^{OUT}}(2) + \widetilde{s_{ij}^{OUT}}(5)). \tag{2.12}$$

and also $\widetilde{OC}_j^m$, $\widetilde{IC}_j^m$ and $\widetilde{TC}^m$ are obtained accordingly. In this way, we can assess if and how some countries as nodes are more connected than others. For the full picture, we consider both, absolute and relative measures based on s_{ij}^m or $\widetilde{s_{ij}^m}$ respectively, in order to attribute changes in connectedness to a specific country or the system entity. The connectedness matrices $\widetilde{S^m}$ are asymmetric by construction and can be represented as directed network graphs. Note that this is also true for S^{OUT} while the in-sample version S^{IN} is actually symmetric and yields a directed network only through the normalization in $\widetilde{S^{IN}}$.

When clear from the context, the superscript $m \in \{IN, OUT\}$ of a connectedness measure is omitted for improved readability in the rest of the paper.

2.3 Data

Default risk is commonly measured by CDS spreads and asset swap spreads of bonds. We employ daily 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) and Spain (ES) [8]. The CDS are of five years maturity and denominated in US Dollars.[9] The data is retrieved from Bloomberg and covers the time period from 02/02/2009 until 05/02/2014. 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, 2016; 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.[10] The reference rate of the asset swap is the three month Euribor and the underlying bonds are denominated in Euro. 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

[8] Greece is excluded from our study because trading of Greek sovereign bonds ceased after the disclosure of its budget deficit on 10/20/2009.

[9] In Section 2.4.2, we control for exchange rate risk among others and find that its effect is negligible.

[10] 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).

also Gyntelberg et al., 2013b) and should be preferred over bond yield spreads, which include interest rate risk. Figure 2.11 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%. This gives us the percentages 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. Country-wise summary statistics of spreads and spread returns, as well as the results of the unit root tests, are provided in Table 2.7 in 2.6.1.

2.4 Results

2.4.1 Dynamic Specification

In the underlying rolling window VAR-type specification (3.5), we aim for a parsimonious model fit while maximizing forecasting power, as our main goal of interest is the connectedness measure based on the forecast error variance decomposition. We obtain the optimal number of lags by minimizing the normed MSE[11] of different models for each rolling window. We find that the model generally most suited to our needs is a first order difference VAR with one lag, i.e. a VAR(1) of spread returns across different estimation and forecast windows $T_e,\ T_s \in [100; 400]$ with $T_e \leq\ T_s$. This coincides also with the in-sample optimal lag length according to AIC. Note that 100 and 400 working days correspond to 4.5 months and 1.5 years of data, respectively. In the following, we take $T = T_s = T_e$, where $T = 200$ corresponds to nine months of data and minimizes the mean MSE across all windows. In this data-driven way, we ensure that windows with $T = 200$ are large enough for achieving forecasting accuracy from sufficient estimation precision and small enough to discern past less relevant crisis events.[12] Also, when comparing rolling window in-sample fits via the mean AIC, the MSE-driven choice of $T = 200$ performs well and is thus used for the rest of the paper.[13]

[11] Correlation in the forecast error is negligible, thus the properties of optimal forecasts hold for MSE (Patton and Timmermann, 2007).
[12] See Figure 2.12 in the Appendix for details.
[13] exemplary values of mean AIC: 19.9/17.5/23.6 for a window sizes of $T = 200/100/400$ observations respectively.

For a valid connectedness analysis, the dynamic VAR(1) specification must yield unbiased low variance predictions. We therefore benchmark the chosen VAR-model against VECM and VARX alternatives according to out-of-sample MSE performance. The results for the VECM comparison are depicted in Figure 2.16 in the Appendix. Even though we find mild evidence for cointegration relationships in a few time periods as indicated by the Johansen test for cointegration, in terms of forecasting power, the first-differenced VAR performs equally well as a respective VECM in non-crisis periods but substantially outperforms it during the crisis. This also corresponds to the intuition that a VECM captures the long term relations between the variables and these become less important during the crisis because agents become more short-sighted.[14] There is no improvement in the forecasting power of the VAR by including exogeneous variables controlling for common changes among the CDS spreads, such as change in Euribor reflecting financing conditions, VIX as a proxy for investors' fear and iTraxx Europe representing aggregate credit market development (Avino and Nneji, 2014)[15]. As illustrated in Figure 2.18 in the Appendix, the MSE of the VARX persistently exceeds that of the VAR indicating overall inferior performance of the larger model. For completeness, we also provide the in-sample AIC, BIC and log-likelihood in Table 2.9 in the Appendix.

In our connectedness analysis, we are particularly concerned with understanding the effects of specific policy and regulatory announcements and actions, such as country-specific bailout packages, but also EU-wide support programs. The exact dates considered can be found in the timeline in 2.6.3, which might have also imposed structural breaks in the mean return dynamics. Thus, in order to account for structural breaks we include event dummies that equal unity from the considered events onwards. If our approach was not out-of-sample, breaks could be accounted for by time-varying parameter models as in Giannone et al. (2015). We test for parameter constancy in the underlying VAR model using F-type (Andrews, 1993; Andrews and Ploberger, 1994) and OLS-based MOSUM (Chu et al., 1995;Kuan and Hornik, 1995) stability tests. The p-values of MOSUM-tests are given in Table 2.2 for both with and without event dummies and $T = 200$.[16] The null hypothesis of no structural change is rejected for the country-regressions of Belgium, France and Ireland at the 0.05-level in the VAR without event dummies. On the other hand, the null cannot be rejected at least at the 0.1-level for the model containing event dummies. Hence, we observe no further evidence for structural breaks after including time dummies to the model.

Regarding the F-type test, we apply the *supF*-statistic, which is the most sensitive to

[14] 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.

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

[16] For robustness, the MOSUM stability tests are also carried out for window sizes 130, 260 and 400. The results for these window sizes are similar and are provided upon request.

Table 2.2: P-values of MOSUM stability test

Under the null hypothesis of no structural break the limiting process for the empirical MOUSM proecess is a standard Brownian bridge. The MOSUM stability test is applied for each equation (i.e. country) of the VAR with a window width of 200. The first line represents p-values of the MOSUM test for a VAR without event dummies and the second line shows p-values of the MOSUM test for a VAR including event dummies.

	Belgium	France	Germany	Ireland	Italy	Netherlands	Portugal	Spain
w/o dum	0.021	0.029	0.098	0.046	0.235	0.134	0.068	0.185
w/ dum	0.274	0.318	0.338	0.628	0.525	0.157	0.510	0.677

Table 2.3: P-values of supF test statistic

The null hypothesis of no structural change is rejected when the maximal F statistic of all potential break points gets too large. The p-values shown in the table are the country-wise means of the p-values for the *supF*-statistic across all rolling windows of length 200.

	Belgium	France	Germany	Ireland	Italy	Netherlands	Portugal	Spain
w/o dum	0.184	0.186	0.17	0.185	0.309	0.131	0.205	0.272
w/ dum	0.8	0.82	0.812	0.684	0.748	0.786	0.666	0.785

structural change among those proposed by Andrews (1993) and Andrews and Ploberger (1994). The F-test is applied for each rolling window of length 200 and the means of the corresponding p-values for each country are given in Table 2.3. Once again, we observe larger p-values for the model with event dummies, underlining their importance. We therefore finally stick to a VAR(1) model with event dummies at the specifically considered dates listed in 2.6.3. The resulting connectedness measures are only mildly affected by the inclusion of time dummies at the event dates,[17], which might be attributed to the relatively short estimation windows (see also Blatt et al., 2015).

As in the literature on connectedness effects (see Diebold and Yilmaz (2014) and Antonakakis et al. (2014), among others), we aim at capturing all unconditional variance spill-over effects with our measures. Therefore, conceptually, pre-filtering for idiosyncratic heteroskedasticity is not required. The results, however, would not differ substantially if pre-filtering was applied. In particular, for the relatively small rolling window

[17]See Figure 2.13 in the Appendix.

estimation sizes of $T = 200$ and with event dummies, heteroscedasticity effects play only a minor role. We apply the ARCH-LM-test by (Engle, 1982) to each estimation window and find that we cannot reject the null of no heteroscedasticity (ARCH disturbances) at the 5%-level (1%-level) in more than 62% (81%) of the cases (see Figure 2.15a in the Appendix for a boxplot of all p-values). Furthermore, as a simple validity check, we have recalculated the total connectedness after GARCH pre-filtering and plotted it against the unfiltered total connectedness in Figure 2.15b in the Appendix. The results are almost identical.

2.4.2 Results on Sovereign Connectedness

Advantages of the Out-of-Sample Measure

In the following, we provide evidence that the novel out-of-sample technique provides significant additional information relative to the standard in-sample method by Diebold and Yilmaz (2014), in particular, it responds more quickly to unforeseen events.

First, we determine significant differences between the novel out-of-sample connectedness and the standard in-sample method by Diebold and Yilmaz (2014) with a Diebold-Mariano Test (DM-Test) for the same underlying dynamic set-up. We clearly reject the null hypothesis that both coincide at levels below 1%. In particular, we find significant deviations of the level of forecast errors (maximum p-value$< 2.2 \cdot 10^{-16}$) as well as when comparing connectedness measures at country-level (maximum p-value = 0.000568) and total connectedness (p-value$< 2.2 \cdot 10^{-16}$). See Table 2.4 for detailed p-values of DM-tests of differences in country-wise in-sample and out-of-sample connectedness.

Table 2.4: P-values of test for equality of out-of-sample and in-sample Connectedness

P-values of Diebold-Mariano tests for country-wise connectedness with $H_0 : (\widetilde{OC})^{OUT}_{j,t} = (\widetilde{OC})^{IN}_{j,t}$ versus $H_1 : (\widetilde{OC})^{OUT}_{j} \neq (\widetilde{OC})^{IN}_{j}$ for all $j = 1, \ldots, 8$.

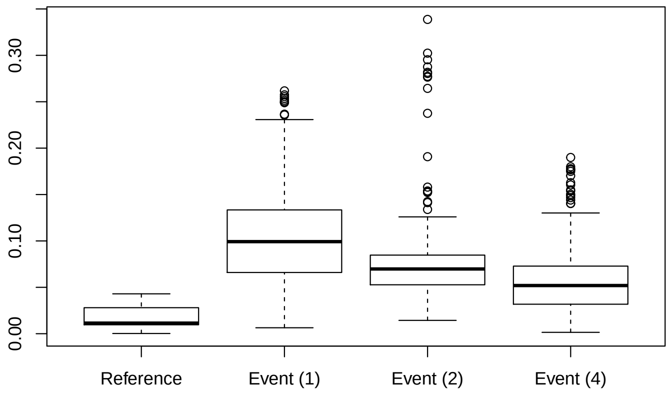
	Belgium	France	Germany	Ireland
p-value	$5.68 \cdot 10^{-4}$	$9.74 \cdot 10^{-10}$	$2.31 \cdot 10^{-49}$	$2.30 \cdot 10^{-14}$
	Italy	Netherlands	Portugal	Spain
p-value	$1.21 \cdot 10^{-8}$	$3.87 \cdot 10^{-34}$	$2.69 \cdot 10^{-62}$	$4.18 \cdot 10^{-94}$

Second, we find that the level of the out-of-sample measure is generally higher than that of the in-sample measure when unexpected crisis-related events occur (see Figure 2.1), often responding more quickly to such events.

Figure 2.1 shows boxplots of the aggregated relative differences in country-wise out-of-sample and in-sample connectedness around the bailout dates of Ireland (event 1 at 12/01/2010), Portugal (event 2 at 04/06/2011) and Greece (event 4 at 07/21/2011). The differences around these state-specific actions are much larger than those of an

Figure 2.1: Exemplary boxplots of $(\sum_{j=1}^{8} \frac{|(\widetilde{OC})_{j,t}^{OUT} - (\widetilde{OC})_{j,t}^{IN}|}{(\widetilde{OC})_{j,t}^{IN}})$

These boxplots depict the aggregated relative difference of country-wise out- and in-sample relative connectedness based on CDS in a window of ten working days before and after bailout dates of selected countries. The event classification follows Table 2.6.3. The reference period contains the 20 working days in the period 01/12/2012 -02/09/2012 which is not marked by specific events.

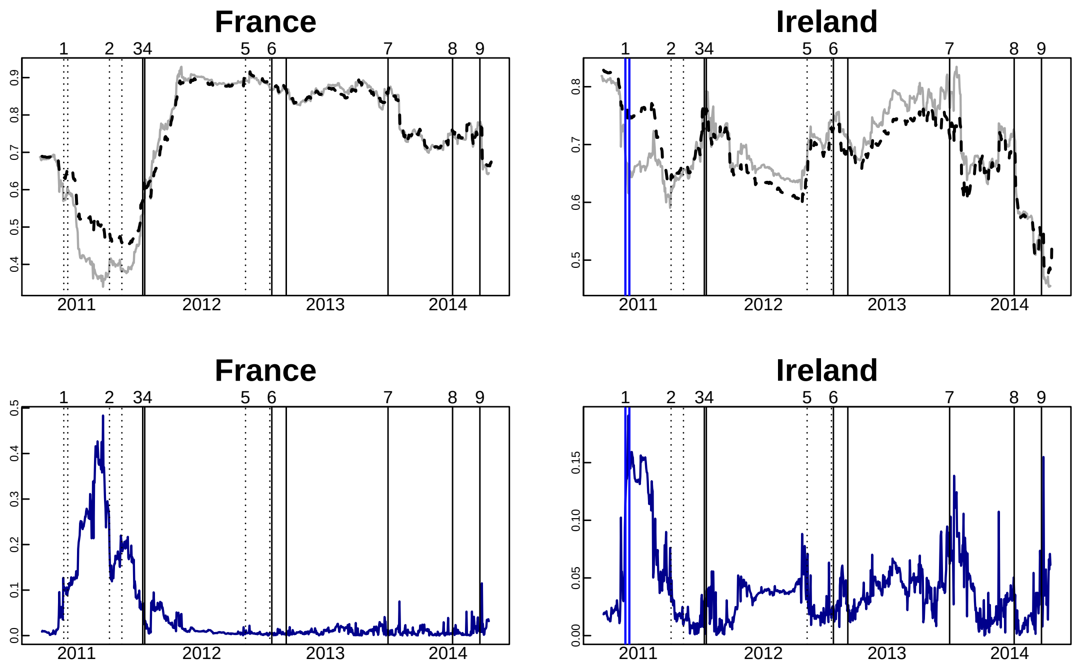


exemplary reference period without specific events about 6 months after the last of the three considered events. Moreover, Figure 2.2 shows for an exemplary core and periphery country the evolution of $(\widetilde{OC})_{j,t}^{OUT}$ and $(\widetilde{OC})_{j,t}^{IN}$ in the upper part and the relative differences in the two lower graphs over the entire time period. Even though the out-of-sample measure often exceeds the in-sample measure, there are also periods were the contrary is true. Also, the differences between the two measures decrease over time as events become less unexpected. Hence, the use of out-of-sample measures appears preferable in order to obtain more reliable estimates of connectedness, especially, for unexpected key events.

On the network level, we confirm the impression that the out-of-sample measure reacts faster when unexpected events occur. In particular, we compare element-wise differences $\widetilde{C}^{OUT} - \widetilde{C}^{IN}$ for all directed edges in the network at three days around event 4 in Figure 2.2 which is the bailout of Greece, but also around the bailout of Portugal (event 2, networks shown in Figure 2.22) and the announcement of the OMT (event 9, networks shown in Figure 2.23). In Figure 2.3, the CDS-based results for the Greek bailout indicate that out-of-sample connectedness exceeds the in-sample one already before the event picking-up leaking information more quickly. The same is confirmed but less pronounced for asset swaps (Figure 2.20). For completeness, we also provide the results for asset swap spreads in 2.6.6. Differences between CDS and bond data are discussed in detail in the following subsections.

Figure 2.2: Comparison of out-of-sample and in-sample connectedness

The upper two plots show $(\widetilde{OC})^{OUT}_{j,t}$ in black dashed lines and $(\widetilde{OC})^{IN}_{j,t}$ in grey solid lines for the two countries j, where as in the two lower graphs the blue lines depict the relative differences i.e., $\sum_{j=1}^{8} \frac{|(\widetilde{OC})^{OUT}_{j,t} - (\widetilde{OC})^{IN}_{j,t}|}{(\widetilde{OC})^{IN}_{j,t}}$. All plots are based on CDS data. Important events (see the specification in Table 2.6.3) are marked with vertical lines with country-specific events in blue.



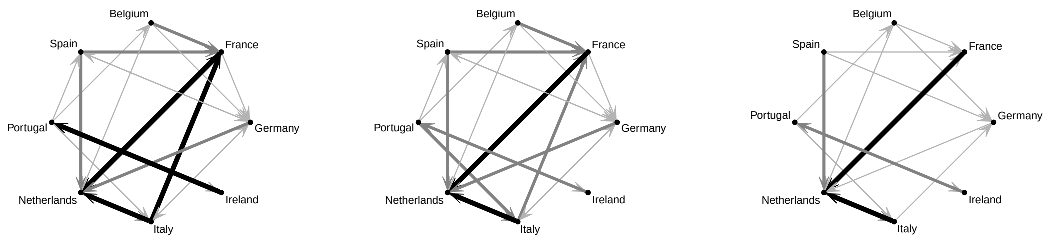
A Comprehensive Picture of Sovereign Connectedness around Important Events

We employ our out-of-sample measure for a real-time forecasters' perspective on risk interconnectedness around characteristic events during the crisis. As seen in the previous subsection, the strictly predictive nature of the out-of-sample measure provides appropriate forecasts deviating from those of the standard in-sample analysis by Diebold and Yilmaz (2009) in these cases. In particular, we study the period between February 2009 and 2014 involving country specific bailouts of Ireland, Portugal, Greece, the rescue of Bankia by the Spanish government but also EU wide actions such as Draghi's speech "whatever it takes...", the announcement of the OMT, and further announcements of unconventional ECB monetary policy measures.[18] Note that in all following figures,

[18]See again Section 2.8 in the Appendix for a detailed list.

Figure 2.3: Difference between out-of-sample and in-sample connectedness around the second bailout for Greece

The three networks with countries as nodes show $\widetilde{C}_{ij}^{OUT} - \widetilde{C}_{ij}^{IN}$ for $i < j$ depicted by the arrow from j to i and $\widetilde{C}_{ij}^{OUT} - \widetilde{C}_{ij}^{IN}$ for $i > j$ depicted by the arrow from i to j the day before (a), at (b), and the day after (c) a second bailout package for Greece was decided (event 4 in Table 2.6.3) for CDS data. The thickness of each arrow marks the size of $\widetilde{C}_{ij}^{OUT} - \widetilde{C}_{ij}^{IN}$ according to the following scale: Wide, black arrows correspond to values greater or equal than the third quartile; medium, darkgray edges mark values between the median and third quartile, and thin, lightgray edges show small differences between the first quartile and median. Differences below the first quartile are not shown.



(a) 07/20/2011, CDS (b) 07/21/2011, CDS (c) 07/22/2011, CDS

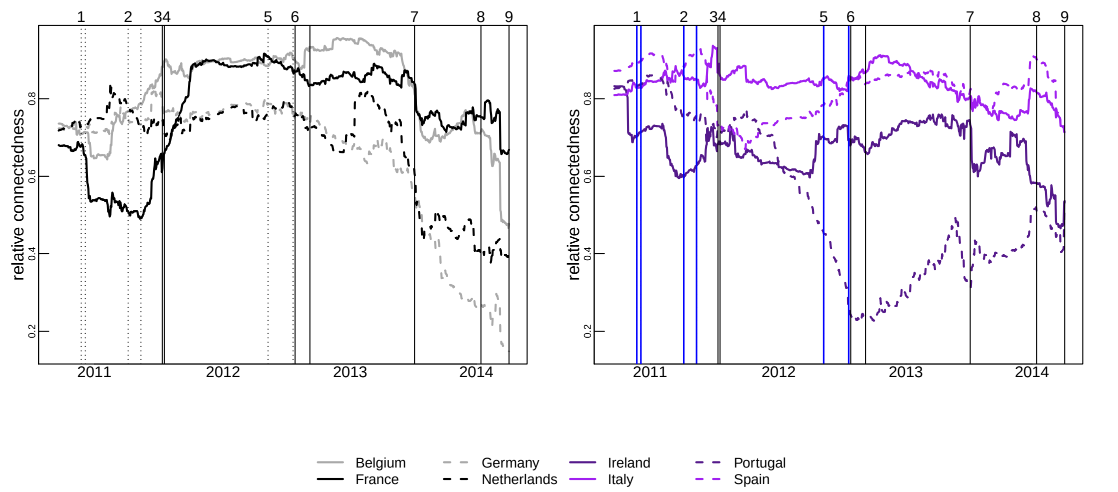
country specific events appear as blue vertical lines if the respective country is contained in the graphs and in dotted black if not. The most important European-wide events are marked by solid black lines.

CDS connectedness in Figure 2.5 shows that generally country-wise relative out-connectedness of the four core countries Belgium, France, Germany and the Netherlands drops significantly only after the ECB's commitment to low interest rates (7). Before, connectedness of Germany and the Netherlands is well above 60%. For France and Belgium it is even above 80%. Connectedness of Germany and the Netherlands already begins decreasing after Draghi's speech and the announcement of the OMT (6). While connectedness of Germany and the Netherlands seems unaffected by the bailouts of Ireland (1) and Portugal (2), connectedness of both Belgium as well as France rises during this period of the sovereign debt crisis. Their connectedness measures remain on a high level, comparable to that of Italy, until mid 2013 (7). This reflects the slightly unstable financial situation of France and the impaired banking sector of Belgium.

Among the periphery countries, both Italy and Spain remain on a high level of connectedness which does not decrease until the beginning of 2014, after the European Commission adapts the Risk Finance Guidlines (8). The new guidelines improve SMEs' and midcaps' access to funding and apparently have a stabilizing effect on countries which had been weakened by the crisis. Portugal shows a different behavior from all other countries with connectedness declining sharply between the second bailout for Greece

Figure 2.5: Country-specific outgoing connectedness for CDS spreads

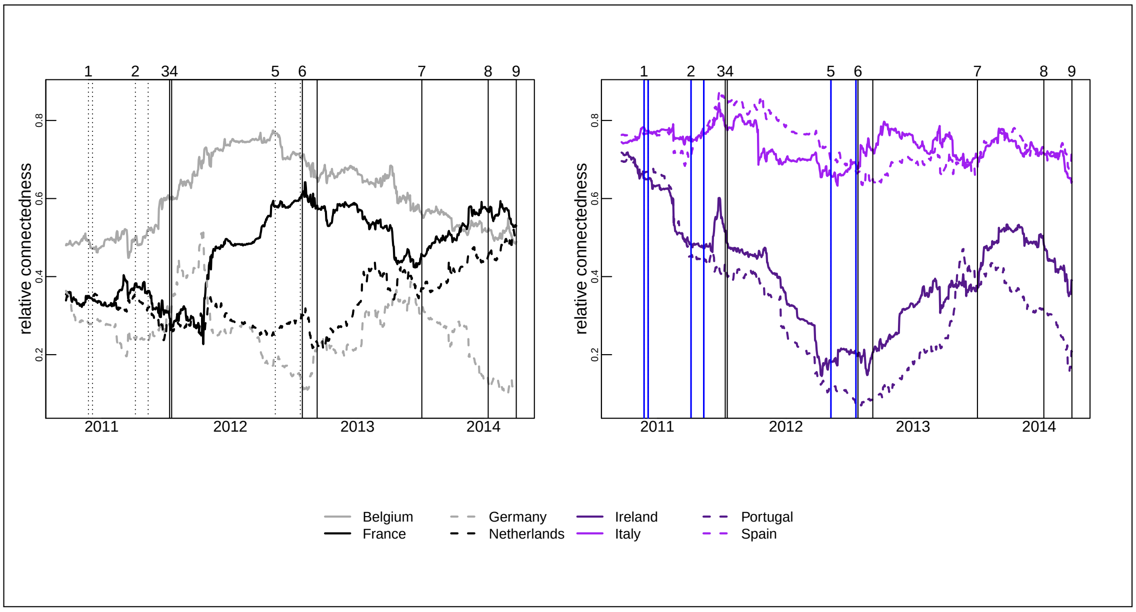
Country-specific outgoing connectedness using relative variance decomposition components for CDS spreads for each country grouped for core countries on the left, and the four periphery countries on the right. Important events are marked with vertical lines. A detailed timeline with their exact specification can be found in the Appendix in Table 2.8.



(4) and Draghi's speech (6). This can be explained by fast and effective implementation of austerity measures and structural reforms as e.g. in labor markets and institutions (see e.g European Commission (2014)) as well as by reduced speculation and trading in Portugal after the announcement of the naked CDS ban in October 2011. Moreover, Ireland is the only periphery country for which connectedness drops in mid 2013 after (7) similar to the core countries, showing its structural recovery since the turbulence in 2010. The different picture of Ireland's asset swap connectedness in Figure 2.6 as compared to the CDS based measure can be attributed to the fact that the country actually lost access to market funding in 2010 and entered a financial assistance program by the EU and the IMF until the end of 2013. When exiting the program, the ASW-measure shows that the spill-over impact on other EU-countries quickly decreased as the country managed to fully rely on market based financing restoring market confidence (see IMF (2015)).

Figure 2.6: Country-specific outgoing connectedness for ASW spreads

Country-specific outgoing connectedness using relative variance decomposition components for ASW grouped for core coutnries on the left, and the four periphery countries on the right. Important events are marked with vertical lines. Country specific events appear as blue vertical lines if the respective country is contained in the graphs and in dotted black if not. The most important European-wide events are marked by solid black lines. A detailed timeline with their exact specification can be found in the Appendix in Table 2.8.



Generally, for asset swap connectedness, we observe a defragmentation among the periphery countries' connectedness already from 2011 onwards (see also Ehrmann and Fratzscher, 2017). In CDS connectedness, this becomes visible only from 2014 onwards, after it was clear that restructuring in Portugal and Ireland was successful and both countries could survive without EU and IMF funding schemes. Hence, during the financial assistance periods, the CDS-based measure appears to capture volatility spill-over effects of credit conditions for periphery countries more realistically in terms of economic fundamentals (see also Fontana and Scheicher, 2016). Moreover, relative asset swap connectedness of the four core countries and of Ireland is generally on a lower level than connectedness based on CDS indicating that the bond market captures less volatility spill-overs. While for France and Belgium the dynamics of the asset swap based measure is comparable to CDS connectedness, for Germany and the Netherlands this is not the case. This can be explained by flight to liquidity and flight to quality effects which play an important role for bonds but not for CDS (Fontana and Scheicher, 2016). Italy, Spain and Portugal are the only countries for which both, the level as well as the dynamics of outgoing connectedness is similar irrespective of the underlying dataset. Generally, however, when ranking countries by connectedness, the obtained ordering is the same for CDS and ASW for almost all points in time. Nevertheless, differences in the two measures might contain valuable additional information for understanding the role of a country within the system.

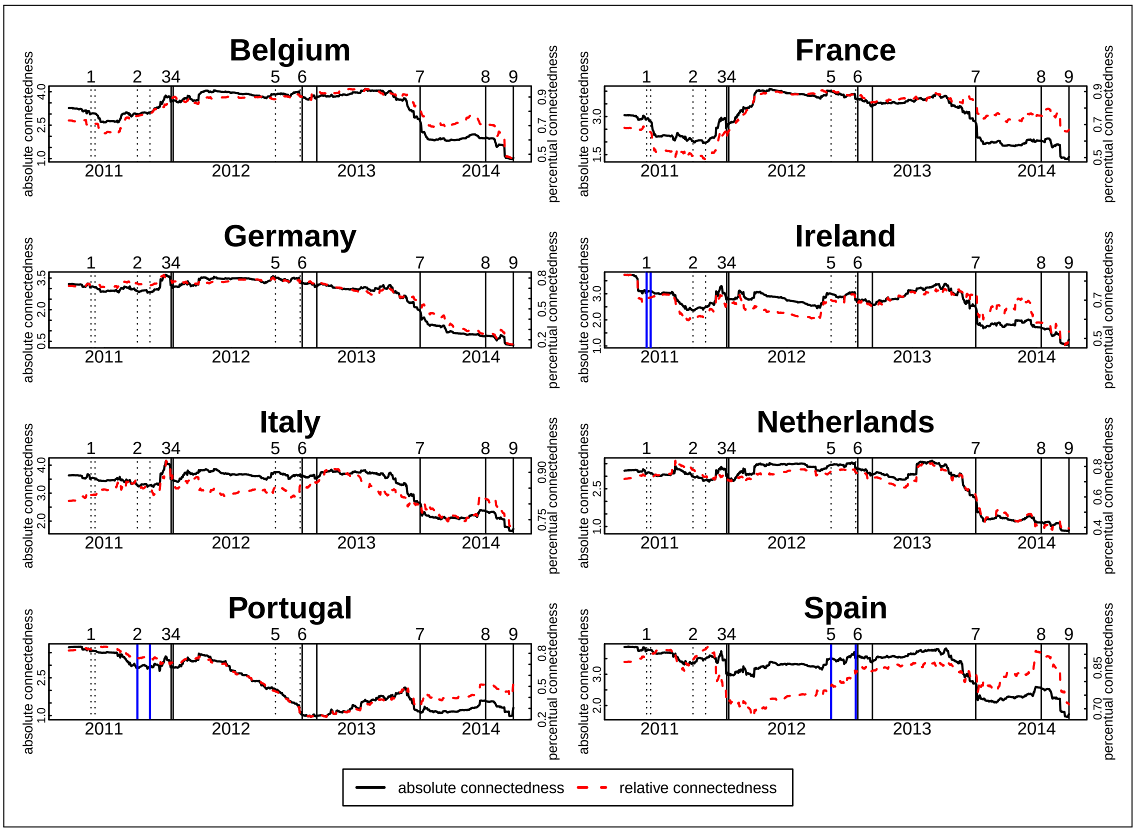
A rise in relative connectedness can originate from an increase in absolute individual connectedness or from a decline in absolute ingoing connectedness of that country. Thus, a comparison of the two measures reveals a more comprehensive picture of the spill-over risk each country imposes on the system while only relative levels allow for a connectedness comparison across CDS and ASW data sets. Figure 2.7 shows the outgoing country-wise CDS connectedness for each country in absolute and relative terms. During the period between the stress test results (3) and the beginning of 2012, Spanish relative connectedness drops, while absolute connectedness only decreases slightly. This shows that absolute ingoing connectedness of Spain increased in this time period which comprises the Greek bailout (4). The opposite behavior of relative and absolute measures occurs for Belgium, France, Ireland, Portugal and Spain after the ECB's commitment to low interest rates (7). For these countries, absolute measures decline more than relative measures, indicating a strong decrease in idiosyncratic volatility.

Draghi's speech marks the point in the crisis after which connectedness for most countries starts an overall decrease. We therefore study this key event in more detail, investigating the spill-over channels on the granular network level. Individual connectedness measures before Draghi's speech and after the announcement of the OMT are visualized in network graphs in Figure 2.8, in which thicker arrows depict a larger magnitude of connectedness from one country to another. Generally, we observe thinner connections after the announcement of the bond-buying plan but only a few vanish. Hence, while the overall level of connectedness decreases, the effective spill-over channels remain almost entirely active. In the CDS case, only Portugal is less connected to the system confirming its special role detected in the country-wise connectedness also by the network topology. For ASW, there appear much less spill-over channels. The more sparse network, however, contains many strong links of the CDS graph. On the other hand, it also misses out on many valid edges as e.g. between France and Germany, so it could only partially serve as ranking device for the many CDS connections.

For absolute individual connectedness, shown in Figure 2.25 in the Appendix, CDS networks remain comparable to relative measures, while in the ASW network a strong increase in thin connections is observed. Generally, both absolute measures indicate a stronger decline by the event compared to relative connectedness measures. In particular, this is the case for Ireland, Italy and Portugal which after the ECB's policy

Figure 2.7: Absolute and relative connectedness measures

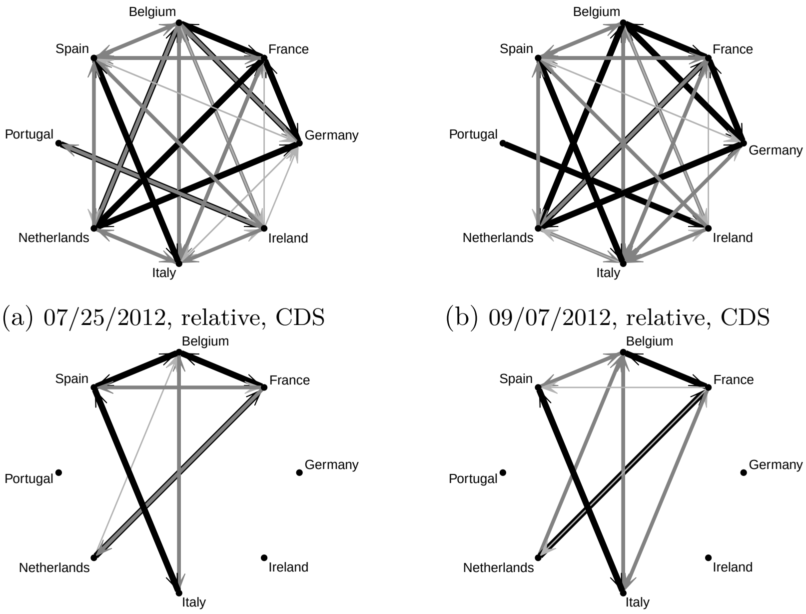
Country-Specific Outgoing Connectedness Using Absolute and Relative Variance Decomposition Components for CDS spreads for each country. Absolute connectedness is depicted by a solid black line and its scale is on the left-hand axis. Relative connectedness is depicted by a dashed line and its scale is 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 2.8. The sample period is as in Figure 2.10.



announcement affect the system less than before.

Figure 2.8: Connectedness before Draghi's speech and after the OMT.

Individual relative connectedness before Draghi's speech (07/25/2012) and after the announcement of the OMT (09/07/2012). The same definitions as in Figure 2.3 apply. Absolute connectedness is shown in the Appendix in Figure 2.25 for completeness.



(a) 07/25/2012, relative, CDS
(b) 09/07/2012, relative, CDS
(c) 07/25/2012, relative, ASW
(d) 09/07/2012, relative, ASW

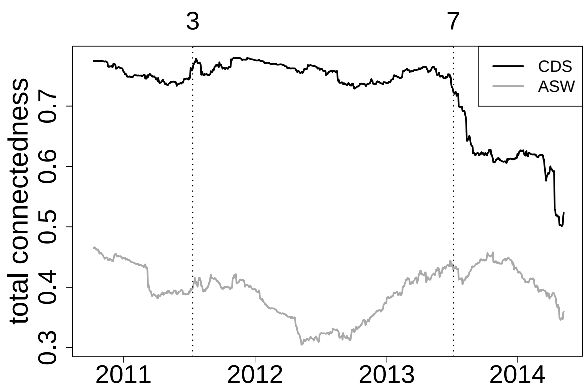
Determinants of the Difference in Connectedness of Sovereign CDS versus Asset Swap Spreads of Bonds

In the previous two subsections we have seen advantages of the out-of-sample connectedness measure and documented differences between measures based on CDS and asset swap data. Here, we investigate the driving determinants of this discrepancy.

CDS spreads and asset swap or bond yield spreads have both been used in the literature to measure default risk. Since it is well-known that European countries are politically and economically tightly interconnected, CDS and asset swap spreads should react in all countries when crisis-related events occur. 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. Various research papers have studied the determinants of the difference between CDS and bonds in levels (see e.g. Fontana and Scheicher, 2016; or Bai and Collin-Dufresne, 2011), but only few have compared volatility type measures using both datasets so far (see Caporin et al., 2013 and Lange et al., 2016). Figure 2.10 illustrates total connectedness of CDS and asset swap spreads. Globally aggregated, variance decomposition measures of asset swap spreads appear to systematically detect less connectedness relative to variance decomposition measures of CDS spreads.

Figure 2.10: Total relative connectedness of CDS and asset swap spreads.

Both connectedness measures 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 (marking the stress test results and the ECB interest rate commitment) designate the period in which the time dummy is used in the panel regression. The sample covers the period from 02/02/2009 until 05/02/2014, which leads to out-of-sample connectedness measures from 08/25/2010 until 05/02/2014.



We investigate the driving determinants of the difference between connectedness measures of CDS and asset swap spreads. We denote this as difference in connectedness and estimate it by a fixed effect panel regression:

$$z_{jt} = \alpha_j + \beta \mathbf{x}_{jt} + \gamma D_t \mathbf{x}_{jt} + \varepsilon_{jt}, \tag{2.13}$$

where $z_{jt} = \sum_{i=1,i\neq j}^{K} \widetilde{C}_{ij,t}^{OUT,CDS} - \widetilde{C}_{ij,t}^{OUT,ASW}$ is the difference in outgoing connectedness for each country j and $\mathbf{x}_{jt}$ represents a vector of explanatory variables. Country fixed effects are captured by α_j and the errors ε_{jt} are independent, strictly exogenous. In order to control for heterogeneity across time, we add a dummy variable D_t equal to unity between 07/15/2011 (event marked 3) and 07/04/2013 (event marked 7). The regressors contained in $\mathbf{x}_{jt}$ are the bid-ask spread of CDS and bonds, the debt-to-GDP ratio, the VIX and the Euribor-Eurepo three month spread. 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 plays an important role for the difference between CDS and bonds. We use the debt-to-GDP ratio to capture the country's credit quality and the VIX as a global measure for risk aversion. Both the debt-to-GDP ratio and the VIX are expected to have a positive impact on the CDS and asset swap spreads and possibly also on their connectedness measures. 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 short-sell bonds, thus a high Euribor-Eurepo spread would drive CDS and bonds apart. These factors are jointly significant and are individually more significant than other highly correlated explanatory variables. The regression results are summarized in Table 2.5.

The difference between the connectedness measures of CDS and bonds is largest during the most turbulent time of the crisis, between 15.07.2011 (event 3) and 04.07.2012 (event 7). The dummy estimate for this period underlines that there is a significant positive shift, which we have already seen earlier in Figure 2.10. It shows that part of this shift is explained by crisis-related conditions during this period. Apart from the level shift between 2011 and 2013 we also observe a change in the effect of the explanatory variables. Liquidity, proxied by the bid-ask spreads of CDS and bonds, has the largest effect on the difference in connectedness of CDS and asset swap spreads. It is noteworthy that the effect of bond liquidity is only significant during the most turbulent period of the crisis with a total effect of 6.32. The impact of CDS liquidity is almost half the size (-3.27) during more tranquil times compared to bond liquidity and decreases to -0.51 between 2011 and 2013.[19] Apart from macro factors, liquidity affects the correlation in bond spreads during the crisis (Boffelli et al., 2016). In times of crises, bonds of countries in financial distress are barely traded, whereas bonds of creditworthy countries become more liquid, thus pushing their yields down. The value of CDS, in contrast, depends less on its liquidity. In this sense, flight to quality and flight to liquidity in bond markets during the crisis drive the connectedness measures of CDS and asset swap spreads apart.[20] Fontana and Scheicher (2016) find evidence for the same effect on CDS and bonds in levels. The country fixed effects in Table 2.6b show that stable countries generally yield higher differences in connectedness, thus confirming the flight to quality or liquidity argument (Beber et al., 2009) . The debt-to-GDP ratio and the VIX both have a smaller, but significant positive impact on the difference in connectedness, meaning that the CDS-based connectedness measure reacts slightly stronger to a change in these variables than the bond-based connectedness measure. The effect of the arbitrage proxy

[19]The total effects for the turbulent crisis period equal the sum of the baseline estimates and the dummy interaction estimates.

[20]The difference between CDS and bonds is intensified by ECB bond purchases.

Table 2.5: Panel regression results

Table 2.6a lists the coefficient estimates and standard deviations for the panel regression of the difference in connectedness including fixed effects, using 785 observations of nine countries. The numbers in parentheses are robust standard errors and ***, **, * indicate significance at the 0,1%, 1%, and 5% level. The within adjusted R-squared is 0.82 and the coefficients are jointly significant with an F statistic of 2578.37. 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. We use a time dummy for the most turbulent period of the crisis between 07/15/2011 (event 3) and 07/04/2012 (event 7). In the second block titled "turbulent crisis period" we list the estimates of the interaction terms. Standard errors are robust to serial correlation and cross-sectional correlation according to Driscoll and Kraay (1998). Countries in Table 2.6b are ordered by size of the fixed effect.

	Variable	Estimate	Std. Dev.
entire period (baseline)	Bid-ask CDS	-3.27	$(1.97)^{\cdot}$
	Bid-ask ASW	-1.52	(4.37)
	Debt/GDP	0.01	$(0.00)^{\cdot}$
	VIX	0.08	(0.02)***
	Euribor-Eurepo	0.18	(0.36)
turbulent crisis period (3-7)	Dummy constant	1.02	(0.20)***
	D * Bid-ask CDS	2.76	(0.81)***
	D * Bid-ask ASW	7.84	(2.94)**
	D * Debt/GDP	0.00	(0.00)
	D * VIX	-0.04	(0.01)***
	D * Euribor-Eurepo	0.13	(0.23)

(a) Estimates and Standard Deviations

Country	Fixed Effect
Italy	-1.58
Portugal	-1.55
Ireland	-1.39
Spain	-1.38
Belgium	-1.35
France	-1.28
Germany	-1.14
Netherlands	-1.04

(b) Country Fixed Effects in Levels

Euribor-Eurepo is insignificant for the difference in connectedness at all times.

We have additionally conducted seperate regressions for CDS connectedness and asset swap connectedness in order to identify advantages of each dataset. Here, z_{jt} corresponds to the outgoing connectedness of country j using CDS or ASW data.[21] The regression results are summarized in 2.6.5. The asset swap panel regression reveals that the ordering of the country fixed effects are, apart from the position of Belgium, identical to the previous regression of the difference in connectedness. Country fixed effects of CDS connectedness, on the other hand, are not ordered intuitively. This shows that

[21] $z_{jt} = \sum_{i=1,i\neq j}^{K} \widetilde{C}_{ij,t}^{OUT,CDS}$ and $z_{jt} = \sum_{i=1,i\neq j}^{K} \widetilde{C}_{ij,t}^{OUT,ASW}$, respectively.

asset swaps are important for determining the approximate position of countries concerning connectedness. While asset swaps play a crucial role for evaluating the position of a country compared to others, CDS connectedness accounts for the factors driving connectedness. Liquidity, the debt-to-GDP ratio and VIX all have a significant impact on CDS connectedness. At the same time, both instruments have drawbacks: Bond liquidity diminishes in the presence of CDS and during the crisis (Massa and Zhang, 2012), while CDS are affected by speculative trading (Oehmke and Zawadowski, 2017). These disadvantages can be compensated by using both instruments simultaneously and thus measure default risk connectedness more precisely.

The complementarity between CDS and asset swap spread connectedness is illustrated on a country level using network graphs in Section 2.4.2 and 2.4.2.

2.5 Conclusion

Interconnectedness has been a crucial element of the financial and European sovereign debt crisis and its propagation. Accordingly, appropriate measures to quantify this interconnectedness are necessary. We provide a method for measuring and forecasting connectedness via the out-of-sample forecast error variance decomposition, which allows for precise measurement results after unexpected events. In contrast to the standard in-sample variance decomposition, our method uses forecast errors predicted for points outside the estimation sample instead of in-sample forecast errors directly computed from the MA representation formula, and it thus incorporates more aspects of unknown shocks. We have shown empirically that around crisis-related events, the out-of-sample measure reflects changes in connectedness faster than the standard variance decomposition as proposed by Diebold and Yilmaz (2014). A detailed comparison at specific events shows that out-of-sample measures are advantageous, especially when using CDS data.

We find, however, that CDS and asset swap spreads contain complementary information for evaluating connectedness. The difference between the respective measures is explained by liquidity effects, credit quality, risk aversion and crisis-related conditions. Asset swaps are important for determining the overall risk position of countries while CDS reflect more detailed information on country-specific risk.

We analyze connectedness in Europe during the sovereign debt crisis by evaluating both relative and absolute connectedness measures. In general, levels of connectedness measures decrease after financial aid packages to impaired countries and the ECB's policy measures, while the channels through which they are transmitted prevail.

In this paper we have shown that out-of-sample connectedness of CDS captures effects of unexpected events instantaneously. The results for CDS and asset swap spreads motivate a look at intra-day data for extracting more precise information on their driving forces. We will explore this in our future work given data availability.

2.6 Appendix

2.6.1 Summary Statistics

Figure 2.11: 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 05/02/2014.

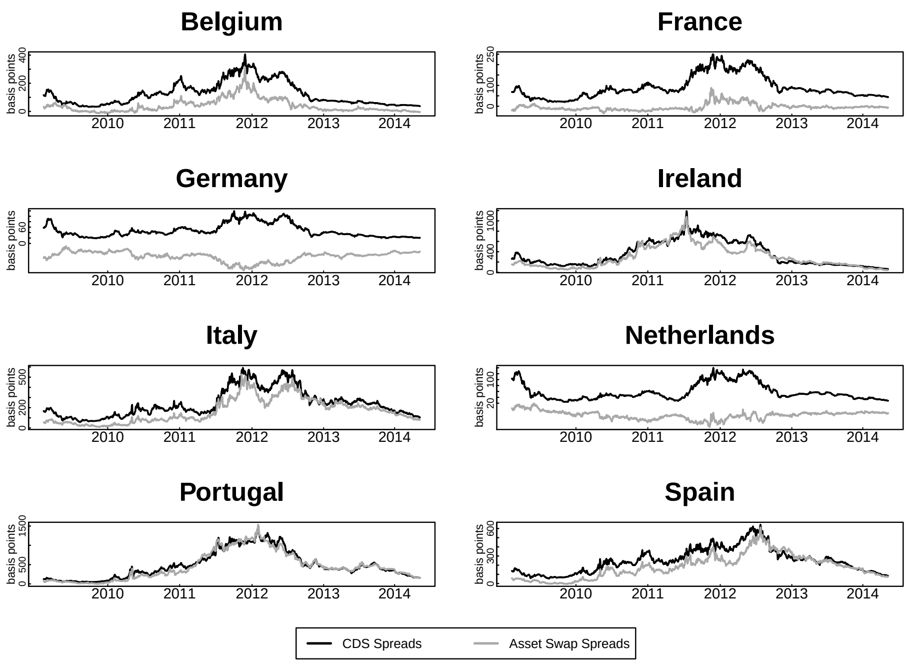


Table 2.7: Descriptive statistics

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.

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

2.6.2 Generalized Variance Decompositon

Here we develop the main steps for the in-sample variance decomposition components from Equation (3.7) via the impulse response function.[22] Koop et al. (1996) define the generalized impulse response function $\mathbf{GI}$ of $\mathbf{y_t}$ at horizon H for a shock of size δ and a known history $\mathbf{\Omega}_{t-1}$ as follows:

$$\mathbf{GI}(H, \delta, \mathbf{\Omega}_{t-1}) = E(\mathbf{y}_{t+H}/\mathbf{u_t} = \delta, \mathbf{\Omega}_{t-1}) - E(\mathbf{y}_{t+H}/\mathbf{u_t} = 0, \mathbf{\Omega}_{t-1}) \tag{2.14}$$

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

$$\mathbf{GI}_j(H, \delta_j, \mathbf{\Omega}_{t-1}) = E(\mathbf{y}_{t+H}/\mathbf{u_{tj}} = \delta_j, \mathbf{\Omega}_{t-1}) - E(\mathbf{y}_{t+H}/\mathbf{\Omega}_{t-1}) \tag{2.15}$$

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

$$E(\mathbf{u}_t/\mathbf{u}_{tj} = \delta_j) = (\sigma_{1j}, \sigma_{2j}, \cdots, \sigma_{nj})' \frac{\delta_j}{\sigma_{jj}} = \Sigma_u e_j \frac{\delta_j}{\sigma_{jj}} \tag{2.16}$$

Thus, the generalized impulse response is given by

$$\mathbf{GI}_j(H, \delta_j, \mathbf{\Omega}_{t-1}) = \mathbf{\Phi}_H \Sigma_u e_j \frac{\delta_j}{\sigma_{jj}} \tag{2.17}$$

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 $t + H$:

$$\mathbf{GI}_j(H, \delta_j, \mathbf{\Omega}_{t-1}) = \sigma_{jj}^{-1/2} \mathbf{\Phi}_H \Sigma_u e_j \tag{2.18}$$

As in Pesaran and Shin (1998), this is used to derive the generalized forecast error variance decomposition components $s_{ij}^{IN}(H)$:

$$s_{ij}^{IN}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \Phi_h \Sigma_u e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Phi_h \Sigma_u \Phi_h' e_i)} \tag{2.19}$$

[22]See Hamilton (1994) for the link between impulse responses and forecast error variance decomposition.

2.6.3 Timeline

Table 2.8: Timeline of important events during the European debt crisis.

11/21/2010	(1) Ireland seeks financial support; EU-IMF package for Ireland is agreed: 12/02/2010
04/06/2011	(2) Portugal asks for support by the Eurozone; aid to Portugal is approved: 05/16/2011
07/15/2011	(3) Stress test results are published
07/21/2011	(4) Eurozone agrees a second bailout package for Greece
05/09/2012	(5) Spanish government rescues Bankia, which is entirely nationalized later; announcement that Spain will seek financial assistance for its banking sector: 06/09/2012; financial aid is granted: 07/20/2012.
07/26/2012	(6) Draghi promises the ECB would do "whatever it takes" to sustain the euro.
09/06/2012	Details of ECB's new bond-buying plan are announced.
07/04/2013	(7) ECB reveals that key interest rates would remain at present or lower levels for an extended period of time.
01/15/2014	(8) European Commission adapts Risk Finance Guidlines 4.
04/03/2014	(9) ECB states that it is disposed to apply unconventional measures such as bond purchasess or quantitative easing.

2.6.4 Forecasting Power of Different Model Specifications

Figure 2.12: Mean MSE for different window sizes

For each window length between 100 and 400, we compute MSEs across all rolling windows. The dots in the graph represent the mean of the Frobenius norm of the MSEs for each window size.

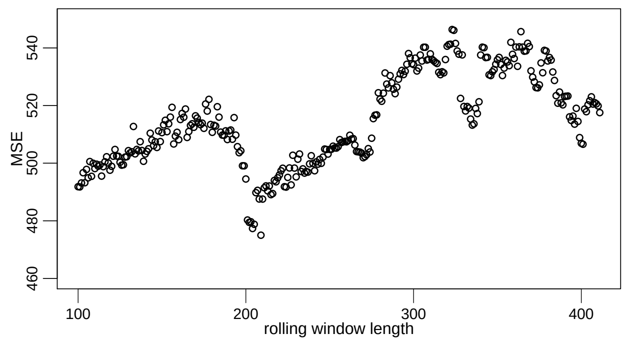


Figure 2.13: Total connectedness with and without time dummies for events

Total connectedness measures for CDS spreads with (black) and without (grey) time dummies included in the underlying VAR. Both are computed with out-of-sample forecast errors, calculated from relative measures and averaged across one, two and five forecast periods ahead. The sample covers the period from 02/02/2009 until 05/02/2014, which leads to out-of-sample connectedness measures from 08/25/2010 until 05/02/2014.

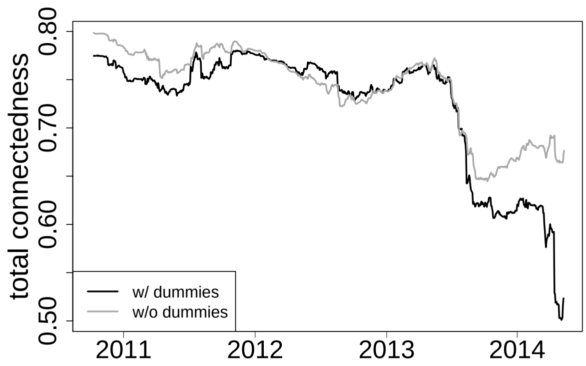
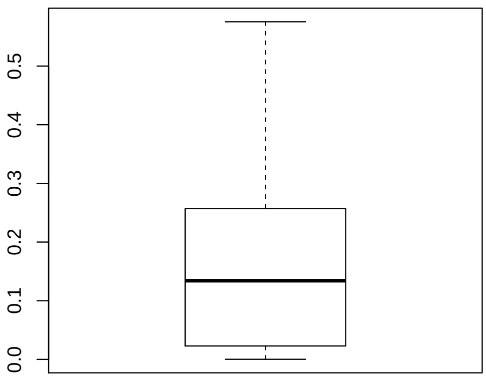
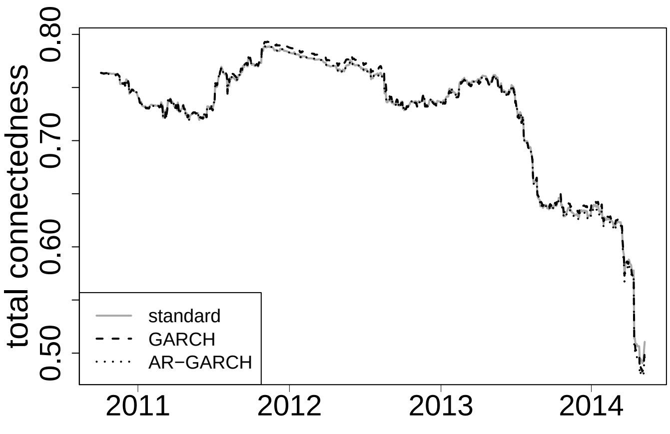


Figure 2.14: Heteroscedastic effects



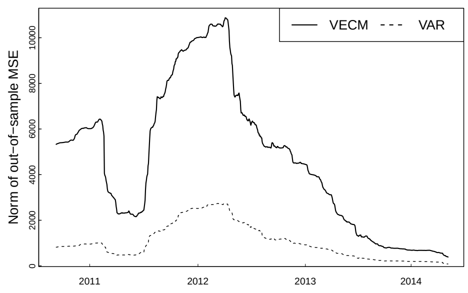
(a) Boxplot of p-values of ARCH-LM-test for all rolling windows, LM-test as proposed by Engle (1982).



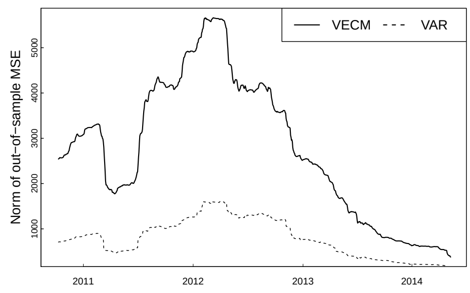
(b) Total connectedness with unfiltered data (standard), GARCH(1,1)-filtered data and AR(1)-GARCH(1,1) filtered data.

Figure 2.16: MSE of VECM and VAR

This figure shows the normed[23] MSE of a VAR(1) and a VECM across all rolling windows, using CDS data in figure 2.17a and bond data in figure 2.17b. The number of cointegration relationships of the VECM is adapted for each estimation window. 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 08/25/2010 until 05/02/2014.



(a) Based on CDS data



(b) Based on ASW data

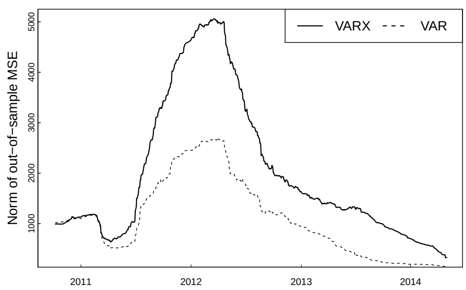
Table 2.9: AIC, BIC and log-Likelihood of a selection of models

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.

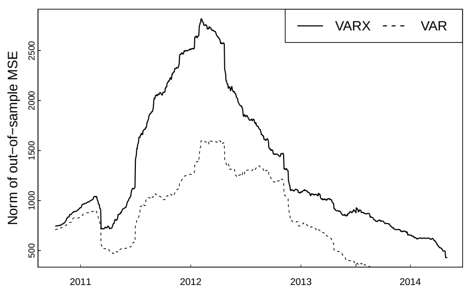
	CDS spreads			Asset swap spreads		
	VAR	VECM	VARX	VAR	VECM	VARX
AIC	20.48	20.66	20.48	25.09	25.26	25.08
BIC	22.03	23.28	22.03	26.42	27.66	26.40
logLik	-4186	-4084	-4187	-4648	-4557	-4649

Figure 2.18: 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 2.19a and bond data in figure 2.19b. 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 08/25/2010 until 05/02/2014.



(a) using CDS data



(b) using bond data

2.6.5 Panel Regression Results

Table 2.10: Panel regression results for CDS connectedness

Table 2.11a lists the coefficient estimates and standard deviations for the panel regression of connectedness computed with CDS data including fixed effects, using 785 observations of nine countries. The numbers in parentheses are robust standard errors and ***, **, * indicate significance at the 0,1%, 1%, and 5% level. The within adjusted R-squared is 0.79 and the coefficients are jointly significant with an F statistic of 2160.36. 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. We use a time dummy for the most turbulent period of the crisis between 07/15/2011 (event 3) and 07/04/2012 (event 7). In the second block titled "between (3) and (7)" we list the estimates of the interaction terms. Standard errors are robust to serial correlation and cross-sectional correlation according to Driscoll and Kraay (1998). Countries in Table 2.11b are ordered by size of the fixed effect.

	Variable	Estimate	Std. Dev.
entire period (baseline)	Bid-ask CDS	-4.56	(1.89)*
	Bid-ask ASW	1.17	(2.74)
	Debt/GDP	0.00	(0.00)
	VIX	0.05	(0.02)*
	Euribor-Eurepo	0.12	(0.25)
turbulent crisis period (3-7)	Dummy constant	0.54	(0.24)*
	D * Bid-ask CDS	3.61	(0.91)***
	D * Bid-ask ASW	9.19	(2.03)***
	D * Debt/GDP	0.00	(0.00)
	D * VIX	-0.03	(0.01)*
	D * Euribor-Eurepo	0.15	(0.13)

(a) Estimates and Standard Deviations

Country	Fixed Effect
Netherlands	0.57
Belgium	0.48
Spain	0.45
France	0.38
Germany	0.37
Ireland	0.37
Italy	0.37
Portugal	0.29

(b) Country Fixed Effects in Levels

Table 2.12: Panel regression results for ASW connectedness

Explanation as in Table 2.11a, with outgoing asset swap connectedness as dependent variable. The within adjusted R-squared is 0.42 and the coefficients are jointly significant with an F statistic of 429.55.

	Variable	Estimate	Std. Dev.
entire period (baseline)	Bid-ask CDS	-1.94	(0.38)***
	Bid-ask ASW	-0.31	(1.17)
	Debt/GDP	0.00	(0.00)
	VIX	0.01	(0.01)
	Euribor-Eurepo	-0.07	(0.05)
turbulent crisis period (3-7)	Dummy constant	0.23	(0.16)
	D * Bid-ask CDS	0.44	(0.34)
	D * Bid-ask ASW	3.13	(0.53)***
	D * Debt/GDP	0.00	(0.00)
	D * VIX	-0.01	(0.00)*
	D * Euribor-Eurepo	-0.09	(0.11)

(a) Estimates and Standard Deviations

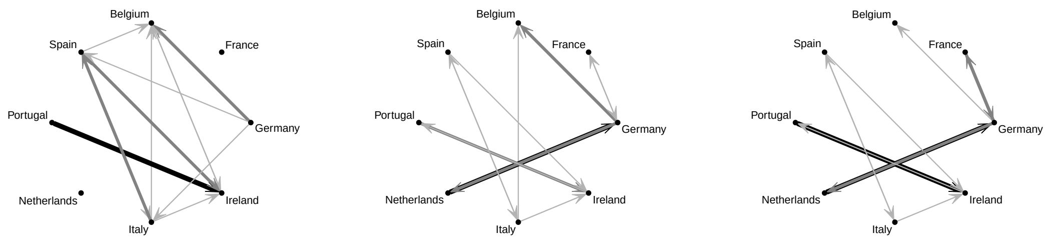
Country	Fixed Effect
Italy	1.36
Spain	1.32
Belgium	1.30
Ireland	1.20
Portugal	1.20
France	1.19
Netherlands	1.19
Germany	1.11

(b) Country Fixed Effects in Levels

2.6.6 Networks

Figure 2.20: Difference between out-of-sample and in-sample connectedness around the second bailout for Greece using ASW data.

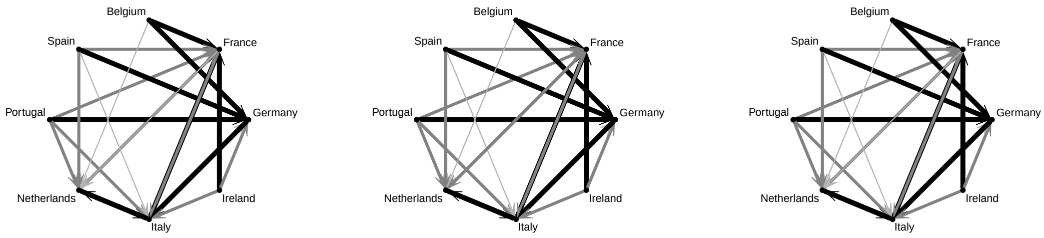
The same definitions as in Figure 2.3 are applied.



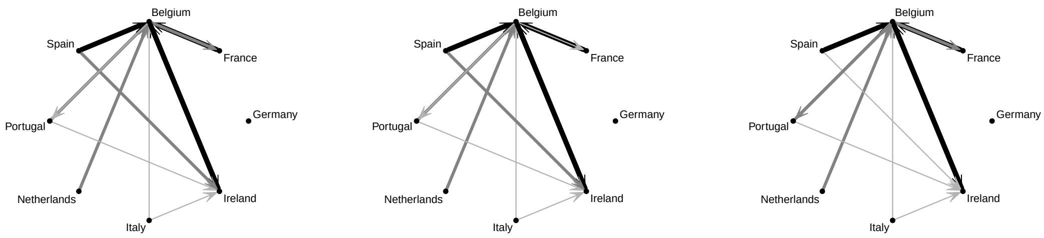
(a) 07/20/2011, ASW (b) 07/21/2011, ASW (c) 07/22/2011, ASW

Figure 2.22: Difference between out-of-sample and in-sample connectedness around Portugal's bailout

Difference between individual out-of-sample and in-sample connectedness one day before ((a),(d)), at ((b),(e)) and one day after ((c),(f)) the bailout of Portugal. Figures (a)-(c) are computed using CDS data, while Figures (d)-(f) are based on asset swap data. The same definitions as in Figure 2.3 apply.



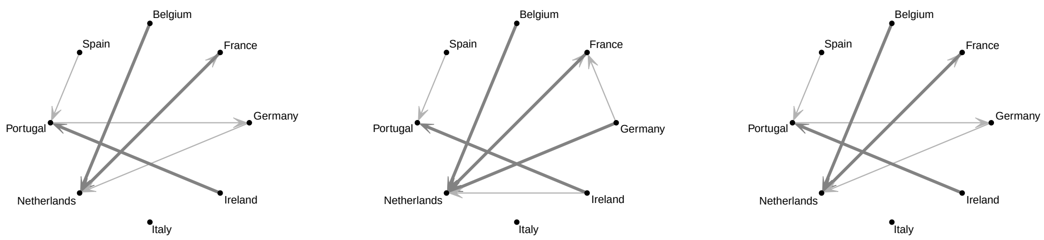
(a) 05/13/2011, CDS (b) 05/16/2011, CDS (c) 05/17/2011, CDS



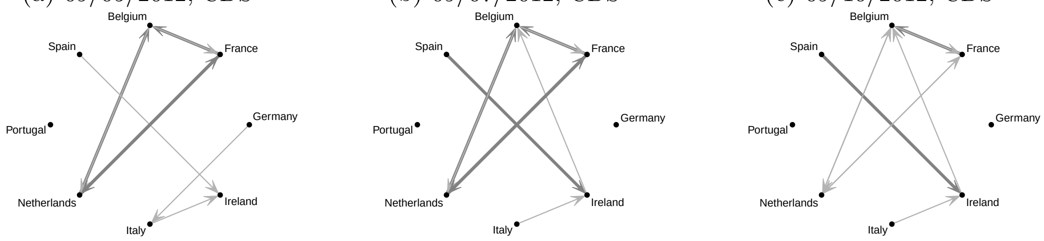
(d) 05/13/2011, ASW (e) 05/16/2011, ASW (f) 05/17/2011, ASW

Figure 2.23: Difference between out-of-sample and in-sample connectedness around the announcement of the OMT

Difference between out-of-sample and in-sample connectedness one day before ((a),(d)), at ((b),(e)) and one day after ((c),(f)) the announcement of the OMT. Figures (a)-(c) are computed using CDS data, while Figures (d)-(f) are based on asset swap data. The same definitions as in Figure 2.3 apply.



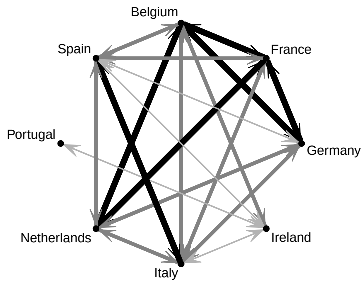
(a) 09/05/2012, CDS (b) 09/07/2012, CDS (c) 09/10/2012, CDS



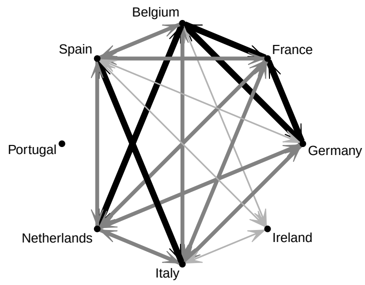
(d) 09/05/2012, ASW (e) 09/07/2012, ASW (f) 09/10/2012, ASW

Figure 2.25: Absolute connectedness before Draghi's speech and after the OMT

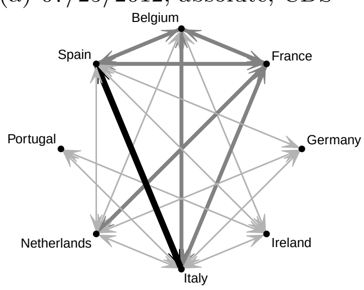
The figure shows absolute connectedness before Draghi's speech (07/25/2012) and after the announcement of the OMT (09/07/2012). The same definitions as in Figure 2.3 apply.



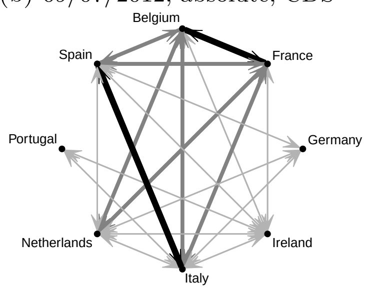
(a) 07/25/2012, absolute, CDS



(b) 09/07/2012, absolute, CDS



(c) 07/25/2012, absolute, ASW



(d) 09/07/2012, absolute, ASW

3 Effectiveness of Policy and Regulation in European Sovereign Credit Risk Markets - A Network Analysis

3.1 Introduction

There is large empirical evidence that markets have calmed down after the recent EU sovereign crisis. But it remains still unclear if and to what extend it is policy interventions or rather regulatory changes which have impacted and mitigated systemic risk most significantly. A thorough understanding however, is crucial for judging the current and long run implications for the resilience of the system. We use novel intra-day sovereign CDS and bond data for the years 2009-2014 which comprises both, policy interventions and regulatory actions such as the SMP programs, the ban of trading naked sovereign CDS or the new ISDA rules. We show that with the higher than daily observation frequency it is possible to empirically disentangle, record the impact and judge the significance of the different types of events. This complements the many studies on the evolution of systemic risk in the EU sovereign context in the course of policy interventions, which rely only on shorter span daily data before and just shortly after the most important regulatory measures were implemented[1]. Thus, the limitation of the data prevented investigations on the impact of regulatory changes, and derived point estimates for policy interventions were of unknown precision. In contrast, we provide finite sample adequate bootstrap tools to assess if changes in systemic risk are significant. In order to obtain tight confidence intervals for the impact of closely succeeding events, high-frequency observations are key. In this sense, we contribute to the vast literature on providing point estimates of systemic risk measured as spillover effects in a network set-up (see e.g. Diebold and Yilmaz (2014), Hautsch et al. (2015), Engle et al. (2014), Betz et al. (2016)).

For assessing systemic risk we focus on volatility spillovers. In this way, we investigate the short-term aim of policy interventions and regulatory changes to calm financial

[1] Most of the empirical studies in fact only use daily data until 2012/13 (see e.g. Diebold and Yilmaz (2014), Alter and Beyer (2014)) where the short-selling ban for sovereign CDS was just introduced and the new ISDA rules have not been implemented and/or focus only on ECB policy interventions (see Eser and Schwaab (2016), Falagiarda and Reitz (2015) or Gibson et al. (2016) and Arghyrou and Kontonikas (2012)).

markets. Though, this step is also the key for a sustainable rebalancing of the economy in the long run.[2] For stabilization of a country's financial sector, the decrease of volatility in respective yields and spreads is a main concern and therefore a key indicator (see e.g. Vergote et al. (2017), Gros et al. (2014)). With our data, we can thoroughly assess this short-term effect, which in the longer run should then also impact a country's or region's economic outlook and be measurable in key economic indicators such as economic growth, employment rates, fiscal sustainability and financial stability (see e.g. IMF (2010)).[3] Moreover, we can determine if the interventions have reduced the transmission of financial volatility shocks amongst countries and have therefore also decreased the vulnerability of the financial system as a whole. This clearly is the goal of any macro-prudential policy and requires a network approach.

Technically, we determine interconnections via the order invariant generalized forecast error variance decomposition (see Pesaran and Shin (1998)). We go beyond the status quo of only computing point estimates of unknown precision for this measure (see e.g. Diebold and Yilmaz (2014)) and assess the statistical significance of connectedness by constructing bootstrap confidence intervals. Thus, we can distinguish significant volatility effects from others and thus infer which changes in the measures allow for a meaningful interpretation. In particular, we can apply this to all aggregation levels of the detected spillover network. We can therefore discover significant overall aggregated spillover changes over time but also determine significant spillover channels on the network level at each point in time. This approach enables us to comprehensively evaluate and categorize the effectiveness of crisis-related policy measures and regulation in the CDS market. It is important to note that all our empirical results do not depend on the fact that we use variance decomposition for measuring volatility spillovers or a specific type of decomposition method (see A.Chan-Lau (2017)). In particular, we show in detail that our results prevail when using realized volatility cross-effects.

Our novel intraday CDS dataset allows for a better accuracy in estimating spillovers and judging the impact of policy and regulation measures on the dynamics of the European sovereign CDS market. Up to our knowledge, this is the first study investigating the significance of connectedness using intraday CDS data. In particular due to this intraday data, it is possible to evaluate the connectedness on a high precision level. This is especially important when studying the impact of specific events on reducing systemic risk where spillovers in respective pre- and post-event windows are compared in order to judge the effectiveness of this policy or regulatory event (see also Vergote et al., 2017). For our intraday data, there are sufficiently many observations within estimation windows of only a few trading days in order to obtain meaningfully precise estimates. Larger windows covering more trading days would inevitably contain effects

[2]See e.g. the communication of the ECB on the direct and indirect mechanisms of the asset purchasing programs `https://www.ecb.europa.eu/explainers/tell-me-more/html/app.en.html`.

[3]Note that such data, however, is very limited so far as generally available only on quarterly frequencies preventing a thorough analysis of the considered regulatory measures at the current point in time.

of other closely succeeding events and dilute the picture.

We investigate the two most important regulatory changes in the EU sovereign CDS market and show evidence for their success in terms of reducing connectedness and speculation in affected countries. First, we study the permanent ban of so-called 'naked sovereign CDS' contracts implemented in 2012. Second, we focus on the introduction of new CDS definitions and standard reference obligations in 2014 which marked an important change to CDS trading. By quantifying volatility spillovers on all network aggregation levels and taking liquidity effects into account, we uncover the size, the channels and the drivers of the impact of the ban and the new definitions. In particular, we show that there is more than a simple liquidity story behind the success of the ban and the new ISDA regulation. Moreover, throughout the crisis, we cannot determine any fragmentation within our CDS sovereign spillover networks and thus conclude that there must be multiple sources of contagion. This insight goes beyond previous studies (see e.g. Ehrmann and Fratzscher (2017)) with bond yields which in contrast to CDS, have been shown to suffer from many problems in representing credit risk (see Pan and Singleton (2008) and Ang and Longstaff (2011)). In addition, we provide evidence for public learning effects in unconventional monetary policy measures leading to a decrease of their effectiveness. Furthermore, European-wide measures prove to impact connectedness in a more sustainable manner than measures aimed at one particular country. Unconventional policy interventions which aimed at mitigating systemic risk include economic adjustment programs (EAP) (two for Greece, one for Ireland, Portugal and Spain) and the bond purchases as part of the Security Markets Program (SMP) of the ECB, which was succeeded by the OMT program. The OMT was introduced after Draghi's speech stating the ECB would do 'whatever it takes' to sustain the Euro. Both the SMP and Draghi's speech are examples of European-wide interventions.

Our paper contributes to the recent literature on network spillover measures (e.g. Engle et al., 2014; Diebold and Yilmaz, 2009) pointing out the importance of checking cross-effects for significance. In particular, for the connectedness literature (see e.g. Diebold and Yilmaz, 2014; Alter and Beyer, 2014) we provide a finite sample accurate bootstrap procedure in order to determine the significance of spillover effects and changes in spillovers. Our empirical results confirm that many changes in spillovers where indeed not significant and should therefore be interpreted with care especially on the granular network level but also when evaluating aggregate network characteristics. We obtain these results despite the use of high-frequency data, which generally allows for a much better estimation precision than studies with only daily observations which are the standard case in this literature (see also e.g. Claeys and Vašíček, 2012, 2014). Moreover, in contrast to Ehrmann and Fratzscher (2017), De Santis and Zimic (2018) and others, we focus on credit default swaps which pick up credit information more accurately and quickly than bonds (Buse and Schienle, 2019) being less affected by funding liquidity and flight-to-safety issues (see Pan and Singleton, 2008; Ang and Longstaff, 2011). All three points are key in particular when evaluating the impact of policy or regulatory actions.

Although we are the first to use intraday CDS data to study network spillover effects, the advantages of intraday data in general have been pointed out by several papers. Neil and Fillion (1999) have already stressed that high frequency data should be used to assess the impact of interventions. Similarly, Vergote et al. (2017) argue that daily data is not sufficient to assess the effectiveness of the SMP. For further discussions see also Gyntelberg et al. (2018).

Moreover, according to our knowledge, this paper is the first to consistently analyze ECB programs, economic adjustment programs, the ban of naked sovereign CDS as well as the ISDA regulations from 2014. In particular, the impact of the ISDA regulation in 2014 is a key point which has not been studied in the literature so far but turns out as important also to put the previous measures in context relative to its effect. Compared to the ISDA regulation, the academic discourse on the ban on short-selling of naked sovereign CDS is long and heated with controversial views. In line with Portes (2010) and Kiesel et al. (2015), we find empirical evidence that banning naked sovereign CDS has stabilized markets and reduced speculation. This is in contrast to models by e.g. Oehmke and Zawadowski (2015) that claim that a ban on naked CDS can raise borrowing costs and this potentially drastic liquidity reduction makes the ban overall counter-productive. While their model predicts a negative CDS-bond basis, we empirically find this basis to be almost consistently positive. Short-selling bans have also been analyzed for other markets, e.g. Beber and Pagano (2013) examined stock markets and found reduced liquidity and a slow-down of the price discovery process. However, a direct comparison with our findings is difficult, because bans on stocks were only temporary and limited to certain stocks. Research on the effectiveness of the ECB's unconventional policy measures mainly focused on the ECB's asset purchasing programs and analyzed bond yield data, see for example Eser and Schwaab (2016), Falagiarda and Reitz (2015) or Gibson et al. (2016). Also Arghyrou and Kontonikas (2012) analyse the euro area debt crisis using daily bond data focusing on contagion amongst sovereign entities. By analyzing the effects of policies on CDS markets of both asset purchasing programs as well as EAPs, our paper puts effects of these measures in relative context opening up a much broader perspective on each single action.Arghyrou2012

The paper is organized as follows: The following Section 4.3 carefully describes the intraday data. The model and methods are explained in Section 4.2. Section 4.4 details the results. Section 4.5 concludes the paper.

3.2 Data

Our intraday CDS data consists of price quotes provided by CMA (Credit Market Analysis Ltd.) Datavision. CDS are traded over-the-counter (OTC), which makes the data collection and checking challenging. CMA continuously gathers information on executable and indicative CDS prices directly from the largest and most active credit investors. After cleaning and checking the individual quotes, CMA applies a time and liquidity weighted aggregation so that each reported bid and offer price is based on the most recent and liquid quotes. A detailed descriptive statistics of our data are presented in Appendix 4.6.1. The dataset has specific characteristics which require a closer investigation. The two most important aspects are the number of observations and the intra-daily volatility. First, as can be seen from the average number of observations per day in Table 3.3, there are less observations in 2009 and from mid 2014 onwards. Second, the data provider changes the data aggregation model from 2013 onwards, leading to higher volatility of the data. We show in Appendix 3.6.2 that both of these specifics do not affect our results. The time series of CDS spreads are presented in Figure 3.1. The evolution of euro area sovereign CDS spreads clearly shows the severity of the euro area sovereign debt crisis, as compared to the financial crisis with only a small peak after the Lehman default in 2008. Figure 3.1 also indicates that the time from 2009 until end of 2014 is indeed the most relevant period.

Most of the activity for European sovereign entities in the CMA database is concentrated between 8:30 and 17:30[4], which is why we restrict our intraday analysis to this period. The available number of indicative tick-by-tick quotes for CDS does not allow higher equidistant data frequency than 30 minutes. Hence, we have 18 data points or time-stamps per day. We have tested that for the 30 minute-aggregation of intraday data, we do not observe microstructure noise or volatility smiles which are typical for high-frequency data. The euro area sovereign CDS markets were thin prior to 2009, which makes any type of intraday analysis before 2009 challenging. Therefore, we analyze the CDS market from 2009 until 2014 and focus on 5 year USD denominated CDS which are most liquid.[5]

We use CDS spreads of seven countries: Greece (GR), Ireland (IE), Italy (IT), Portugal (PT) and Spain (ES), the countries which were most affected by the European sovereign debt crisis, as well as France (FR) and Germany (DE).[6] Germany is included as a risk-free country and France as a near risk-free control country. Reliable data for Greece is only available until June 2011. CDS trading for Greece ceased entirely with the restructuring in early 2012.

Most missing values are due to bank holidays. The following treatment of missing values is carried out for a total of 27,180 time stamps between 2009 and 2014, which amounts to approximately 163,080 observations[7]: If, at a given time stamp, four coun-

[4]All times quoted refer to Central European Time (CET).

[5]Sovereign CDS contracts are typically denominated in a currency different from the main tender of the deliverable obligations. The main reason for this is that faced with a credit event, it is assumed that the local currency will come under considerable pressure.

[6]We verify that our results are not affected by the choice or number of selected countries by repeating the analysis with four additional euro area members: Austria, Belgium, Finland and the Netherlands. The results are almost identical and are provided in Appendix 3.6.3

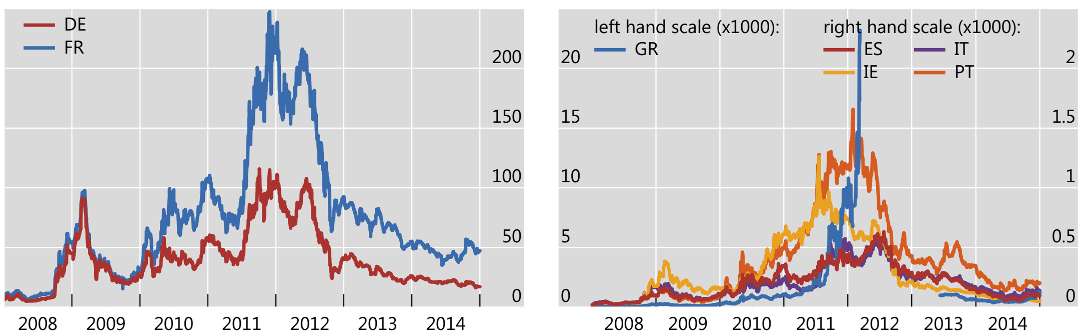
[7]These figures concern the entire dataset from 2009 until 2014 without Greek data.

tries or more have missing values, the entire time stamp is removed which amounts to 7.6% of all time stamps. The rational behind this procedure is our aim to analyze all countries together in a network analysis. After removing these timestamps, the dataset contains 25,107 timestamps and a total of 150,642 observations. The remaining 2,434 missing observations in the CDS dataset are interpolated via Kalman smoothing.[8]

Since liquidity plays an important role especially for the analysis of CDS market regulations, we consider various liquidity proxies, all of which are plotted in Appendix 3.6.4. First, we compute intraday relative bid-ask spreads[9] from the data provided by CMA. In addition, we examine weekly CDS-trading volume from the Depository Trust and Clearing Corporation (DTCC) in form of net notional outstanding and trade counts.

Figure 3.1: CDS levels

The figure illustrates the time evolution of CDS spreads based on intraday data. The data is plotted from 2008 onwards to show the impact of the collapse of Lehman Brothers compared to the sovereign debt crisis.



We test for unit roots and stationarity using the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (see Appendix 4.6.1). All tests consistently indicate that the system of EU sovereign CDS returns is nonstationary of unit root type, hence in our analysis we use first differenced data, i.e. returns.

[8] We have also implemented linear interpolation as a robustness check and find that the two interpolation methods lead to equivalent results.

[9] Relative bid-ask spreads are defined as (ask price-bid price)/((ask price+bid price)/2).

3.3 Model

3.3.1 Dynamic volatility spillover networks

We identify interconnection channels in the EU sovereign credit risk market from time-varying volatility spillover networks of the respective sovereign CDS market. Such dynamic networks are essentially characterized by an adjacency matrix $S = ((s_{ij}))_{ij}$ containing all volatility cross-effects in the system at each point in time. If we have adequate econometric techniques to obtain estimates of S over time (see below) then with each element s_{ij} we can characterize the size of the impact from country j to i at each point in time. In particular, we obtain the directed relative effect as

$$\widetilde{s}_{ij} = \frac{s_{ij}}{\sum_{l=1}^{K} s_{il}}, \tag{3.1}$$

where K represents the number of countries in the network (in our case $K = 7$) and the time index is suppressed for notational convenience. We call $\widetilde{s}_{ij}$ the individual connectedness in accordance with the literature (Diebold and Yilmaz (2009)). Note that the row normalization in Equation (3.1) causes impacts to be directed apart from generating row-wise and thus country-wise comparable percentage values. The resulting connectedness matrices $\widetilde{S} = ((\widetilde{s}_{ij}))_{ij}$ are interpreted as directed adjacency matrices and their components $\widetilde{s}_{ij}$ mark the strength of the effect in the directed edge of node j on i in a network graph. Moreover, we also work with the following two aggregate characteristics of the network, summarizing country-wise and overall effects, respectively. In particular, all connectedness that entity j transfers to all other entities of the system is denoted as country-wise connectedness and computed as a weighted out-degree network descriptive statistic for country j:

$$\widetilde{s}_{j} = \sum_{i=1, i \neq j}^{K} \widetilde{s}_{ij}. \tag{3.2}$$

The network density of the entire system aggregates all cross-correlation spillover effects by summing up all off-diagonal elements of $\widetilde{S}$:

$$\widetilde{s} = \frac{1}{K} \sum_{i,j=1, i \neq j}^{K} \widetilde{s}_{ij}. \tag{3.3}$$

It is denoted by total connectedness. Note that the normalisation $1/K$ in Equation (3.3) ensures that the total connectedness and the country-wise connectedness are on the same scale (see Diebold and Yilmaz (2014)).

If we stack all $K = 7$ considered EU sovereign CDS returns in a system vector $\mathbf{y_t}$, there are several options to obtain the volatility based directed network adjacency matrix $\tilde{S}$ over time. The most straightforward and simple way is to calculate simple descriptive realized correlations

$$s_{ij}^d := RCorr_{ij} = \frac{\sum_{t=1}^{T'} y_{ti} y_{tj}}{\sqrt{\sum_{t=1}^{T'} y_{ti}^2 \sum_{t=1}^{T'} y_{tj}^2}} \tag{3.4}$$

in rolling windows of length T' over time $t = 1, \dots, T$.

In this paper, however, we take a different route with an underlying dynamic system model which thus allows for forecasting and inference in the spillover measures. With this, it is also possible to characterize the surprise effect of events which makes it especially suitable for evaluating crisis periods and unconventional policy or regulation interventions (Buse and Schienle, 2019). In our setting, the adjacency matrix $S = ((s_{ij}))_{ij}$ is derived from the forecast error variance of an appropriate vector autoregression (VAR) model for a subperiod[10]. In particular, we use variance decomposition (Lütkepohl, 2006) to determine the effect of a shock in entity j on the forecast error variance in entity i as s_{ij}. This corresponds to the approach in Diebold and Yilmaz (2014).

In order to estimate the variance decomposition components, we first model $\mathbf{y}_t$ as a VAR for any sub-period of length T_e as

$$\mathbf{y}_t = \sum_{i=1}^{p} A_i \mathbf{y}_{t-i} + \mathbf{u}_t, \quad t = 1, 2, \dots, T_e, \tag{3.5}$$

where A_i are the $(K \times K)$ coefficient matrices and $\mathbf{u}_t$ is a white noise process with zero mean ($E(\mathbf{u}_t) = \mathbf{0}$) and variance $E(\mathbf{u}_t \mathbf{u}_t') = \Sigma_u$ with elements σ_{ij} and $E(\mathbf{u}_t \mathbf{u}_s') = 0$ for $t \neq s$. Note that we have ensured that $\mathbf{y}_t$ is covariance-stationary, thus there exists a moving average representation $\mathbf{y}_t = \sum_{i=0}^{\infty} \Phi_i \mathbf{u}_{t-i}$. As our main goal is the analysis of relevant effects of novel policy and regulation measures, the underlying dynamic structure of the system cannot be captured in a static VAR over the entire sample length T. Instead we require substantial model flexibility allowing for different VAR specifications in different subperiods. Please see the subsequent Subsection 3.3.2 how we determine the length of T_e and the respective p in Equation (3.5) empirically. Moreover for our event study, the rolling window based approach is superior in econometric accuracy to a general time-varying parameter VAR model for the full sample which can only capture smooth changes over time. Please also see the next subsection how we empirically ensure that estimation sub-intervals are small enough that there are no jumps in parameter values in the VAR in Equation (3.5).

Then the H step ahead forecast error variance of the system can be derived using a

[10] VAR models have been widely used in the literature to assess contagion (see for example Ahelegbey et al., 2016)

moving average (MA) representation of (3.5) for any sub-period.

$$E\Big[\big(\mathbf{y}_{t+H}-\mathbf{y}_t(H)\big)\big(\mathbf{y}_{t+H}-\mathbf{y}_t(H)\big)'\Big]=\sum_{h=0}^{H-1}(\Phi_h\Sigma_u\Phi_h'),\tag{3.6}$$

where Φ_h is the h-th coefficient of the MA-representation. $\mathbf{y}_t(H)$ represents the theoretical optimal predictor and can be written in MA-representation as $\mathbf{y}_t(H)=\sum\limits_{i=H}^{\infty}\Phi_i\mathbf{u}_{t+H-i}$, for known Φ_i. In order to obtain a valid connectedness measure, we use variance decomposition of the forecast variance matrix in Equation (3.6). In particular, we employ the generalized variance decomposition (see Koop et al. (1996), Pesaran and Shin (1998)) which is generally preferred to Cholesky decomposition since it is independent of variable ordering. For each entity $i,j=1,\dots,K$, the variance decomposition component for H forecast steps ahead is given by

$$s_{ij}(H)=\frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}(e_i'\Phi_h\Sigma_u e_j)^2}{\sum_{h=0}^{H-1}(e_i'\Phi_h\Sigma_u\Phi_h' e_i)}.\tag{3.7}$$

where e_l is a unit vector in T_e, which is 1 in its $l-th$ component and zero otherwise. For a detailed derivation of Equation (3.7) please see Appendix 3.6.5. For our empirical analysis, we set $H=1$, i.e., we generally compute variance decomposition matrices for one forecast step ahead. This is without loss of generality, since meaningful alternatives with $H=18$ (one day) and $H=90$ (one week) forecast steps ahead yield nearly identical results.[11] For notational convenience, we write s_{ij} instead of $s_{ij}(H)$ in the sequel.

3.3.2 Empirical determination of network effects

We empirically determine network spillovers in the EU sovereign credit risk market from the variance decomposition of the forecast error variance of an underlying VAR in the system. In particular, we focus on size and significance of the impact of the 9 key monetary policy actions and 5 most important regulatory changes on (aggregate) network cross-effects in the years 2009-2014 as displayed in Figure 3.17.

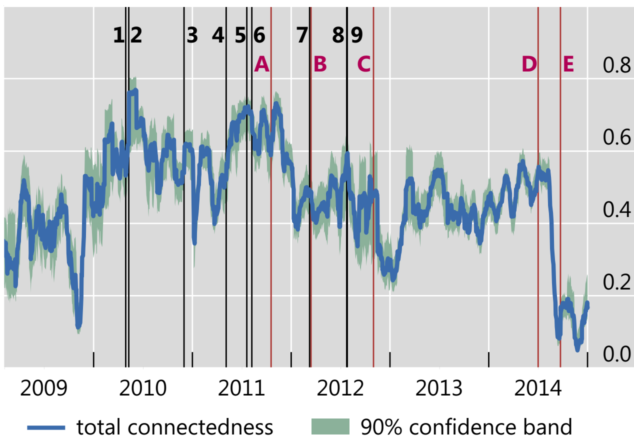
For the volatility spillover measures, we generally aim for a parsimonious model fit in the underlying VAR specification. In particular, the lag order p of the VAR-model is selected according to the Akaike information criterion (AIC)[12] for each estimation window and is restricted to a maximum lag order of three. Including a constant does not improve the model fit. For the analysis of connectedness across time we use a rolling window approach, which incorporates dynamic effects (see Figure 3.17). The window width only affects the variability but not the dynamic structure of the resulting

[11] Results are provided upon request.
[12] Akaike performs better than Schwarz in small samples (Lütkepohl, 2006).

connectedness, which we have compared for different window sizes between 5 days (90 observations) and 40 days (720 observations) with and without Beta-weighting scheme[13]. However, wider rolling windows incorporate effects of certain events for a longer time

Figure 3.2: Time line events and total connectedness

The figure illustrates total connectedness with 90% confidence intervals. Crisis related events are marked as black lines and regulatory interventions are shown by purple lines. The connectedness is computed with a rolling window of 20 trading days and take daily steps for new windows. A fixed number of days implies that when observations are missing, there might be less than 360 observations in one estimation window.



1: Greece: crunch talks	28.04.2010
2: SMP 1st wave	10.05.2010
3: Ireland EAP	30.11.2010
4: Portugal EAP	03.05.2011
5: Greece 2nd EAP	21.07.2011
6: SMP 2nd wave	08.08.2011
7: Greek default	09.03.2012
8: Spanish banks EAP	20.07.2012
9: Draghi's speech	26.07.2012
A: agreement on ban	18.10.2011
B: announcement of ban	14.03.2012
C: implementation of ban	01.11.2012
D: "FAQ" new CDS rules	01.07.2014
E: implementation of rules	22.09.2014

period. We only want to focus on the effects of each individual event and not include a long history of data which may include other effects. Therefore, in order to discern effects on connectedness of events that lie close by one another, it is useful to work with shorter rolling windows. For regulatory changes characterized by a lengthy process we set the rolling window size to 180 observations and for the short-term analysis of crisis-related policy events we look on a finer scale of 90 observations for each window[14]. We also compare individual connectedness (see Equation (3.1)) based on pre-event and post-event windows to evaluate the effectiveness of interventions. The pre- and post-event connectedness networks are calculated using data of five trading days prior to and after an event, whereby the post-event window is shifted by four trading days.[15]

[13] For more details on the beta-weighting scheme see Ghysels et al. (2007).
[14] Due to missing data 90 (180) timestamps may correspond to slightly more than five (ten) trading days.
[15] The rational behind the shift of the start of the post-event window by four days is that we want to

The OLS-based MOSUM stability test (Chu et al., 1995; Kuan and Hornik, 1995) yields evidence of no structural breaks for rolling window sizes of 90 and 180 observations at a significance level of 10%. This is in line with Blatt et al. (2015), who show that structural breaks are less important for small estimation windows. We also verify that heteroscedastic effects are negligible in our data set by applying an ARCH-LM-test as proposed by Engle (1982) and a multivariate Portemanteau test for serial correlation, adjusted for small sample sizes to each estimation window (of size 180). Since the most important part of the data is not significantly affected by heteroscedasticity[16] and in favor of a parsimonious model we exclude heteroscedastic effects from the model. Thus an underlying VAR dynamic specification in rolling windows (3.5) captures the system dynamics in an adequate way.

Our obtained network results are independent from our underlying dynamic model specification and variance decomposition method. We illustrate this by comparing the total connectedness derived from s_{ij} of the variance decomposition in Equation (3.7) to the one based on s^d_{ij} from Equation (3.4) using model-free realized correlation (see Figure 3.3). In Figure 3.3 we see that the dynamics of the two measure are very similar. Therefore, the dynamics of the resulting connectedness measures does not appear to be impacted by specification choices of the underlying model. Thus we conclude that our empirical results in the following are not specific to the variance-decomposition type of spillover measures we use but they prevail in general and thus constitute robust findings.

3.3.3 Significance and precision of volatility impact measures

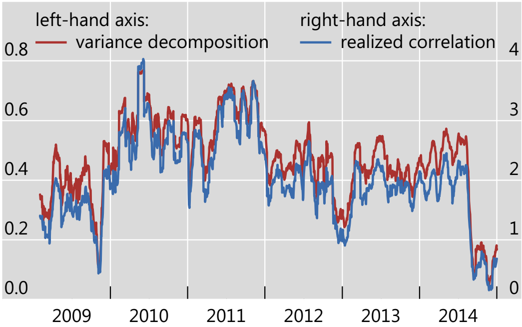
One main technical contribution of this paper is that, in addition to the point estimates of network spillover measures, we also evaluate the respective statistical accuracy of these measures. In particular, we provide bootstrap procedures for deriving the precision of these measures on all network aggregation levels which are valid even if the amount of available data in between successive events is scarce. Hence, we can determine statistically significant effects and distinguish them from less relevant spillovers which might be negligible when evaluating the impact of crisis events, or policy and regulation measures on connectedness.

analyze the medium to long-term effectiveness of the interventions on the network (connectedness) and not the short-term joint adjustment of the CDS spreads of all entities due to the event. The joint short-term co-movement of markets results in a short-term strengthening of connectedness. The four days shift is chosen based on the assumption that credit risk markets react fast to news (see e.g. Daniels and Jensen, 2005). Gyntelberg et al. (2013a) have found half-lives which were on average four days during the crisis period. We have repeated the computation with a shift of three and five days and observe robust results.

[16]Results of both tests show that for the large part, the null of no heteroscedasticity cannot be rejected. The only exception to this is the period before October 2010 for ARCH-tests and the last part of the data after December 2013 for the Portemanteau test in which only few rolling windows show evidence for heteroscedasticity.

Figure 3.3: Realized correlation versus variance decomposition

The figure shows the total connectedness based on correlation and on variance decomposition. The realized correlation is computed for rolling windows of $T' = 20$ trading days.



Bootstrap confidence intervals are commonly computed for impulse response functions (Lütkepohl, 2000) using the MA-representation of the underlying VAR(p) dynamics in Equation (3.5). The following bootstrap method is applied for $B = 1000$ repetitions:

1. Use OLS to derive estimates $\hat{A}$ of the VAR(p) parameters and $\hat{\Phi}_i$ of respective MA coefficients in Equation (3.5) and obtain corresponding centered residuals $\tilde{\mathbf{u}}_t = \hat{\mathbf{u}}_t - \bar{\hat{\mathbf{u}}}_t, t = 1, \ldots, T_e$.
2. Construct $b = 1, \ldots, B$ series of bootstrap residuals $(\hat{\mathbf{u}}_1^{*,\mathbf{b}}, \ldots, \hat{\mathbf{u}}_{T_e}^{*,\mathbf{b}})$ by resampling with replacement for $t = 1, \ldots, T_e$ from the centered residuals $\tilde{\mathbf{u}}_t$, for $t = 1, \ldots, T_e$.
3. Construct the bootstrapped time series recursively as $\mathbf{y}_t^{*,b} = \sum_{i=0}^{\infty} \hat{\Phi}_i \mathbf{u}_{t-i}^{*,b}$ for $b = 1, \ldots, B$. Obtain bootstrapped estimates $\hat{A}^{*,b}$ and $\hat{\Phi}_h^{*,b}$ using OLS for $\mathbf{y}_t^{*,b}$ in Equation (3.5).
4. Use new bootstrap time series to compute $s_{ij}^{*,b}(H) = \frac{(\sigma_{jj}^{*,b})^{-1} \sum_{h=0}^{H-1} (e_i' \Phi_h^{*,b} \Sigma_u^{*,b} e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Phi_h^{*,b} \Sigma_u^{*,b} \Phi_h^{*,b\prime} e_i)}$ as in Equation (3.7). This yields the connectedness measures $\tilde{s}_{ij}^{*,b}(H)$, $\tilde{s}_i^{*,b}(H)$ and $\tilde{s}^{*,b}(H)$ analogous to Equations (3.1) to (3.3) for all $b = 1, \ldots, B$.
5. Define network confidence interval $CI(1 - \alpha)$ as $CI(1 - \alpha) = \left[q_{\alpha/2}, q_{1-\alpha/2}\right]$ where $q_{\alpha/2}$ and $q_{1-\alpha/2}$ are the respective quantiles of the empirical distribution of $\tilde{s}^{*,b}(H)$ over all $b = 1, \ldots, B$.

Note that we set precision bounds with respect to total connectedness. These constitute the statistically adequate finite sample confidence intervals for the overall network density over time and allow to judge overall significant effects of events on total connectedness in the system. Technically, it would also be possible to derive confidence intervals for country-wise or element-wise connectedness within each network at each point in time. But we decided to assess these more granular network measures all with respect to a single network-specific accuracy interval per point in time instead of individual quantities.[17] Thus evaluation of relevant network spillovers occurs by a common shared benchmark and which is computationally attractive to obtain.

3.4 Results

During the European sovereign debt crisis there have been various efforts to stabilize and calm markets. We investigate how these interventions affected connectedness respective systemic risk in credit-risk markets using intraday CDS spreads. In addition, we analyze the channels of the volatility spillovers and investigate the topology of corresponding cross-effect networks. The considered period from 2009 until the end 2014 contains crisis-related policy measures and general regulations relating to the CDS market. The chronological evolution of events is shown in Appendix 3.6.6. In the following, we discuss the impact of events in thematic subsections structured along the importance of our main empirical findings. We start with the analysis of the effectiveness of regulations such as the ban and the new ISDA rules. We then investigate the unconventional monetary policy of the ECB.

3.4.1 The effect of regulatory actions

The large significant impact of the ban and the new ISDA rules

There have been two important regulatory changes in the CDS market: the ban on short-selling uncovered sovereign CDS in 2012 and the market-led change to CDS trading resulting in new CDS definitions and standard reference obligations defined by the ISDA in 2014.[18] Both of these regulations were successful in the sense that they succeeded in calming markets (reduced total connectedness) and in the case of the uncovered CDS ban in reducing speculation.

Starting with the discussion of the introduction of the new CDS definitions, we find a dramatic reduction in total connectedness in the left-hand panel of Figure 3.4 between the publication of the details of the rules (01.07.2014, marked by D) and their implementation (22.09.2014, marked by E). This reduction is strongly significant, as can be seen from the confidence intervals in the time series plot of total connectedness (left-hand

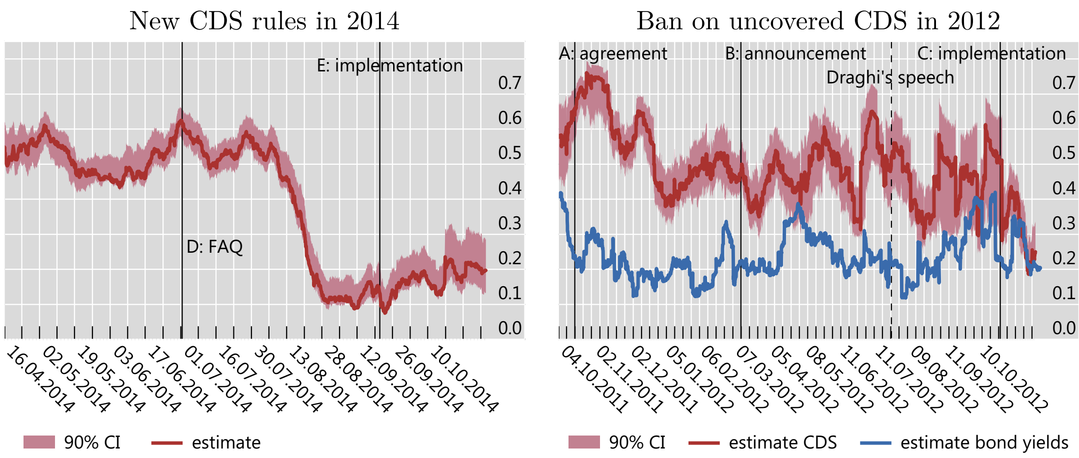
[17] Note that by construction, individual connectedness is not necessarily smaller (larger) for the lower (upper) confidence interval boundary from total conncetedness.

[18] A big benefit of the new rules is the standardization of the reference obligation and hence a reduction of trade break risk. Furthermore, it removes potential basis risk between transactions that have the same reference entity but different reference obligations. The new rules also allow for consistent treatment of cleared and uncleared transactions.

panel of Figure 3.4). Disagregating the total connectedness into its individual components, country-wise connectedness, supports as expected this finding. The country-wise connectedness of all countries decreases strongly and almost synchronously (results are provided upon request). We can conclude that the new CDS rules have strongly and significantly reduced spillover risk and hence have been effective.

Figure 3.4: Evolution of connectedness linked to regulations in the CDS market

The figure shows the evolution of connectedness linked to the introduction of new CDS rules in 2014 (left-hand panel) and the ban of naked sovereign CDS in 2012 (right-hand panel). The right-hand panel shows the time evolution of total connectedness computed with CDS in red and with bond yields in blue. A 180 observations rolling window is used to compute the time series graph for total connectedness.



The permanent ban on outright short-selling of sovereign CDS contracts across all members of the European Economic Area (EU regulation 236/2012) was introduced in 2012 due to concerns that speculative behavior in the sovereign CDS market led to excessively high credit spreads in the most distressed countries. The period between the first agreement on the ban (18.10.2011, event A) and its implementation (01.11.2012, event C) covers a time span in which further important crisis-related events took place, such as Draghi's speech. In order to disentangle the effects of the CDS ban from other events we compare the connectedness measures of CDS spreads (in red in Figure 3.4) and bond yields[19] (in blue in Figure 3.4). In particular, the fact that the credit situation of a sovereign entity can be inferred from both bonds or CDS, allows for identification of the impact of the ban since bonds are not directly affected by this CDS regulation. After it became clear that a permanent ban will be implemented (18.10.2011, denoted by

[19]We use 5-year zero coupon sovereign intraday bond yields from MTS.

A), we observe a significant decrease in CDS connectedness while connectedness based on bond yields remains at a steady level (0.1-0.4). Hence the ban was the driving force in reducing CDS connectedness. Figure 3.4 suggests only a slight impact of the Draghi speech on connectedness of both bond yields and CDS.

In order to assess the success of the ban in more detail, we examine country-wise behavior using CDS spreads in levels and country-wise connectedness in Figure 3.5. CDS spreads (left-hand panel of Figure 3.5) decrease most for Portugal and Ireland, the countries which were most affected by speculation (Greece as well, however the ISDA triggered a Greek default in 2012 and hence we do not consider Greece from 2012 onward). In Table 3.1 we present figures of net notional amounts outstanding CDS contracts divided by the amount of bonds traded on the MTS platform (as a proxy of bond market size) aggregated on annual frequency. We see that up to and including 2012 the CDS market grows faster than the bond market. Most importantly the growth is strongest for Greece, Ireland and Portugal, supporting our notion of strong speculations against these countries in the CDS market.

Table 3.1: CDS trading volume versus bond trading volume

The table presents annually aggregated net notional amounts of CDS outstanding based on weekly DTCC data devided by aggregated bond trading volumes based on tick-by-tick data from MTS.

	France	Germany	Greece	Ireland	Italy	Portugal	Spain
2009	3.1	6.8	15	10.7	1.1	0	6.0
2010	2.3	7.0	23.7	12.0	1.1	4.6	4.4
2011	3.3	10.1	127.3	44.9	1.1	20.8	7.2
2012	4.6	15.1		85.4	1.4	27.2	6.9
2013	2.7	7.3		34.2	0.8	14.1	3.0
2014	2.1	8.4		5.5	0.5	1.5	1.5

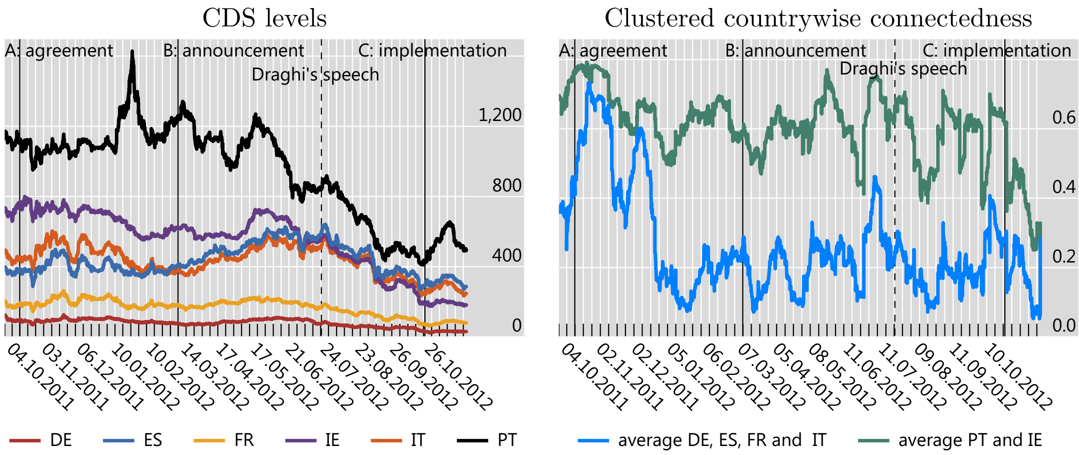
In line with our above reasoning we also find consistently that country-wise connectedness shown in the right-hand panel of Figure 3.5 for Ireland and Portugal falls most.[20] While country-wise connectedness of France, Germany, Italy and Spain remain rather unchanged after the announcement of the ban, the connectendess of Ireland and Portugal decreases quickly, suggesting that speculators left the market as intended by the ban. This behavior is in contrast to the time evolution of country-wise connectedness after

[20] Country-wise connectedness is represented by averages of Ireland and Portugal in green and for the other countries in blue for graphical clarity. A graph with each country-wise connectedness shown individually can be provided upon request.

the CDS rules in 2014, where the individual connectedness of all entities react equally strong and almost synchronously.[21] Clearly, the provided evidence together with the statistical significance suggest that the ban was successful in reducing speculation and spillover risk. Our findings are in line with Che and Sethi (2014) and also support the early call of a ban of naked sovereign CDS from Portes (2010).

Figure 3.5: Evolution of CDS levels and clustered countrywise connectedness

The figure illustrates CDS levels and clustered country-wise conectedness: one cluster contains Portugal and Ireland, the other cluster France, Germany, Italy and Spain.



No pure liquidity story

Despite the positive impact of CDS regulations shown above, there have also been concerns about negative side-effects on liquidity (see, e.g. Duffie, 2010). It is a common belief that the results presented above can be entirely explained through liquidity leading to reduced price informativeness (see, e.g. Silva et al., 2016), in a sense that the CDS market has dried out and does not price credit risk efficiently after the ban.

Since CDS are traded over-the-counter (OTC), it is challenging to measure liquidity reliably. However, with the available data we find no signals that the CDS market for sovereign CDS dried out due to the ban or the new ISDA definitions. This is illustrated by the relative bid-ask spreads in Figure 3.6 which only increase modestly around the regulatory interventions. Our finding that the ban had no compelling impact on liquidity is in line with the ESMA final report 2013/614 and shows that the allowance to trade

[21] A graph of the behaviour of individual connectedness is provided upon request.

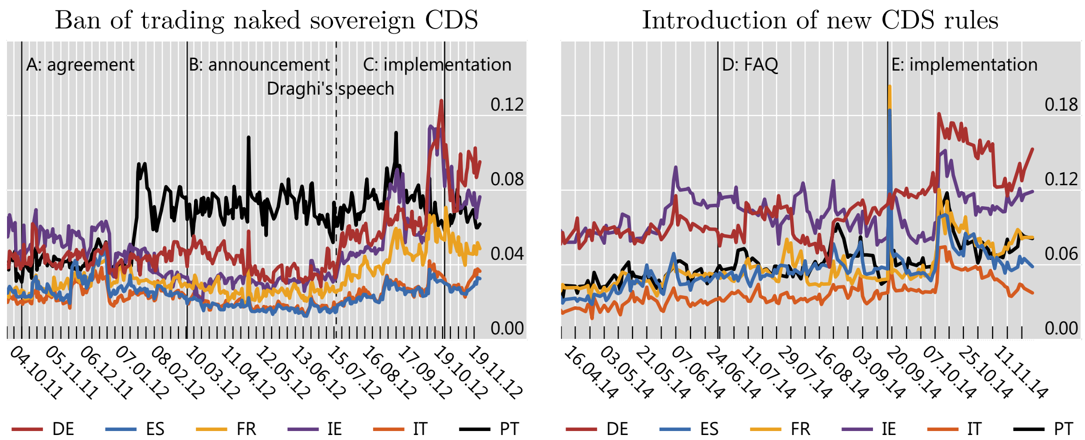
naked sovereign CDS for market making worked as intended. The left-hand panel of Figure 3.6 shows a slight decrease of liquidity beginning after the Draghi speech and ending with the implementation of the ban. This is an indication that both Draghi's speech and the ban have reduced speculation. A further indication of less speculation against the most distressed countries is the increase of Portuguese bid-ask spreads after the announcement of the ban (in between events A and B).

Across the entire sample between 2009 and 2014, the relative bid-ask spreads (Figure 3.15 in Appendix 3.6.4) only change moderately.[22] This evidence for a rather stable liquidity is confirmed by comparing two further proxies for liquidity: net notional amounts outstanding and number of trade counts. Although volume of net notional amounts outstanding slightly decreases from 2011 onwards, trade counts showed an upward trend, indicating increased market activity (see Figure 3.16 in Appendix 3.6.4).

Hence, our findings with regard to connectedness or systemic risk cannot be explained by a simple liquidity argument only. Thus, with the combined evidence of Subsection 3.4.1 and 3.4.1 we conclude that the ban and the ISDA regulations were successful.

Figure 3.6: Evolution of liquidity around the ban in 2012 and the ISDA regulations in 2014

The figure illustrates the time evolution relative CDS bid ask-spreads for individual countries.



[22]Liquidity increases in 2009 due to the introduction of the first clearing houses and standardization of contracts. The ISDA "Big Bang Protocol" has increased transparency and market integration and hence increased market activity.

3.4.2 The effect of unconventional monetary policies

During the European sovereign debt crisis, several policy interventions targeted a specific country, e.g. the bailouts for Greece, Ireland, Portugal and the Spanish banks (events 1, 3, 4, 5 and 8 in Figure 3.17). Furthermore, there have been ECB-programs for the entire euro area, namely the Securities Markets Program (SMP) (events 2 and 6 in Figure 3.17) and the Outright Monetary Transactions (OMT) which were announced by Draghi's speech "whatever it takes" (event 9 in Figure 3.17).

Public learning diminishes effectiveness

Public learning dynamics about unconventional policy measures influence their impact. This is true for both country-specific bailouts as well as the European-wide SMP.

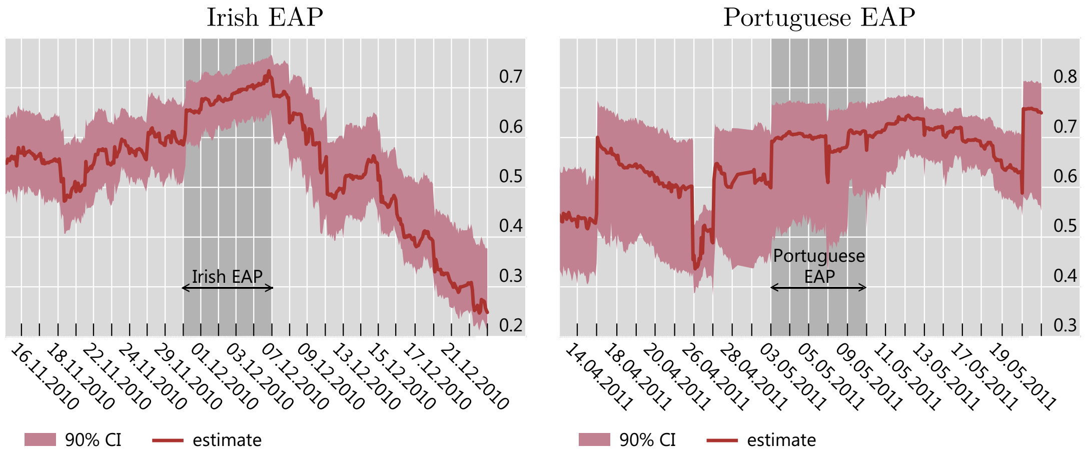
Generally, we find that the impact of sovereign bailouts decreased progressively. The Greek bailout in 2010 was the first of its kind. As it came as a surprise, because it undermined the Maastricht treaty, this unconventional policy had a strong effect (see Figure 3.8). When comparing the two consecutive bailouts of Ireland and Portugal respectively (total connectedness around these events are shown in Figure 3.7) we observe weaker effects. After financial aid for Ireland was decided, total connectedness decreased significantly. However, the Portuguese bailout six months later seems to have no impact on connectedness. The shrinking effectiveness of bailouts on stability was counteracted when a second EAP for Greece was discussed.[23] The second bailout of Greece was linked to an enormous increase in the European Financial Stability Facility (EFSF) from €440bn to €780bn. Unconventional policies remain effective as long as they stay unconventional, otherwise the size of the intervention needs to increase in order to ensure their effectiveness. Accordingly and in contrast to the Portuguese financial aid package, we see an effect of the second Greek EAP on total connectedness in Figure 3.9.

Similarly to increasing the scope of the EFSF for the second Greek bailout, the amount of bonds bought within the second round of the SMP was by far larger than during its first implementation. The second wave of the SMP, despite being more aggressive than the first SMP, was only able to level out total connectedness (see Figure 3.9). In contrast to this, the first wave of the bond purchases within the SMP was able to significantly reduce spillover risk and CDS spreads in levels (see Figure 3.8). This confirms reduced effectiveness of interventions over time for both European-wide as well as country-specific unconventional policies, as also supported by the Lucas critique (Lucas, 1976). Market participants adjust their behavior with changes of decision makers' policies and regulations and price in any potential future intervention.

[23] On 21.07.2011, the Euro Summit came to an agreement on a second bailout for Greece, just one day after Merkel and Sarkozy met to develop a common stance on Greece.

Figure 3.7: Evolution of spillover risk, evidence from the Irish and Portuguese EAP

The graphs show the evolution of total connectedness around the bailouts. The grey area in the left and right panel designates the time period in which the effect of an event is included in the rolling windows following the event.



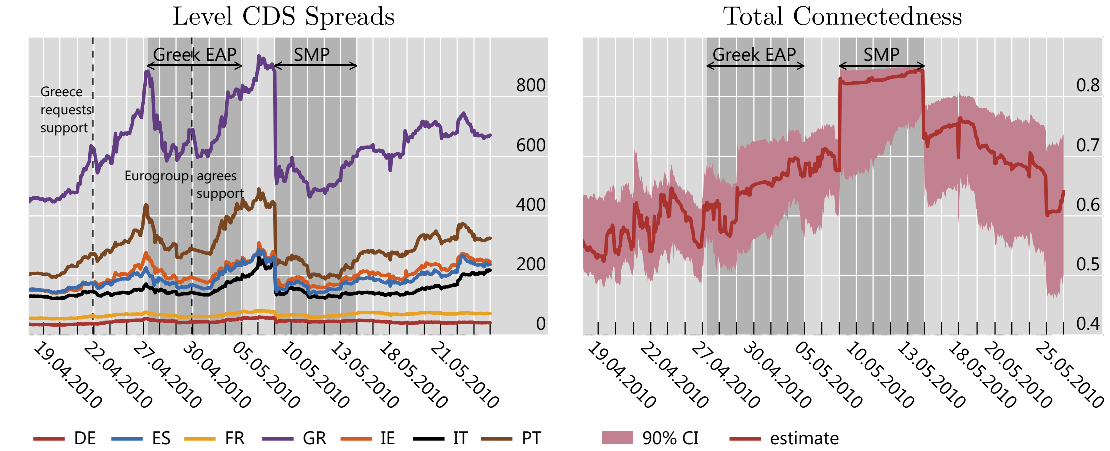
Impact of European-wide measures versus single country actions

We show that European-wide interventions have a stronger and longer lasting impact than events which only target a particular country. One example for this is the first Greek bailout and the subsequent implementation of the SMP. CDS levels and connectedness around these events are shown in Figure 3.8. The key observation is that the effect of the Greek EAP was not sustainable while the SMP was able to reduce CDS spread levels and total connectedness.

On 28.04.2010 (beginning of the grey background in Figure 3.8) EU and IMF officials held crunch talks with German politicians, from which rumors of a €120bn emergency package for Greece emerged. The levels of CDS spreads fell abruptly after this meeting but it had only a short-term effect. Despite the bailout for Greece agreed upon by the Eurogroup (03.05.2010, marked by the second dashed line in the graph) we observe a strong increase of CDS levels one day later. Total connectedness increased steadily during this period because the short-term effects were meaned out. While the bailout for Greece had a strong yet unsustainable effect, the SMP had a more lasting effect in the long run. On 09.05.2010 the ECB decided on the SMP, within which it started to buy large amounts of bonds on the secondary market the following day. Consequently, spread levels fell abruptly and to a larger extent than after the Greek EAP was agreed. The SMP was also successful in reducing connectedness, even though it does not significantly attain pre-event levels due to the revealed instability in Greece.

Figure 3.8: First Greek EAP and SMP

The figure illustrates the time evolution of CDS spreads (left-hand panel) and total connectedness (right-hand panel) as well as two network graphs, showing individual connectedness. The grey area in the left and right panel designates the time period in which the effect of an event is included in the rolling windows following the event.



More than one year later, the same observation (of a higher effectiveness of European-wide interventions than country-specific measures) is made for the second Greek EAP and implementation of the SMP. Again, there is a longer lasting effect on reducing spillover risk due to the SMP as compared to the second Greek EAP. Connectedness drops after the bailout but soon increases again, whereby the second wave of the SMP generates a downward trend in systemic risk. Even though CDS levels react strongly after the second Greek bailout, they slightly raise afterwards again.

For Draghi's speech and the Spanish bailout, the picture is less clear as their close timely succession makes it hard to disentangle effects. Although total connectedness decreases after Draghi's speech (26.07.2012), the close sequence of the Spanish bailout (20.07.2012) and the speech does not allow to strictly separate the effect of the two events on connectedness. However, there is a decrease of CDS levels after Draghi's speech (first dashed line in Figure 3.10), whereas after the Spanish bank bailout CDS spreads rise (first solid line). This points to the more stabilizing effect of Draghi's promise to sustain the euro. Generally, changes in total connectedness are small and our bootstrapped confidence intervals indicate that these changes are not significant and thus not interpretable.

Thus generally for policy interventions, it is their scope which matters most for judging significance and persistence of their impact on systemic risk.

Figure 3.9: Second Greek EAP and second wave of SMP

For details concerning the figures we refer to Figure 3.8.

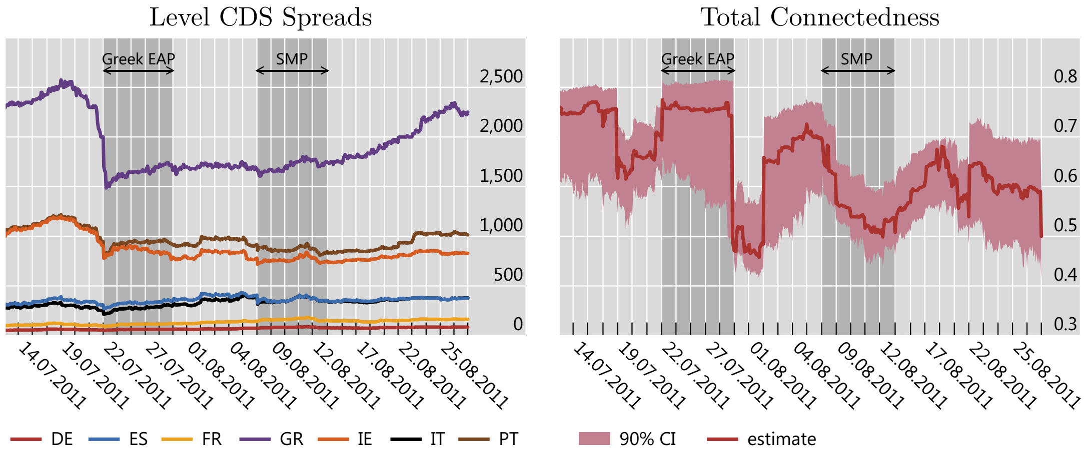
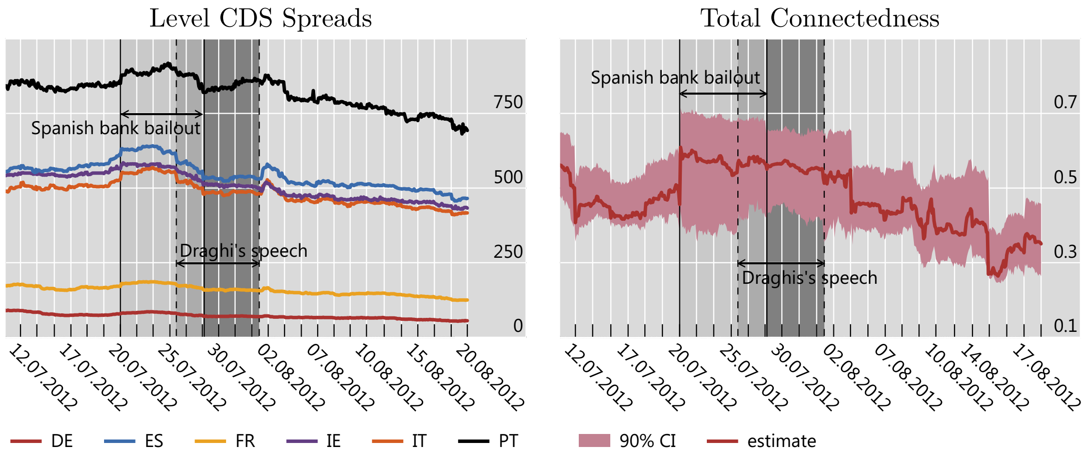


Figure 3.10: Spanish bank bailout and Draghi speech

For details concerning the figures we refer to Figure 3.8.



No fragmentation of European sovereign credit risk

We are the first to evaluate individual connectedness using intraday CDS data in order to analyze credit risk spillovers. Overall, we find balanced networks, in a sense that we do not observe fragmentation defined as a split-up of the network into independent subnetworks (fragments).[24] Also, we do not find a centering of an impaired country such as Greece in the network structure. This is in sharp contrast to existing studies using daily bond yields such as e.g Ehrmann and Fratzscher (2017), Santis (2014) or Caporin et al. (2013) where the latter even find evidence for disintegration as still on-going at the end of their sample in April 2013. Though, in contrast to CDS spreads, the bond market was driven by flight-to-safety effects and hence was directly impacted by the SMP and OMT. Thus for assessing credit risk, CDS based measures are also generally considered as more suitable than bonds (see, e.g. Pan and Singleton, 2008; Ang and Longstaff, 2011). The advantage of CDS versus bonds in this context has also been documented empirically by a lead-lag behaviour (see, e.g. Buse and Schienle, 2019; Alter and Beyer, 2014).

Between the agreement of the permanent ban of naked sovereign CDS trading (end 2011) and the announcement of the technical details of the ban (beginning 2012) we observe a statistically significant drop of connectedness. This effect appears later than what is reported in networks using bond yields (see, e.g. Ehrmann and Fratzscher, 2017; Caporin et al., 2013). A possible reason for an earlier effect in networks based on bond yield data are the economic adjustment programs and the close supervision of these countries under bailout by the Troika as well as dry-out of bond trading in these impaired countries. It can be observed in the left-hand panel of Figure 3.11 that all countries become less connected during the period October 2011 to March 2010. Especially the volatility spillover channels for Ireland and Portugal with other countries weaken, however they become not disconnected or fragmented. Unlike Ehrmann and Fratzscher (2017) we do not find a segregation of Italy and Spain. On the contrary, Italy and Spain are equally connected to other countries (see left-hand panel of Figure 3.11).

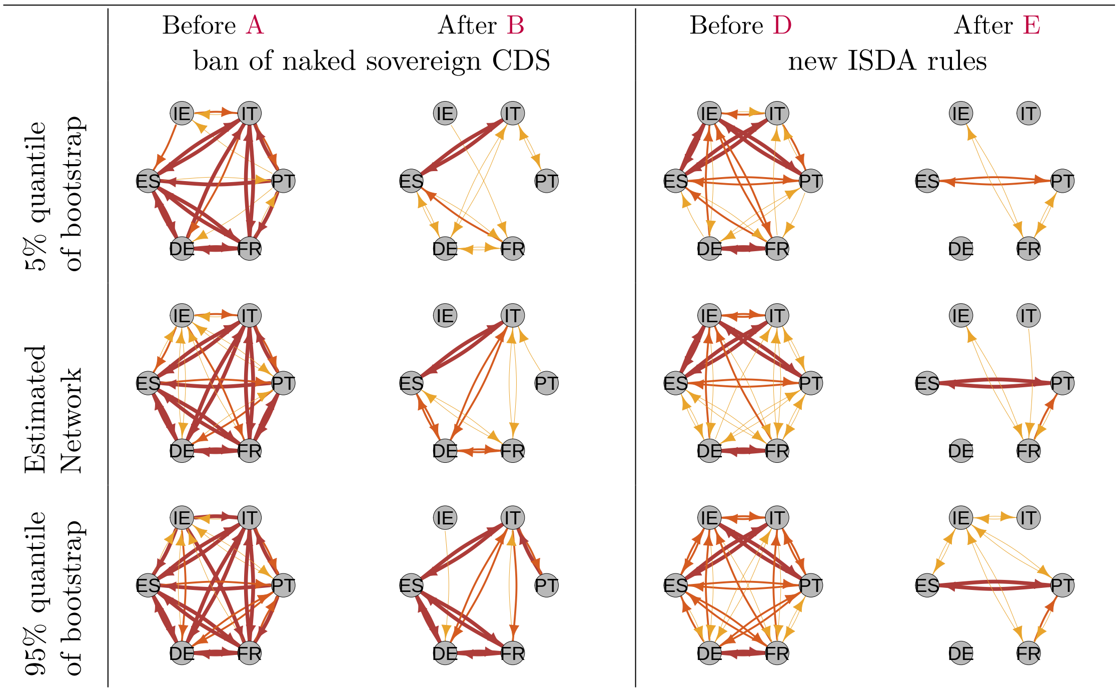
We are the first to analyze changes in credit risk spillover induced by the new ISDA rules in 2014. The rules are implemented in September 2014 (marked E in Figure 3.11), however the technical details of the implementation are known to market participants already 01.07.2014 (marked D). Comparing the networks (see right-hand panel) we recognize a dramatic reduction in individual connectedness. We want to stress that the network graphs of the post implementation period do not show a fragmentation. Similar to the ban, the network remains balanced after the ISDA rules, however, our results prove that the market-led regulations have been extraordinary successful in reducing credit risk spillovers.

Connectedness rises dramatically between the end of 2009 and the first Greek bailout in April 2010, leading to a strong integration of the sovereign network. This increase at the beginning of the sovereign debt crisis is comparable to “wake-up call” contagion as identified for the bond market by Giordano et al. (2013). Before the first Greek bailout (a violation of the Maastricht treaty), we can see two groups of countries in the network (see left-hand panel in Figure 3.12). The first group consists of peripheral countries,

[24]Ehrmann and Fratzscher (2017) define fragmentation as a reduction in credit risk spillovers, while we define fragmentation as used in colloquial language.

Figure 3.11: Evolution of connectedness linked to the CDS ban and the new ISDA rules

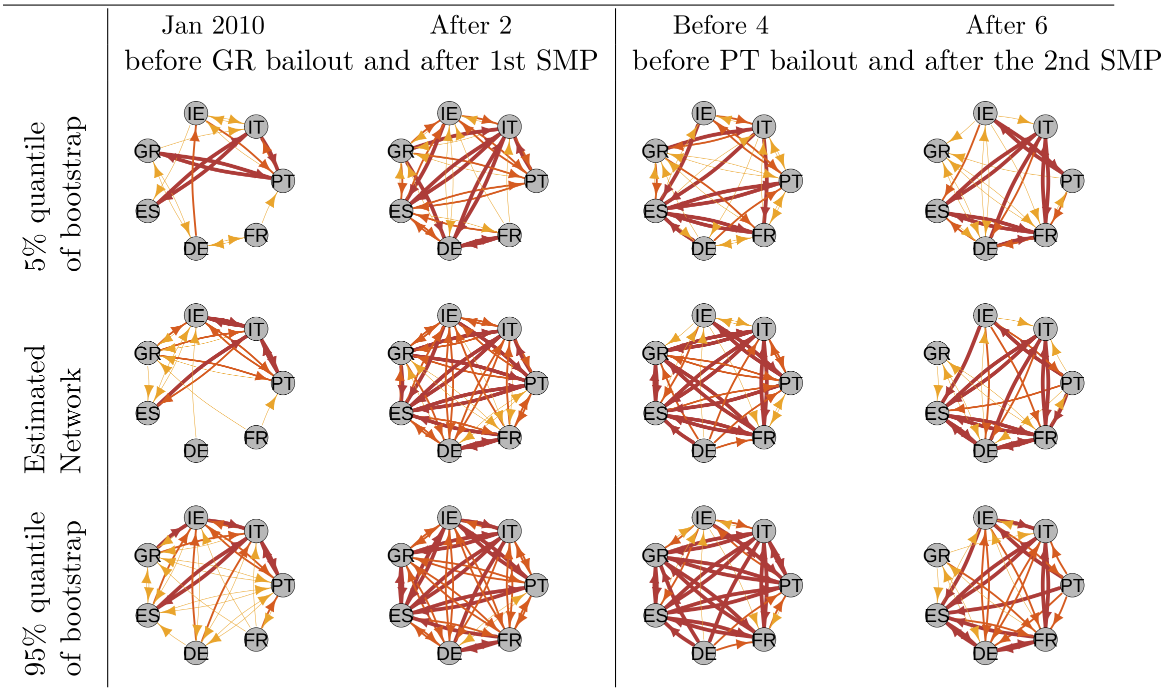
The figure illustrates individual connectedness in form of network graphs including estimates (middle), lower confidence interval boundary (top) and upper confidence interval boundary (bottom). The network graphs are computed with five trading day windows. Nodes represent countries and arrows represent individual connectedness measures, e.g. an arrow from country j to country i visualizes $\widetilde{s}_{ij}$ (see Equation (3.1)). The width and colour of the connecting lines indicate the strength of the connectedness: bold red lines indicate strong connectedness (fourth quartile), orange lines indicate upper medium connectedness (third quartile), thin yellow line indicate lower medium connectedness (second quartile) and no connecting line indicates small connectedness (first quartile). The arrows at each line show the directedness of the connectedness.



which are strongly connected among each other. The second fragment consists of France and Germany, which are weakly connected with other countries. This observation is in contrast to results of Ehrmann and Fratzscher (2017) for bond markets. Our analysis clearly shows two effects on the network after the bailout and the SMP: It becomes more balanced or less fragmented and the high level of overall total connectedness decreases significantly in size (see Figure 3.8) at the expense of more spillover channels. This is because large countries such as France and Germany now also share credit risk of the crisis countries due to the bailout facility.

Figure 3.12: Evolution of connectedness linked to the Greek and Portuguese bailout

The figure illustrates individual connectedness in form of network graphs. For details we refer to Figure 3.11.



After the first Greek bailout and implementation of the SMP the structure of networks remains relatively stable throughout the crisis. The bailouts for Ireland and Portugal and the “whatever it takes” speech do not induce a significant change in individual volatility spillovers. Even though total connectedness decreases after Ireland‚Äôs bailout, the network connections mostly remain the same. Of all events during the crisis, volatility spillovers change most after the second Greek bailout and bond-buying within the SMP in 2011. However, only the decreasing connections of Italy with Portugal and Ireland were significant. Similarly, the only significant changes in the network structure after the first Greek bailout and SMP implementation in 2010 are between Germany and Italy and from Greece to Ireland.[25]

An important exception to the unaltered networks is the isolation of Greece between the Portuguese bailout and the second Greek bailout and SMP implementation (see right-hand panel of Figure 3.12). Thanks to this isolation and the reduced exposure of financial intermediaries to Greece its (official) default on 09.03.2012 did not strongly affect other countries in the network.

3.5 Conclusion

The focus of the paper is the analysis of the effectiveness of regulations and policies during the euro area sovereign debt crisis, from beginning 2009 until end 2014. In our context, we define effectiveness as a statistical significant drop in connectedness between sovereign entities within the network. We have estimated connectedness based on variance decomposition and computed corresponding confidence intervals employing a bootstrap methodology to judge the statistical significance of our results. Our analysis rests on intraday sovereign CDS data. A key advantage of intraday data is that the large amount of observations enables us to compute precise connectedness measures for a particular regulatory or policy event unblurred by other nearby events. The reason behind this advantage is that we can chose much smaller event windows in our analysis as compared to research based on daily data (e.g. Ehrmann and Fratzscher (2017) and Caporin et al. (2013)).

We focused on two important regulations of the credit risk market, the ban on trading naked sovereign CDS in 2012 and the implementation of the new ISDA rules in 2014. We show that they have been important in reducing connectedness between European sovereigns. The new ISDA rules on CDS definitions and standard reference obligations resulted in a fast, strong and statistically significant reduction in connectedness. With respect to the ban, total connectedness reduced also strongly during the period of the announcement and the implementation. However, the period is rather lengthy and it was at the height of the crisis with many events taking place. Therefore, linking the reduction to the ban is not straightforward. By comparing connectedness measures

[25]The relevant network graphs are provided upon request.

based on bond data, which is affected by credit conditions, but not by the ban, we can conclude that the CDS ban was crucial for calming markets. Furthermore, by disentangling total connectedness into its components, we have found that Irish and Portuguese connectedness dropped most. Ireland and Portugal were most affected by speculation. Hence, we can conclude that the ban on uncovered CDS was effective and especially successful in reducing speculation for Ireland and Portugal. The ban and the new ISDA rules had some moderate adverse impact on liquidity, however far from the fear that the markets may dry out and lead to an inferior CDS market for single name sovereign CDS. With respect to volatility spillovers between sovereign CDS, the regulations seemed to be more important than other interventions such as Draghi's speech.

A key finding of our analysis is that the economic adjustment programs for Greece, Ireland and Portugal were able to reduce spillover risk only for a short period, until negative market perceptions bounced back. Euro-wide programs such as the SMP had a longer lasting and stronger effect. Furthermore, the effect of an unconventional policy measure diminishes when it is implemented more than once. The decreasing effectiveness can be counteracted by an increase in the size of the intervention. Before the second Greek economic adjustment program, the bailout facility was drastically enlarged in order to counteract the reduced effectiveness.

Finally, we do not observe fragmentation in European sovereigns credit markets. The networks are balanced and there was no single source of contagion in a sense of a central node network. After the start of the second SMP we see that Greece is slightly isolated, which can be judged as one reason why the latter Greek default did not impact the network.

The analyzed events indicate that the implemented active policy and regulatory measures helped to substantially reduce the impact of the European debt crisis. Here in particular, regulatory actions played a key role producing sustainable effects in contrast to monetary policy measures where the effect was only short-term and vanished over time. Thus in severe crisis situations, monetary policy actions can only pave the way until regulatory adjustments are taken and do not provide a long-term solution in themselves.

3.6 Appendix

3.6.1 Descriptive Statistics

The descriptive statistics of the intraday CDS data is presented in Table 3.3. We have split the data in 5 periods, within which we have found similar statistical behavior. The first period covers the entire year 2009 and the second period starts in 2010 and ends on the 18.10.2011, when it became clear that the anticipated ban of uncovered sovereign CDS will become permanent. The third period ends in December 2012 and contains the discussion period on how the ban should look like in detail and the implementation of the ban. The fourth period starts in January 2013 and lasts until end of June 2014. This period contains the consultation period and announcement of the important changes on credit derivatives definitions and standard reference obligations, which became effective on the 22.09.2014 and which falls in our last period.

We report the mean, median and standard deviation as well as the mean bid-ask spread and the average number of observations. The mean and median reported in Table 3.3 are consistent with the timeseries plots in Figure 3.1. The standard deviation growth as expected with the mean/median. We furthermore measure the changes within a day relative to the changes from one day to the next by comparing mean absolute differences (MAD) in a ratio.[26] A ratio smaller than 1 shows that the data varies less within one day than across days. This is almost always the case, with exception of Germany, France and Ireland in 2013 and 2014. While we have almost no-empty timestamps in 2010-2012 we recognize that data availability slightly decreased in 2013 and more in 2014, which is reported in the average number of observations per day in Table 3.3.

We have also analyzed the first differences of CDS spreads and have found that the mean and the median of the first differences are around zero. The standard deviation is in the order of one, with slightly larger values for the crisis countries. The standard deviation for Greece in the second period is largest and equal to 14.32.

Results on the unit root and stationarity tests are presented in Table 3.2 for levels and first differences. We conclude that all series are integrated of order one.

[26] For robustness reasons, we consider averages of the first and second half of one day, which we denote by $\bar{d}_t^1$ and $\bar{d}_t^2$, respectively. Intraday MAD is then computed by $\sum_{t \in T} |\bar{d}_t^2 - \bar{d}_t^1|$ and inter-day MAD is computed by $\sum_{t \in T} |\bar{d}_{t+1}^1 - \bar{d}_t^2|$. The ratio, intraday MAD divided by inter-day MAD shows how much the data varies within one day compared to across days.

Table 3.2: Unit root and stationarity tests for CDS data - 2009-2014

The table reports the statistics of unit root and stationarity tests for the period from January 2009 to December 2014. The null hypothesis of the ADF and PP test is: the data has a unit root. For the KPSS test, the null is stationarity, and the 0.01, 0.05 and 0.10 critical values for the test statistics are 0.739, 0.463 and 0.347, respectively.

	levels			first differences		
Sovereign	p_{ADF}	p_{PP}	KPSS stat.	p_{ADF}	p_{PP}	KPSS stat.
France	0.40	0.53	4.74	0.00	0.00	0.09
Germany	0.25	0.43	3.71	0.00	0.00	0.36
Greece	1.00	1.00	14.31	0.00	0.00	0.65
Ireland	0.76	0.77	5.21	0.00	0.00	0.25
Italy	0.48	0.35	6.23	0.00	0.00	0.17
Portugal	0.96	0.89	6.23	0.00	0.00	0.26
Spain	0.21	0.25	6.24	0.00	0.00	0.17

Table 3.3: Descriptive statistic of intraday CDS spreads

The table presents a detailed descriptive statistics for five periods, for which we have found similar statistical behaviour of the CDS levels. The mean, median and standard deviation (std dev) is reported, as well as the ratio of mean absolute difference (MAD) of intraday and inter-day level changes. Further, the mean of the bid-ask spread and the average number of observations per day is reported. No figures are shown for the last three periods for Greece because of the Greek restructuring.

		1.1.09-31.12.09	1.1.10-18.10.11	19.10.11-31.12.12	1.1.13-30.6.14	1.7.14-31.12.14
Germany	Mean	38.64	48.45	74.78	28.01	20.84
	Median	33.33	43.12	80.97	25.33	20.75
	Standard deviation	19.74	17.62	24.45	6.91	2.28
	MAD intra/inter ratio	0.38	0.22	0.24	2.01	2.09
	Mean bid-ask-spread	0.11	0.06	0.05	0.08	0.12
	Average obs/day	14.42	17.73	17.50	16.64	14.98
France	Mean	41.92	87.46	162.90	63.41	46.76
	Median	35.58	78.75	175.50	64.94	45.87
	Standard deviation	20.85	36.03	48.17	13.90	5.70
	MAD intra/inter ratio	0.38	0.17	0.20	1.47	1.59
	Mean bid-ask-spread	0.11	0.04	0.03	0.04	0.07
	Average obs/day	14.49	17.82	17.55	16.72	15.02
Greece	Mean	172.00	960.53			
	Median	154.16	863.06			
	Standard deviation	54.55	524.13			
	MAD intra/inter ratio	0.29	0.21			
	Mean bid-ask-spread	0.05	0.04			
	Average obs/day	15.18	17.64			
Ireland	Mean	203.06	476.85	521.62	128.42	55.52
	Median	184.33	537.35	575.89	136.83	54.50
	Standard deviation	65.34	247.53	186.00	41.72	5.21
	MAD intra/inter ratio	0.28	0.20	0.28	1.14	1.88
	Mean bid-ask-spread	0.05	0.04	0.05	0.07	0.11
	Average obs/day	15.18	17.87	17.44	16.86	15.14
Italy	Mean	108.72	202.93	422.43	204.81	115.88
	Median	94.75	177.62	437.55	229.50	111.00
	Standard deviation	40.86	94.67	94.21	61.33	20.32
	MAD intra/inter ratio	0.29	0.16	0.19	0.47	0.90
	Mean bid-ask-spread	0.05	0.03	0.02	0.02	0.04
	Average obs/day	15.23	17.86	17.59	17.35	15.67
Portugal	Mean	80.71	492.75	911.46	338.43	188.28
	Median	72.75	432.45	1033.13	362.50	191.83
	Standard deviation	28.54	294.02	284.25	107.28	23.79
	MAD intra/inter ratio	0.29	0.19	0.35	0.50	0.69
	Mean bid-ask-spread	0.06	0.04	0.06	0.04	0.07
	Average obs/day	14.86	17.87	16.75	17.03	15.36
Spain	Mean	93.68	245.05	429.43	191.06	83.07
	Median	87.70	238.50	405.88	214.60	78.00
	Standard deviation	27.37	80.80	92.10	71.86	17.07
	MAD intra/inter ratio	0.27	0.18	0.19	0.54	0.93
	Mean bid-ask-spread	0.05	0.03	0.02	0.03	0.06
	Average obs/day	15.04	17.87	17.60	17.31	15.69

3.6.2 Robustness with Respect to Data Specifics

As mentioned in Section 4.3 and shown in Appendix 4.6.1, the intraday dataset is characterized by two specifics: smaller number of observations in 2009 and second half of 2014 (see Table 3.3), as well as a higher intraday variance for France, Germany and Ireland from 2013 onwards.

First, we assess if a reduced number of observations as in 2009 or in the second half of 2014 affects the connectedness measure. To this end, we gather the structure of missing values from July to December 2014 and delete these values for the subsample covering July to December 2010 (amounting to 183 deleted observations of a total of 2,231 observations). The connectedness measures based on the original subsample of 2010 are similar to those based on the same subsample with deleted values, as can be seen in the left-hand panel of Figure 3.13. Thus we conclude that the relatively low connectedness in 2009 and the drop of connectedness in 2014 is not due to a lower number of observations.

Second, a similar, yet more complex approach, is applied to verify the robustness with respect to higher intraday variance as in Germany, France and Ireland from 2013 onward. In order to assess if this change in variance affects the resulting connectedness measures, we construct a second dataset of the first half of 2013 with a similar intraday variance as in the first half of 2012.[27] To this end, we extract daily variances for the first half of 2012. The intraday values of 2013 are then replaced by their own mean plus a random draw of a normally distributed variable with zero mean and variance of the same day in 2012. We see that the total connectedness based on the dataset with a similar variance structure as in 2012 is much lower than the connectedness measure based on the original dataset of 2013. This explains the increase in connectedness at the beginning of 2013, since there have been no important events at this time.

Thus, the change of data collection and aggregation by the data provider does not affect our results in Section 4.4.

3.6.3 Robustness with Respect to the choice of countries

We evaluate the robustness of the connectedness measure with respect to the countries selected. For this purpose we compute the time evolution of overall connectedness similar to Figure 3.3, but now include four additional euro area members: Austria, Belgium, Finland and The Netherlands. The results presented in Figure 3.14 (left-hand panel) show an almost identical behavior as in Figure 3.3.

[27]The year is chosen arbitrarily.

Figure 3.13: Robustness with respect to missing observation and increased volatility

The figure illustrates two robustness checks linked to the specifics of the data set. In the left-hand panel we have tested the influence of missing observations on total connectedness. As an illustration, the total connectedness of the original data for a chosen time period in 2010 is compared to the same data, but thinned out similar to the data availability in early 2009 and 2014. We find the same behaviour of total connectedness. In the right-hand panel we have tested the influence of the increased volatility of the CDS data in 2013. The variance adjusted volatility leads to a higher total connectedness. This clearly suggests that the increase in total connectedness at the beginning of 2013 is not due to fundamentals, but due to changes in CMAs data cleaning and aggregation.

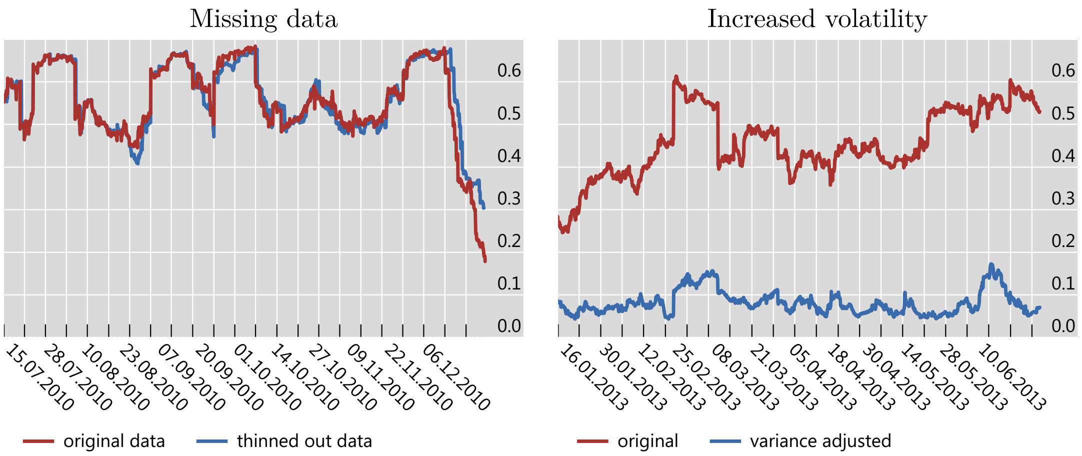
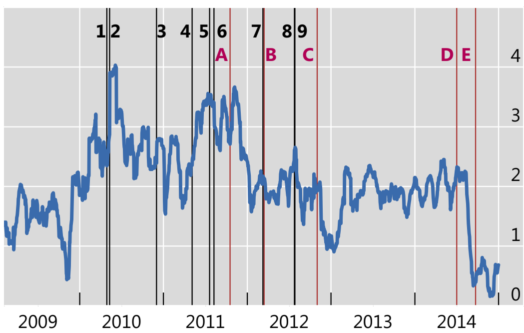


Figure 3.14: Total connectedness for the extended set of countries

The figure illustrates the overall connectedness with 90% confidence intervals based on CDS data for 11 countries: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Portugal, Spain and the Netherlands. For details on the labeling of the events, we refer to Figure 3.17.

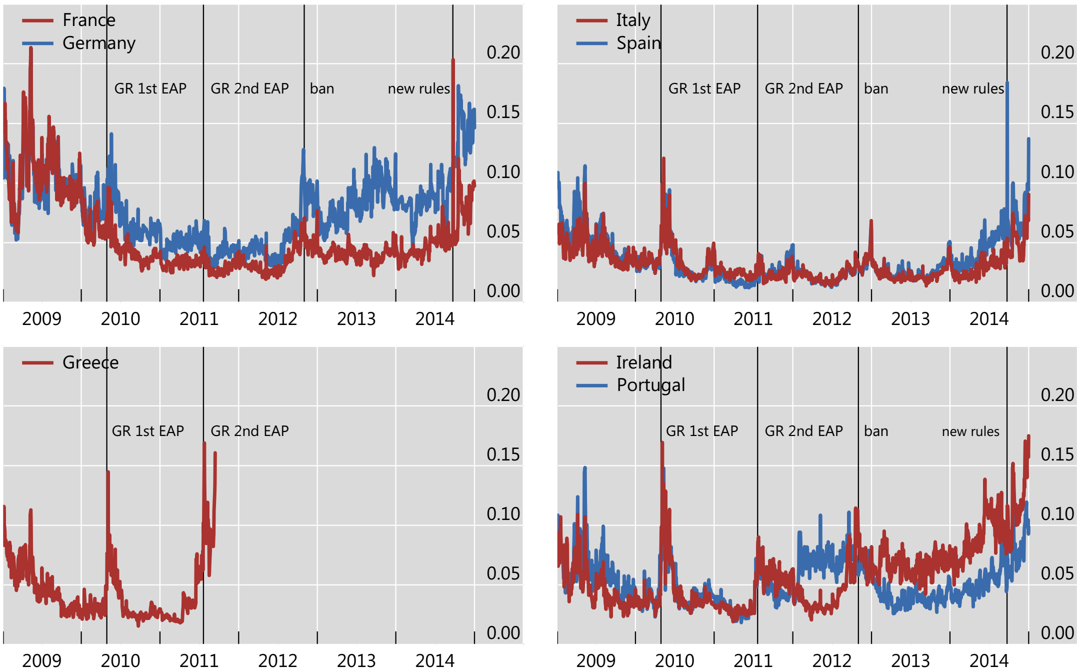


3.6.4 Liquidity Proxys

We present three measures of liquidity. In Figure 3.15 we graph relative BAS spreads defined as (ask price-bid price)/((ask price+bid price)/2). In Figure 3.16 we present volume data (left-hand side) and number of trade counts (right-hand side).

Figure 3.15: Relative bid-ask spreads

The figure illustrates relative bid-ask spreads, defined as (ask price-bid price)/((ask price+bid price)/2) for the period 2008 until end 2014.



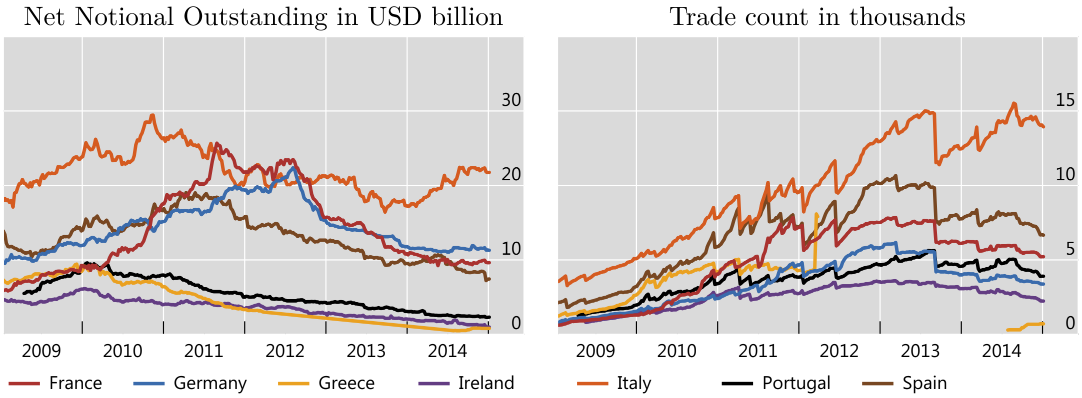
3.6.5 Generalized Variance Decomposition

Here we develop the main steps for the variance decomposition components from Equation (3.7) via the impulse response function.[28] Koop et al. (1996) define the generalized impulse response function **GI** of $\mathbf{y_t}$ at horizon H for a shock of size δ and a known

[28]See Hamilton (1994) for the link between impulse responses and forecast error variance decomposition.

Figure 3.16: CDS trading volume and trade count

The figure illustrates net notional amounts outstanding (left-hand panel) and trade counts (right-hand panel), based on publicly available weekly data.



history $\mathbf{\Omega}_{t-1}$ as follows:

$$\mathbf{GI}(H, \delta, \mathbf{\Omega}_{t-1}) = E(\mathbf{y}_{t+H}/\mathbf{u_t} = \delta, \mathbf{\Omega}_{t-1}) - E(\mathbf{y}_{t+H}/\mathbf{\Omega}_{t-1}). \tag{3.8}$$

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

$$\mathbf{GI}_j(H, \delta_j, \mathbf{\Omega}_{t-1}) = E(\mathbf{y}_{t+H}/\mathbf{u_{tj}} = \delta_j, \mathbf{\Omega}_{t-1}) - E(\mathbf{y}_{t+H}/\mathbf{\Omega}_{t-1}). \tag{3.9}$$

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

$$E(\mathbf{u}_t/\mathbf{u}_{tj} = \delta_j) = (\sigma_{1j}, \sigma_{2j}, \cdots, \sigma_{nj})' \frac{\delta_j}{\sigma_{jj}} = \Sigma_u e_j \frac{\delta_j}{\sigma_{jj}}. \tag{3.10}$$

Thus, the generalized impulse response is given by

$$\mathbf{GI}_j(H, \delta_j, \mathbf{\Omega}_{t-1}) = \mathbf{\Phi}_H \Sigma_u e_j \frac{\delta_j}{\sigma_{jj}}. \tag{3.11}$$

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 $t + H$:

$$\mathbf{GI}_j(H, \delta_j, \mathbf{\Omega}_{t-1}) = \sigma_{jj}^{-1/2} \mathbf{\Phi}_H \Sigma_u e_j. \tag{3.12}$$

As in Pesaran and Shin (1998), this is used to derive the generalized forecast error variance decomposition components $s_{ij}(H)$:

$$s_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \Phi_h \Sigma_u e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Phi_h \Sigma_u \Phi_h' e_i)} \tag{3.13}$$

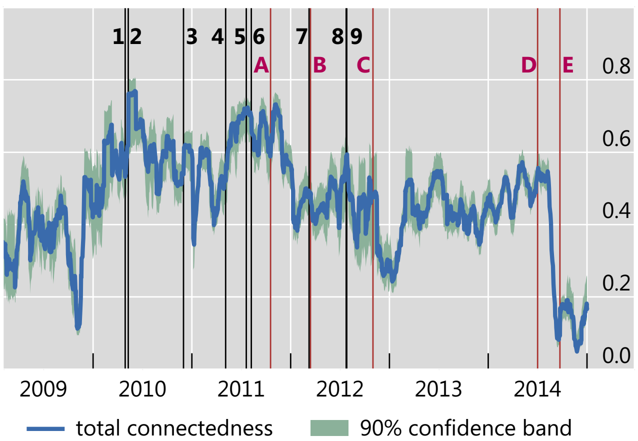
3.6.6 Overview of All Crisis Related and Regulatory Events

The sequence of regulations and crisis related events is presented Figure 3.17 including the total connectedness and the 90% confidence interval. The crisis related events are in black and regulatory events in purple. The choice of what date to chose in an event study is not straightforward. Usually there is close schedule of meetings and announcements in the run-up to an event, whereby different amounts of information are released or even leaked. For example, the new ISDA rules have been discussed long before mid-2014. The ISDA published proposed amendments to the 2003 Credit Derivatives Definitions already on Tuesday 15.07.2013. Nevertheless we have chosen 01.07.2014 (communication of the details of the rules) and 22.09.2014 (implementation of the rules) as the key dates.

In our analysis we have experimented with different dates (see Table 3.4). The dates used in our calculations are boldfaced.

Figure 3.17: Time line events and total connectedness

The figure illustrates total connectedness with 90% confidence intervals. Crisis related events are marked as black lines and regulatory interventions are shown by purple lines. The connectedness is computed with a rolling window of 20 trading days and take daily steps for new windows. A fixed number of days implies that when observations are missing, there might be less than 360 observations in one estimation window.



1: Greece: crunch talks	28.04.2010
2: SMP 1st wave	10.05.2010
3: Ireland EAP	30.11.2010
4: Portugal EAP	03.05.2011
5: Greece 2nd EAP	21.07.2011
6: SMP 2nd wave	08.08.2011
7: Greek default	09.03.2012
8: Spanish banks EAP	20.07.2012
9: Draghi's speech	26.07.2012
A: agreement on ban	18.10.2011
B: announcement of ban	14.03.2012
C: implementation of ban	01.11.2012
D: "FAQ" new CDS rules	01.07.2014
E: implementation of rules	22.09.2014

Table 3.4: Crisis Related Events

The table reports dates connected to events which are analyzed in the main body of the paper in form of event studies. We have boldfaced dates in the table which we consider as key dates for our event studies.

Issue	Date	Event
Greece I & SMP I (1 & 2)	23.04.10 Fri	official request for financial support from Greek government
	27.04.10 Tue	S&P downgrades Greece
	28.04.10 Wed	EU and IMF officials hold crunch talks with German leaders. Rumours of a 120bn € package emerge
	02.05.10 Sun	Eurogroup agreed to provide bilateral loans
	03.05.10 Mon	MoU was signed and ECB announces that Greek bonds will be accepted as collateral no matter their rating
	05.05.10 Wed	S&P downgrades Greece
	10.05.10 Mon	SMP starts
Ireland (3)	21.11.10 Sun	official request for financial support from Irish government
	26.11.10 Fri	Eurogroup approves loan to Ireland
	28.11.10 Sun	Troika and Ireland agreed program
	30.11.10 Tue	detailed discussions ended, program finalized
	01.12.10 Wed	IMF approves loan to Ireland, MoU signed
Portugal (4)	07.04.11 Thu	official request for financial support from Portuguese government
	08.04.11 Fri	Eurogroup approves loan
	03.05.11 Tue	reaches deal for bailout
	05.05.11 Thu	program was announced by Portuguese authorities
	16.05.11 Mon	EU and Portuguese parliament approves bailout package
	20.05.11 Fri	IMF approves loan
Greece II & SMP II (5 & 6)	17.06.11 Fri	Merkel/Sarkozy - agreement on second bailout, private sector involvement
	20.07.11 Wed	Merkel/Sarkozy - meeting to develop common stance on 2nd bailout
	21.07.11 Thu	Euro Summit/EU - agreement on second bailout
	08.08.11 Mon	SMP second wave starts
Greek default (7)	01.03.12 Thu	ISDA declares no credit event for Greece
	09.03.12 Fri	ISDA declares credit event for Greece
Spain & Draghi speech (7 & 8)	09.06.12 Sun	emergency meeting Euro Group regarding Spanish banks
	21.06.12 Thu	decision that 62bn euros will be shared among Spanish banks in need
	25.06.12 Mon	request for assistance by Spanish government
	20.07.12 Fri	Euro Group agrees bailout
	23.07.12 Mon	MoU for Spanish bank bailout signed
	26.07.12 Thu	Draghi speech "... whatever it takes ..."
	06.09.12 Thu	OMT

4 Time-Variation, Impact and Significance of Spillovers between U.S. Industrial Sectors

4.1 Introduction

The recent financial crisis has revealed that spillovers exist not only between institutions within the financial sector, but also between the financial and real sectors. It has also become apparent that such spillovers between different sectors are dynamic and not constant over time. Moreover, it is important to statistically disentangle significant from negligible cross-effects in order to focus on the relevant drivers in a network of industrial (sub-)sectors of a large economic system. Our econometric analysis allows for both, flexible adaptive time-variation in spillover networks and the crystallization of relevant effects with appropriate Bayesian techniques.

In particular, we estimate time-varying spillovers between U.S. stock market sectors for different levels of sector aggregation from five to 49 sectors. This allows to identify large scale cross-interactions but also zooming in on important sub-sectors. Econometrically, we capture the dynamics in the system with a time-varying parameter vector autoregression (TVP-VAR) and obtain spillovers from respective impulse responses. For estimation, we employ two standard Bayesian techniques using the Markov-Chain-Monte-Carlo (MCMC) algorithm and the Kalman filter approach. With a thorough performance study, we empirically document trade-offs between computational feasibility and model generality of these approaches in particular for increasing granularity of subsectors. Our model setup includes Bayes factors and thus allows to construct spillover measures based on relevant estimates only. Furthermore, by constructing credible intervals for the spillover measure, we identify which changes of spillovers are significant. Detailed economic insight is provided by analyzing spillovers between market segments, including financial sectors, commodity industries, and manufacturing industries.

For time-variation, our methodological framework builds on Primiceri (2005) and Del Negro and E. Primiceri (2015) for the MCMC approach and on Koop and Korobilis (2013) for the Kalman filter approach. Using TVP-VARs for measuring spillovers is fairly new in the connectedness literature. To our knowledge, the only comparable studies which use TVP-VARs to measure interconnectedness are those by Geraci and

Gnabo (2018) and by Korobilis and Yilmaz (2018).[1] While Geraci and Gnabo (2018) use the MCMC algorithm to estimate the TVP-VAR underlying their spillover measure, Korobilis and Yilmaz (2018) use the Kalman filter for the TVP-VAR. Apart from the differing estimation approaches, the model for the MCMC algorithm allows for a time-varying error variance, whereas this is not the case for the model underlying the Kalman filter. We compute our spillover measure based on both estimation approaches and illustrate the differences between the two. We show empirically that while the Kalman filter excels through its fast computation time and capacity for high-dimensional VARs, the Gibbs sampler provides more precise estimates which capture changes in spillovers more quickly.

Technically, we contribute to the literature of spillover measures by providing a dynamic measure that is based only on relevant components and thus allows to focus on significant spillovers. The spillover measure is based in generalized impulse responses and is related to the measures utilized by Diebold and Yilmaz (2014) and Alter and Beyer (2014). We improve previous spillover measures based on TVP-VARs by constructing measures that are solely based on parameters that are shown to be non-zero by the Bayes factor. Our spillover measure goes beyond that of Geraci and Gnabo (2018), who also use the Bayes factor but interpret the VAR parameters as spillovers directly. In contrast, our measure is based on impulse responses and thus includes the variance and the dynamic impact between variables. In addition, we allow for an interpretation of significant changes in the spillovers by constructing credible intervals. This is similar to the confidence intervals constructed by Buse et al. (2018), whereas here we take advantage of the Bayesian setup in which the conditional posterior distribution can be used directly.

Empirically, our analysis of spillovers between U.S. stock portfolios in the recent five decades provides a comprehensive view of spillover dynamics between all market segments, including financials, commodities, manufacturing and services. While there are only few studies on interaction effects within the real economy and between the real economy and financial sectors (see, e.g. Baruník et al., 2016), most contagion studies have focused on the financial sector only. Most common is the analysis of linkages between financial institutions (Adrian and Brunnermeier, 2016; Engle et al., 2014; Hautsch et al., 2015; Billio et al., 2012), stock markets (Golosnoy et al., 2015; Asgharian and Nossman, 2011) and sovereign bond yields or CDS spreads (Caporin et al., 2013; Buse and Schienle, 2019). We find that, additionally to the financial sector, especially commodities play an important role in the network topology of the real economy. Our application reveals important developments and changes in spillovers in all market sectors, especially in response to crisis periods.

[1] Additionally, Ciccarelli and Rebucci (2007) use Bayesian TVP-VARs to measure contagion in the Chilean foreign exchange market; however, their model follows a different approach. Instead of measuring spillovers between different entities, they explain the peso/dollar exchange rate by various domestic, regional and global factors.

The paper is organized as follows: The model and methods are explained in Section 4.2. In Section 4.3 we describe the data and its relevant model specifications. Section 4.4 details the results. Section 4.5 concludes the paper.

4.2 Model

4.2.1 Time-Varying Parameter VAR

We model the time-varying dynamics of the system with a TVP-VAR:

$$y_t = c_t + \sum_{i=1}^{p} \beta_{i,t} y_{t-i} + \epsilon_t, \quad t = 1, \ldots, T, \quad y_t \in \mathbb{R}^k. \tag{4.1}$$

The time-varying coefficients $\beta_{i,t}$ follow a random walk. By stacking the coefficients and writing $X_t' = I_k \otimes [1, y_{t-1}', \ldots, y_{t-p}']$, the full state space model can be written as:

$$\begin{aligned} y_t &= X_t' \beta_t + \epsilon_t \\ \beta_t &= \beta_{t-1} + \nu_t \end{aligned} \tag{4.2}$$

where $\epsilon_t \sim \mathcal{N}(0, \Sigma_t)$ and $\nu_t \sim \mathcal{N}(0, Q)$ are independent of one another.

We use two Bayesian estimation approaches which allow for different flexibility in the modeling of the variances of the system. For the MCMC method, we use Gibbs sampling and follow Carter and Kohn (1994) and Primiceri (2005). The Kalman filter approach is adopted from Koop and Korobilis (2013). For both estimation procedures, the above setting of the model is the same. However, the variance-covariance matrix Σ_t of the observation equation errors is constructed differently in the two approaches. Primiceri (2005) uses triangular reduction of Σ_t: $A_t \Sigma_t A_t' = \Xi_t \Xi_t'$, where A_t is a lower triangular matrix with ones on the diagonal and whose free elements are stacked in the vector α_t, and Ξ_t is a diagonal matrix with elements $\xi_t = diag(\Xi_t)$. This transformation leads to $\epsilon_t = A_t^{-1} \Xi_t \varepsilon_t$ with $V(\varepsilon_t) = I_n$. The time varying parameters α_t and ξ_t are specified as

$$\begin{aligned} \alpha_t &= \alpha_{t-1} + \zeta_t \\ ln\xi_t &= ln\xi_{t-1} + \eta_t, \end{aligned} \tag{4.3}$$

where ζ_t and η_t are independently normally distributed vectors with mean zero and homoscedastic variance. On the other hand, for the Kalman filter approach we follow Koop and Korobilis (2013) who adopt an exponentially weighted moving average (EWMA) estimator for Σ_t, with a decay factor κ: $\hat{\Sigma}_t = \kappa \hat{\Sigma}_{t-1} + (1-\kappa)\hat{\epsilon}_t \hat{\epsilon}_t'$. The residuals $\hat{\epsilon}_t = y_t - \beta_{t|t} X_t$ are computed by the Kalman filter.[2]

[2] The variances in the two models would compare more directly if they were constructed similarly. Here, however, we adopt the models of Primiceri (2005) and Koop and Korobilis (2013) as such in order to

The relevance of each element of the parameter vector β_t is determined by evaluating the null hypothesis that the parameter element is zero. This is done by means of the Bayes factor, which is the ratio of the likelihood of the null hypothesis to the likelihood of the alternative hypothesis. A detailed explanation of the estimation technique is given by Koop et al. (2010). Autoregressive coefficients are set to zero for estimated Bayes factors which exceed a given threshold. For the Gibbs sampler approach, we estimate the Bayes factor from the conditional posterior distribution of the parameters. Since the Kalman filter setup does not include a distribution for the model variance Σ_t, adequate draws for the estimation of the Bayes factor are taken from bootstrapped results.

4.2.2 Spillover Measures

Impulse response analysis is a natural choice for measuring spillovers: It traces out the effect of a shock in one variable j on another variable i within a system, accounting for both the autoregressive coefficients as well as the variance-covariance of the estimated TVP-VAR.

We use generalized impulse response functions as proposed by Koop et al. (1996) and Pesaran and Shin (1998). In contrast to the traditional approach using orthogonalization of shocks, the generalized impulse responses are invariant to variable ordering. Given that y_t is covariance-stationary with moving average representation $y_t = \sum_{i=0}^{\infty} \Phi_i \epsilon_{t-i}$, the generalized impulse response (IR) of a shock to the jth equation on the other variables at time t and for forecast horizon H is defined as:

$$s_j^{(t)}(H) = \sigma_{t;jj}^{-1} \Phi_H^{(t)} \Sigma_t e_j, \tag{4.4}$$

where $\sigma_{t;jj}$ is the (j, j) element of Σ_t and e_j is a selection vector with unity as its jth element and zeros elsewhere.

For measuring spillovers we use the cumulated IRs of H forecast horizons, which allows us to represent both contemporaneous as well as future effects of shocks in a compact manner:

$$\dot{s}_j^{(t)}(H) = \sigma_{t;jj}^{-1} \sum_{h=0}^{H} (\Phi_h^{(t)} \Sigma_t e_j). \tag{4.5}$$

We now introduce spillover measures at different aggregation levels, for which we adopt the terminology of the network literature. The impulse responses of all variables are collected in the matrix $S^{(t)} = (\dot{s}_1^{(t)}(H), \dot{s}_2^{(t)}(H), \ldots, \dot{s}_k^{(t)}(H))$. This matrix constitutes the directed adjacency matrix and determines the network structure.

Individual elements in an impulse response or in the adjacency matrix are defined as $s_{ij}^{(t)} = e_i' \dot{s}_j^{(t)}(H) = e_i' S^{(t)} e_j$ and represent the intensity of the edges in a network from node j to node i.

gain insight in the differences of these.

The column-wise mean of the off-diagonal elements of the adjacency matrix $S^{(t)}$ is called out-degree and shows the spillovers from node j to the other nodes of the network[3]:

$$ss_j^{(t)} = \frac{1}{k} \sum_{i=1, i \neq j}^{k} ss_{ij}^{(t)}. \tag{4.6}$$

Finally, the network density is obtained by aggregating all off-diagonal elements of S:

$$ss^{(t)} = \frac{1}{k^2} \sum_{i,j=1, i \neq j}^{k} ss_{ij}^{(t)}. \tag{4.7}$$

We measure significance of spillovers by constructing credible intervals for the impulse responses. Similarly to the estimation of the Bayes factor in Section 4.2.1, we use draws from the posterior distribution and estimates from bootstrapped datasets, respectively, for the two estimation approaches.

4.3 Data

4.3.1 Data Setup

Our monthly market sector dataset consists of average value-weighted industry portfolio returns, including dividends.[4] The portfolios are categorized according to the SIC codes of the stocks that constitute them. Depending on the categorization, the stocks are assigned to different amounts of portfolios. For the first part of our results, we work with five portfolios and for the second part we use 49 portfolios. The abbreviations for the portfolios are defined in Tables 4.2 and 4.3 in the Appendix. The data are retrieved from Kenneth R. French's online data library and cover the period from July 1926 to July 2018. Due to missing observations in some portfolios and in order to obtain an economically meaningful observation period, we begin our empirical analysis with data from July 1969 onward.

The data are stationary according to the augmented Dickey-Fuller (ADF) and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) tests. Summary statistics including correlation between different portfolio returns are included in Tables 4.4 and 4.5 in the Appendix. As required for the Kalman filter, all data are standardized to have mean zero and unit variance.

[3] This is equal to the mean of all elements in one impulse response $dots_j^{(t)}(H)$ except its jth element.

[4] We also compare results for equally-weighted portfolios, for which some asset pricing results typically do not hold (see Hou et al., forthcoming). While the overall level of impulse responses computed with equally-weighted portfolios lies above that of value-weighted portfolios, the dynamics remain the same.

4.3.2 Model Specifications for Given Dataset

In the first part of our empirical analysis, we directly compare the results obtained by the Gibbs sampler and the Kalman filter on a set of five variables. For a best possible comparison between the two approaches, we use the same priors, as specified by Primiceri (2005). These are based on OLS estimates of a selected subsample, which in our analysis includes the first 100 observations.[5] In order to ensure robust results for the Kalman filter at the beginning of the analysis we begin the estimation 10 years earlier, which corresponds to 120 observations, and drop these first estimation results.

In the second part of our analysis, we extend the number of variables in the system to 49. The Kalman filter allows for estimating all 49 variables in one TVP-VAR. For a TVP-VAR of this dimension, it is necessary to use Minnesota priors. The Minnesota prior covariance matrix for the state equation depends on a hyperparameter γ which controls the degree of shrinkage on the VAR coefficients. It is defined as $var(\beta_0) = \underline{V}$ with diagonal elements:

$$\underline{V_i} = \begin{cases} \frac{\gamma}{r^2}, & \text{for coefficients on lag } r \text{ for } r = 1, \dots, p \\ 100, & \text{for the intercepts.} \end{cases}$$

The hyperparameter γ is chosen for each time point t by estimating the model for $\gamma \in \{10^{-5}, 0.001, 0.005, 0.01, , 0.05, 1\}$ and then selecting the best model by dynamic model selection (DMS). For our dataset of 49 variables the optimal value is $\gamma = 10^{-5}$ for all time points t.[6] The decay factor κ of the EWMA estimator for Σ_t is set to 0.96. Since with the Gibbs sampler, estimating models of such high dimensions is not possible, impulse responses for this approach are estimated based on bivariate TVP-VARs. Priors are selected following Primiceri (2005).

For the selection of relevant parameters via the Bayes factor we choose a threshold equal to four, meaning that VAR-coefficients are set to zero if the Bayes factors is equal to four or larger.[7] This choice of the threshold identifies 38% of all VAR-coefficients to have be equal to zero.[8]

Impulse responses are computed for up to three forecast steps ahead. The responses at the first forecast step are the largest and diminish rapidly to zero at the third forecast step ahead. This is why the cumulated impulse responses $ss_j^{(t)}(H)$ are almost identical for $H = 1$ or $H = 3$.

[5] Our results are robust with respect to the sample size for calibrating the priors, which we compare for sample sizes of $\{100, 200\}$.

[6] Thus, the initial condition allows for little time variation in the VAR coefficients.

[7] This choice of the threshold for the Bayes factor is in line with Geraci and Gnabo (2018).

[8] As comparison, we consider results obtained by thresholds of 3 and 5, which leads to a share of 67% and 28% of coefficients set to zero, respectively.

4.4 Results

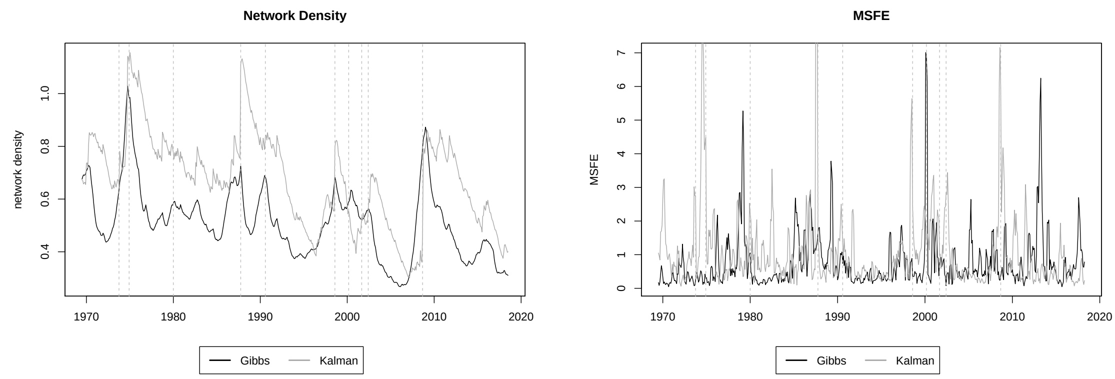
In a first step, we compare the spillovers computed with the Gibbs sampler and with the Kalman filter. In order to allow for a direct comparison, we analyze stocks categorized in five industry portfolios. The results illustrate the advantages and disadvantages of the two estimation techniques. In a second step, the analysis of spillovers between market sectors is extended to 49 portfolios, in which stocks are categorized on a finer scale. This allows for a more detailed economic interpretation of spillovers across time.

4.4.1 Comparison of Gibbs Sampler and Kalman Filter

The Kalman filter excels through its fast computation time. For our model specification, the computation time of the Kalman filter is about 6 times as fast as the Gibbs sampler. Furthermore, it allows for estimating models of higher dimensions than the Gibbs sampler. While the TVP-VAR estimated with the Gibbs sampler should not exceed five variables, we estimate the TVP-VAR with the Kalman filter with up to 49 variables.

Figure 4.1: Network densities and MSFEs for the Gibbs sampler and Kalman filter.

The left-hand panel shows the network density of 5 industry portfolios and the right-hand panel depicts the MSFEs, averaged across all variables and forecast horizons. Results for Gibbs sampler approach are shown in black and the Kalman filter approach in grey. Vertical dashed lines mark important events, which are described in Table 4.1.



On the other hand, results obtained by the Gibbs sampler are more precise. In particular, estimates from the Gibbs sampler capture changes in the data more quickly than those from the Kalman filter. The left-hand panel of Figure 4.1 shows the dynamic network density based on the Gibbs sampler in black and the Kalman filter in grey.

Table 4.1: Events

The table describes all events marked in the plots by vertical lines.

Event	Marked Date	Description
1973 oil crisis	Oct 1973	The oil embargo was decided on 17.10.1973, leading to an oil price increase of up to 400% and a crash of stock markets.
	Dec 1974	Stock prices stop declining.
1979 oil crisis	Jan 1980	The Iranian Revolution leads to an oil price increase of up to 100% between 1979 and 1980.
Black Monday	Oct 1987	Stock markets worldwide fall drastically on 19.10.1987. In the Dow Jones Industrial Average, the largest one-day percentage decline was observed on that day.
1990 oil shock	Aug 1990	After the beginning of the Gulf War (2 August 1990 ‚Äì 28 February 1991), oil prices rise sharply, but fall again more quickly than in the previous oil crises.
Dot com bubble	Aug 1998	The stock market index starts rising in 1995 due to the dot com bubble. From August 1998 onward, the index rises even more rapidly.
	Mar 2000	In March and April 2000, various incidents lead to a bursting of the bubble. The stock market downturn begins.
	Jun 2002	Several accounting scandals diminish investor confidence. Stocks stop falling in October 2002.
September 11	Sep 2001	The destruction of the World Trade Center severely affected global markets.
Lehman default	Sep 2008	The bankruptcy of Lehman Brothers leads to a strong decline in stock markets.

Important events are marked by vertical lines in the plot and explained in Table 4.1.[9] Spillovers between market sectors increase in crisis times for both estimation approaches, but augment earlier with the Gibbs sampler than with the Kalman filter. This observation is backed by the correlation coefficients between the two time series over a grid of lags. While the correlation between the network density based on the Gibbs sampler and lags l of the density based on the Kalman filter, $cor(ss_{Kalman}^{(t-l)}, ss_{Gibbs}^{(t)})$, is decreasing in the function of the lag l, the correlation for opposite lags $cor(ss_{Kalman}^{(t)}, ss_{Gibbs}^{(t-l)})$ is maximized for $l = 10$. A simple Bernoulli-test rejects equality between the two densities $\{ss_{Kalman}^{(t)}, ss_{Gibbs}^{(t-l)}\}$ only up to $l = 6$ and yields evidence for equality in particular for $l = \{7, \dots, 29\}$.

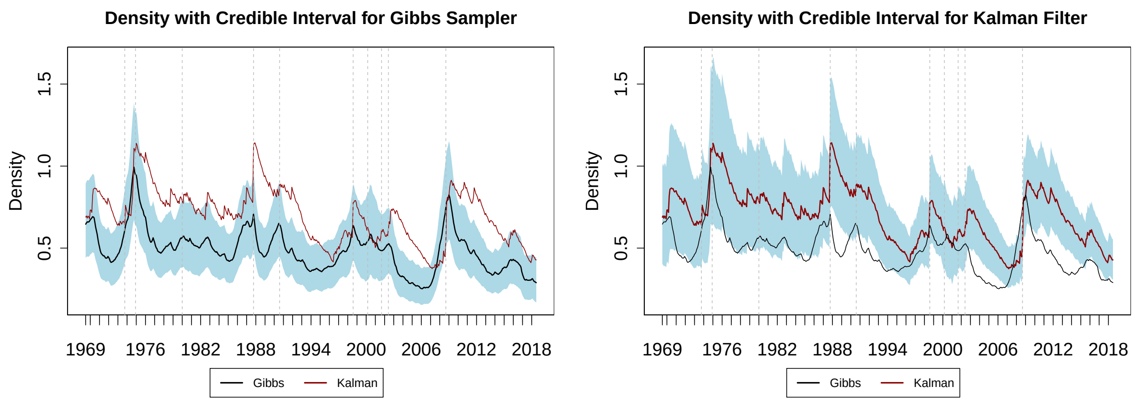
While the forecasting performance of the two methods is very different over time, the Kalman filter predicts poorly when unexpected events occur. This is illustrated in the right-hand panel of Figure 4.1, which shows the MSFEs averaged across all variables

[9] Dynamics of out-degrees and individual spillovers are similar when all stocks are categorized in 5 portfolios, because the individual effects are smoothed out through the portfolio aggregation. Therefore, we only show the network density.

and forecast horizons. Both MSFEs have large spikes at given points in time. For the Gibbs sampler, these spikes seem to occur at random time points. In contrast, for the Kalman filter, the spikes often occur simultaneously with crisis events, which are marked by vertical dashed lines in the plot. When comparing the MSFEs of individual variables and forecast horizons $\{1, 2, 3\}$ and averaged across time, the ratios between the MSFEs of the Gibbs sampler and the Kalman filter are nearly unity.[10] Thus, in our example, the difference between the two exists only across time but not across variables or forecast horizons.[11] Interestingly, the MSFE of the Kalman filter depends on the choice of the prior. In particular, the MSFEs of individual variables and forecast horizon are larger when the initial conditions are based on OLS estimates rather than the Minnesota prior. This shows that the Kalman filter works better for initial values containing a minimum on information.

Figure 4.2: Network densities for the Gibbs Sampler and Kalman Filter including credible intervals.

The figures illustrate the network density, including credible intervals in light blue. The boundaries of the credible intervals are computed as the 25% and 75% quantiles of the MCMC draws and bootstrapped Kalman filter results, respectively. Both panels show the median network density based on the Gibbs sampler in black and for the Kalman filter in red, whereas the credible intervals shown in the left-hand panel are based on the Gibbs sampler and those in the right-hand panel are based on the Kalman filter. Vertical dashed lines mark important events.



In a next step, we analyze the dynamics in the network density for the two estimation approaches by taking into account their significance. Network densities based on

[10]More precisely, they lie between 0.994 and 1.

[11]Koop and Korobilis (2013) find ratios slightly above unity in their application for the first two to three forecast horizons.

both estimation approaches including credible intervals are shown in Figure 4.2. Since the credible intervals are constructed differently for the two approaches, comparisons between the two should be treated with caution. The first striking difference between the two network densities is that in the first half of the sample, the density computed from Kalman filter estimates, depicted by a red line in the plots, is on an overall higher level than the density based on the MCMC algorithm. Moreover, during this time period, both densities do not vary significantly within a certain interval. More precisely, between the aftermath of the first oil crisis 1973-1974 and the 1990 oil shock, the density based on the MCMC algorithm does not significantly exceed values between 0.45 and 0.6 and the density from the Kalman filter does not significantly go beyond an interval between 0.75 and 0.9. From the beginning of the dot com bubble in 1995 onward, the two densities are on a more similar level and both undergo larger significant changes. This can be explained by an increased interrelatedness due to the introduction of the internet and the accompanying dissemination of new technologies. A second important difference between the two densities is the behavior after the occurrence of unexpected crisis events, which are marked by vertical dashed lines in the plots. Both network densities peak at such events. Afterwards, the density computed from the MCMC estimates returns quickly to a lower level, while for the Kalman filter results, it remains on a higher level for a longer period of time.

In summary, when estimating TVP-VARs, the Kalman filter is preferable when computation time is an issue and especially and when a high-dimensional model should be estimated. Whenever these points are not of concern, the Gibbs sampler should be chosen because it delivers more accurate results.

4.4.2 Spillovers between Markets

For a more precise view on spillovers between market sectors, we estimate impulse responses for stocks categorized as 49 industry portfolios. The abbreviations of the portfolios and their descriptions are listed in Tables 4.2 and 4.3 in the Appendix. For each portfolio, we compute the out-degree $ss_j^{(t)}$ (see Equation (4.6)), representing the spillovers that one portfolio j transmits to all other portfolios. For a graphical overview, we sort related portfolios into groups of three to six and plot the corresponding out-degrees of each group in one graph.[12]

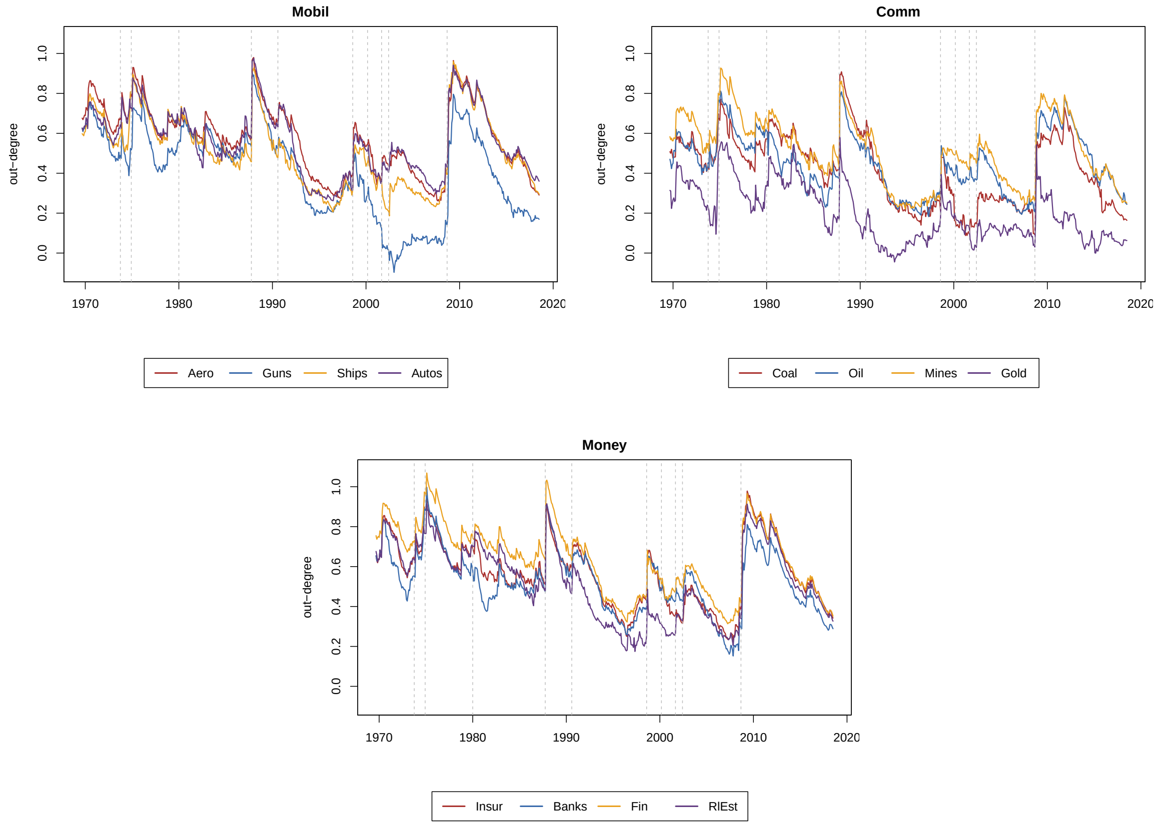
The Kalman filter approach allows to estimate a large TVP-VAR with all 49 portfolio returns in one model, of which the resulting out-degrees are shown in Figures 4.3 and 4.4. Since the results based on the Gibbs sampler provide no additional value in this particular setting, we restrict our analysis here to the Kalman filter results only.

The overall level of the out-degrees of coal, mining and oil industries and gold ores,

[12]We have also compared spillover measures for 12, 17 and 30 industry portfolios from French's data library. The categorization in 49 portfolios contains more differentiation of individual market segments which are smoothed out by the aggregation into a smaller number of portfolios.

Figure 4.3: Out-degree of 49 portfolios estimated with the Kalman filter, part 1

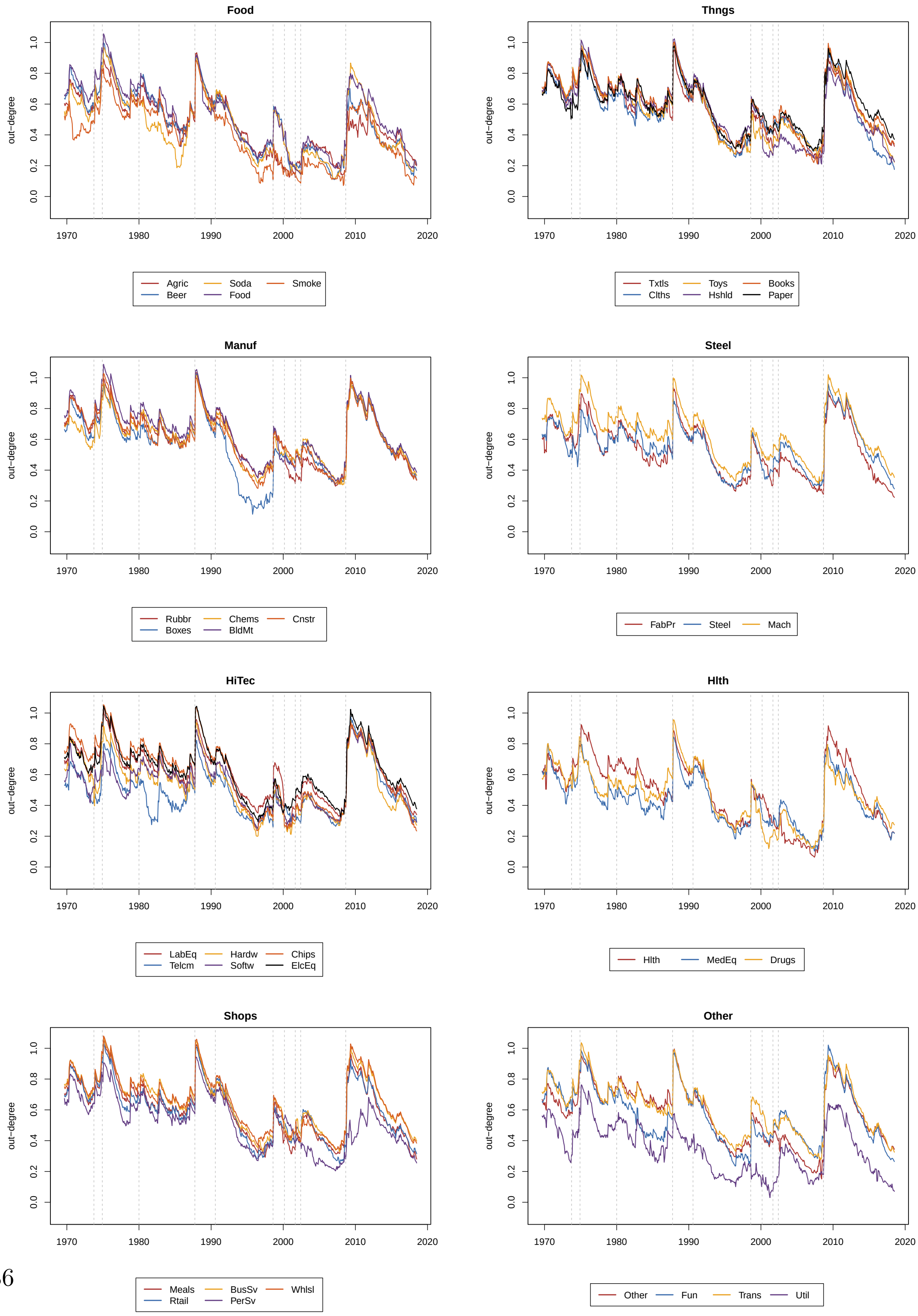
The figure shows the first part of 49 out-degree spillovers estimated with the Kalman filter. Each plot depicts out-degrees of several portfolios of related industries, e.g. the colored line for the market sector j visualizes $ss_j^{(t)}$ (see Equation (4.6)). Vertical lines mark important events.



depicted in the graph titled "Comm" in the right-hand panel in Figure 4.3, is lower compared to out-degrees of other portfolios. The out-degree of gold and silver ores (marked "Gold") stands out particularly with its overall low level. Businesses with these SIC codes include mainly gold mining companies, but also precious metal dealers and commodity brokerage houses. These firm's returns depend on the gold price which, in turn, is unaffected by other stock prices. On the other hand, the gold price is affected by monetary policy and macroeconomic uncertainty. Thus, it is natural that spillovers from gold and silver ore businesses rise in crisis periods, but to a lesser extent than

Figure 4.4: Out-degree of 49 portfolios estimated with the Kalman filter, part 2

The figure shows the second part of 49 out-degree spillovers estimated with the Kalman filter. For more details we refer to Figure 4.3.



out-degrees of other portfolio returns. Similarly to gold, prices of the commodities coal, oil, and metals are less connected with asset prices of other industries. Surprisingly, the out-degree of the oil and gas industry (marked "Oil") is not affected particularly by the oil crises in 1973 and 1979. The soaring oil prices during these periods affected the entire stock market directly, such that the spillover from the oil industry is not identifiable in our monthly data.

Within the financial sector, traders, brokers and trusts ("Fin") have the highest level of out-degrees across the entire observation period, reflecting their high level of interconnectedness and uncertainty. The recent subprime mortgage crisis changed the dynamics especially of real estate firms. After the sudden jump of out-degrees of all portfolio returns after the bankruptcy of Lehman Brothers in September 2008, the out-degrees of the four financial portfolio returns are almost identical. In contrast, real estate spillovers behave differently from other financial spillovers prior to the housing bubble which began growing in 2005. The higher similarity of out-degrees from all financial sectors after the subprime mortgage crisis is explained by their higher interconnectedness after Lehman Brother's default.

Apart from market-wide crises that affect all market segments similarly, out-degrees are also impacted by industry-specific changes in the market. As an example, spillovers from the defense industry (marked "Guns", shown in the upper left-hand panel in Figure 4.3) drop substantially after 9/11. During this period, an increased demand of the government leads to a fragmentation of the defense sector. Outside of this exceptional time after the terrorist attacks, the out-degree of defense businesses is mostly similar to those of other industry portfolios, such as aircraft ("Aero"), shipbuilding and railroad ("Ships") and automobiles and trucks ("Autos") which are shown in the same graph.

For an analysis on a more granular level, we study individual spillovers which we represent in network graphs. For better clarity, we sort the 49 industry portfolios into groups and represent the averages of impulse responses between these groups. We compare the networks of different characteristic time periods and represent the average spillovers across each interval. The first period of interest covers three years between November 1980 and November 1983. It includes the early 1980s recession[13] and is slightly influenced by the second oil crisis between 1979 and 1980. The second period is chosen between January 2009 and January 2010 and the third period covers January 2012 until January 2013. The two latter periods are strongly impacted by the financial crisis.

In a first step, we adapt the aggregation of portfolios in 11 groups as in Figures 4.3 and 4.4. We compare the spillover results obtained from the Kalman filter, in which parameters for all 49 variables are estimated in one model, and the Gibbs sampler, in which parameters for each variable pair are estimated in a bivariate model. The resulting network graphs of the early 1980s are depicted in the left-hand panels of Figures 4.5 and 4.6 and the two networks during the aftermath of the 2008 financial crisis are shown in

[13]In the U.S., this recession began in July 1981 and ended in November 1982.

the middle and on the right-hand sides of Figures 4.5 and 4.6, respectively.

Before analyzing the individual spillovers, we assess the differences and similarities in the networks obtained from the Kalman filter and the Gibbs sampler. Directly after the outbreak of the financial crisis, the abrupt rise of spillovers is captured similarly by both approaches. Accordingly, the spillover networks for January 2009-2010 in the center of Figures 4.5 and 4.6 show a similar picture. The same is true for spillover networks in the time period between November 1980 and 1983, depicted on the left-hand side of Figures 4.5 and 4.6. In contrast, the two estimation approaches deliver different results in the years following the financial crisis from January 2012 to 2013, illustrated on the right-hand side of Figures 4.5 and 4.6. As noted in Subsection 4.4.1, the network density based on the Gibbs sampler drops back to a lower level more quickly after a peak than the network density based on the Kalman filter. This difference is reflected in the network graphs, which stand apart considerably.

When comparing the network graphs for the two time periods in which the estimation approaches deliver similar results, the first striking observation is the higher number of large spillovers in the networks from January 2009 to 2010 compared to the networks from November 1980-1983, indicated by bold red arrows in the network graphs. All market sectors, represented by nodes in the network, are more connected among each other after the subprime mortgage crisis. An important exception to this are commodities (marked by the node “Comm”), which includes the oil, coal and mining industries, as well as gold ores. We observe a similar but less pronounced picture for the vertex “Food”, of which the main constituents are agricultural production and food products. The 2008 crisis led to a sudden decline in all asset prices, but commodity prices soon started rising again, a typical observation in recessions. The effect is stronger for commodities such as oil than for commodities on which people are more dependent, such as food. Another sector that deserves special interest is the financial sector, marked in the graph by “Money”. While the banking, trading, insurance and real estate segments spill over very little to other segments in the economically calmer time period in the 1980s, the impulse responses increase strongly between 2009 and 2010, reflecting the impact of the ailing financial sector on the economy.

The network graphs representing spillovers between 2012 and 2013, in the right-hand panels of Figures 4.5 and 4.6 differ substantially for the two estimation approaches. Although the network based on the Kalman filter is much more dense than that based on the Gibbs sampler, the networks based on the different approaches do not lead to contradictory results. The network graph for January 2012 to 2013 for the Kalman filter in Figure 4.5 is relatively similar to that for January 2009 to 2010: The financial sector is strongly connected, while the food and commodity sectors are less connected to the other market sectors of the real economy. Even though the spillovers based on the Gibbs sampler have dropped to a much lower level in the time period from January 2012 to 2013, they confirm the finding of a strongly connected financial sector and isolated commodity and food sectors. Thus, for a network analysis on an aggregation level of 11 groups, the two estimation approaches lead to different levels of spillovers but similar interpretations of the most important spillover channels.

In order to shed more light on the spillovers of the financial (“Money”) and commodity (“Comm”) sectors, we plot networks in which each portfolio of the respective groups is depicted individually, and all other portfolios are summarized in one group called “Rest”. The network graphs are shown in Figures 4.7 and 4.8 for the same time periods as above.

We first focus on the time periods in which spillovers are similar for both estimation approaches. In the beginning of the eighties, shown on the left-hand side of Figures 4.7 and 4.8, all financial sectors are interconnected among each other. This is in contrast to the networks in the financial crisis, shown in the center of Figures 4.7 and 4.8, where financial sectors are isolated of each other. This reflects the fragmentation induced by the U.S. federal bailouts or nationalization for many financial institutions. On the other hand, all four financial sectors are strongly connected with the manufacturing industry and service sectors, depicted in the graph by the node “Rest”, indicating their strong impact on stock prices and the entire economy. Among all financial sectors, the banking sector (including depository banks, commercial banks, national banks, savings institutions and credit institutions) is the most isolated after the bankruptcy of Lehman Brothers. This can be explained by the fact that depository and commercial banks were less affected by the financial crisis compared to the real estate, trading and insurance sector.

When comparing network graphs for the time period between January 2012 and 2013, depicted on the right-hand side of Figures 4.7 and 4.8, we find that unlike the spillovers between groups of sectors in Figures 4.5 and 4.6, not only the overall level of spillovers but also the individual channels differ between the Kalman filter and the Gibbs sampler results. As noted above, the network graph from the Kalman filter between January 2012 and 2013 is similar to the network graph three years earlier, showing financial sectors that are barely connected among each other. This is in contrast to the corresponding network graph based on the Gibbs sampler, in which the connections between the financial sectors are their most important ones. Unlike the Kalman filter, the Gibbs sampler captures the increased interactions between U.S. financial institutions which can be explained by the impact of the European sovereign debt crisis (see Allegret et al., 2017). This shows a clear advantage of the Gibbs sampler over the Kalman filter for analyzing spillover channels on a granular level during or after crisis periods.

In addition to the financial sectors, a comparison to the oil sector is of special interest because the considered time period from 1980 to 1983 is after an oil crisis. In the network graphs for the financial crisis in the center of Figures 4.7 and 4.8, all financial sectors, with a slight exception of the banking sector (“Banks”), have high impulse responses to the oil sector (“Oil”). This observation holds true for the networks estimated with the Gibbs sampler as well as with the Kalman filter. In the network graph after the oil crisis based on Kalman filter estimates on the right-hand side of Figure 4.7, the oil sector has a higher impulse response to the trading sector (“Fin”) than vice versa. All other financial sectors have no or very little impact on the oil sector. This picture is similar, although to a lesser extent, for the network graphs computed from Gibbs sampler estimates on the right-hand side of Figure 4.8. These findings confirm the high impact of financial sectors due to the financial crisis and illustrate the importance of the oil sector after the oil price increase.

In conclusion, the joint analysis of all market sectors reveals important interactions not only within the financial sector, but also within the commodity industries, between commodities and financials, as well as with the manufacturing industry and service sector. The comparison between the Gibbs sampler and the Kalman filter clearly illustrates the findings that the estimates obtained from the Gibbs sampler react faster to changes in the data. In time periods that are sufficiently beyond a crisis event or on high aggregation levels, the Kalman filter also provides reliable results.

Figure 4.5: Spillovers between market sectors, aggregated group-wise, estimated with the Kalman filter

The networks illustrate individual spillovers between market segments. Individual spillovers of 49 market segments are averaged within 11 groups of related industries for a better overview. The networks represent the average spillovers in three different time periods: The left-hand panel represents spillovers between November 1980 and November 1983, the middle panel illustrates spillovers between January 2009 and 2010 and the right-hand panel shows spillovers between January 2012 and 2013. Nodes represent groups of market sectors and arrows represent individual spillover measures, e.g. an arrow from group j to group i visualizes $ss_{ij}^{(t)}$. The width and color of the connecting lines indicate the size of the spillovers: bold red lines indicate large spillovers (fourth quartile), orange lines indicate upper medium spillovers (third quartile), thin yellow line indicate lower medium spillovers (second quartile) and no connecting line indicates small connectedness (first quartile). The quartiles are chosen with respect to the spillovers computed from the Kalman filter estimates between November 1980 and November 1983. The arrow at each line shows the direction of the spillover.

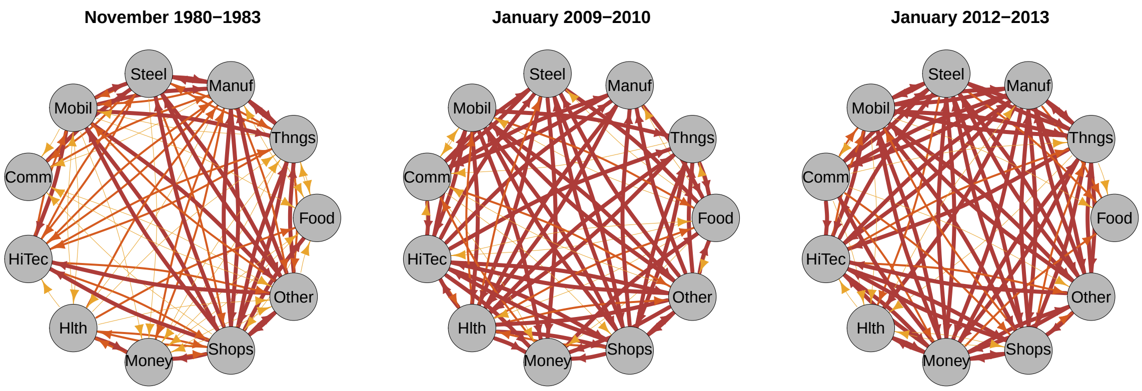


Figure 4.6: Spillovers between market sectors, aggregated group-wise, based on the Gibbs sampler

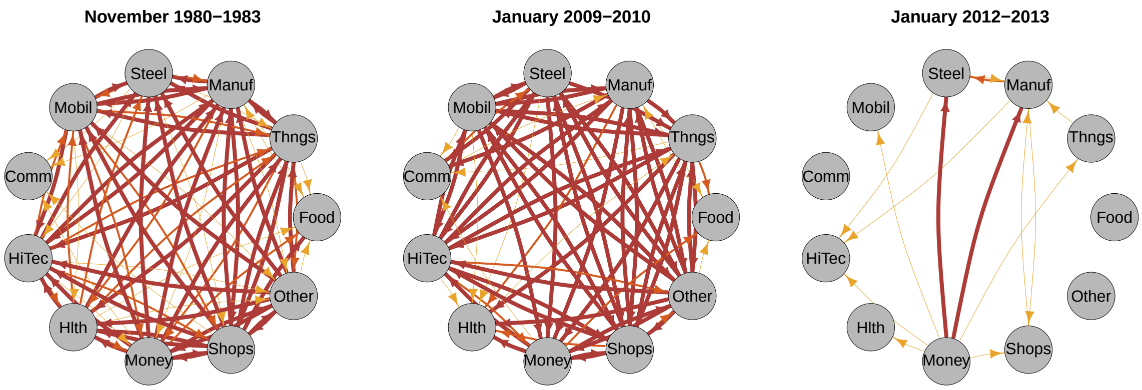


Figure 4.7: Spillovers between financial sectors, commodity industries and the remaining economy based on the Kalman filter

The networks illustrate individual spillovers between market segments. Spillovers for the real estate ("RlEst"), trading ("Fin"), banking ("Banks"), insurance ("Insur"), coal ("Coal"), oil ("Oil"), mining ("Mines") and gold ("Gold") sector are shown individually, while all other spillovers are averaged in one group called "Rest". For more details concerning the network plots we refer to Figure 4.5.

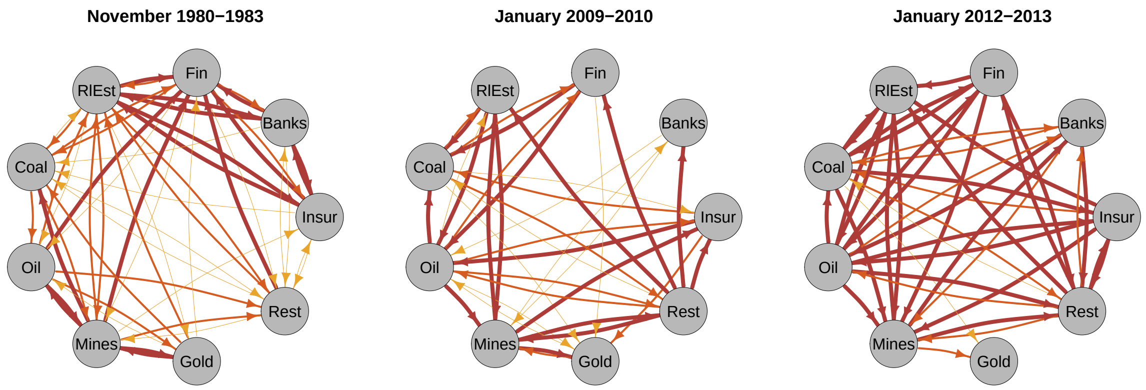
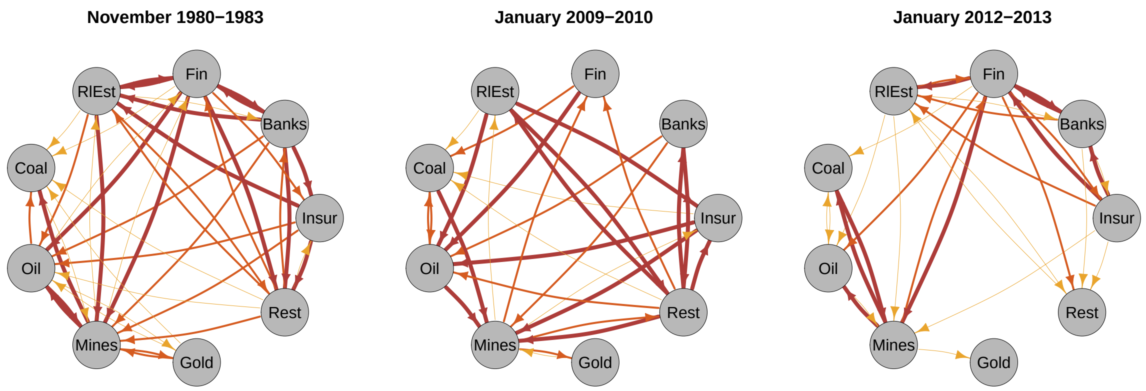


Figure 4.8: Spillovers between financial sectors, commodity industries and the remaining economy based on the Gibbs sampler



4.5 Conclusion

For an accurate assessment of spillovers between entities, it is of high importance to take into account the underlying dynamics. Here, this requirement is met by measuring spillovers based on TVP-VARs and the resulting impulse responses. We improve existing measures by accounting for the relevance of the estimates via the Bayes factor and by constructing credible intervals for the impulse responses, which in turn allow for meaningful interpretation of the evolution of spillover measures.

Our empirical comparison of two estimation approaches for TVP-VARs, the MCMC algorithm and the Kalman filter, points out that estimates obtained with the MCMC algorithm have higher forecasting power when unexpected crisis events occur and captures changes in the underlying dynamics more quickly. However, when computation time is an issue or if one wishes to include a large number of variables in one model, the Kalman filter is preferable and delivers reliable results for aggregated spillovers and after a certain time period after a crisis event.

By applying the spillover measure to a large set of industry portfolio returns on a granular level, we show that during the recent financial crisis, financial sectors have become less interconnected among each other, but more connected with the real economy, most of all the real estate and the trading sector. Spillovers between all market sectors have risen in the past decades, especially in the health sector and technological industry. Of all market sectors, commodity industries such as coal, oil and mining have a relatively low level of spillovers.

In future research, we plan to adapt the Kalman filter approach such that Σ_t is estimated by a Kalman filter instead of an EWMA estimator. This would provide better comparability to the setup of the Gibbs sampler and would allow to sample from the posterior distribution of Σ_t directly instead of constructing new samples via the bootstrap for the estimation of the Bayes factor and the credible intervals.

4.6 Appendix

4.6.1 Descriptive Statistics

Table 4.2: Definitions of 49 Industry Portfolios

Name	Definition	Name	Definition
Agric	Agriculture	Food	Food Products
Soda	Candy and Soda	Beer	Beer and Liquor
Smoke	Tobacco Products	Toys	Recreation
Fun	Entertainment	Books	Printing and Publishing
Hshld	Consumer Goods	Clths	Apparel
Hlth	Healthcare	MedEq	Medical Equipment
Drugs	Pharmaceutical Products	Chems	Chemicals
Rubbr	Rubber and Plastic Products	Txtls	Textiles
BldMt	Construction Materials	Cnstr	Construction
Steel	Steel Works Etc	FabPr	Fabricated Products
Mach	Machinery	ElcEq	Electrical Equipment
Autos	Autos Automobiles and Trucks	Aero	Aircraft
Ships	Shipbuilding, Railroad Equipment	Guns	Defense
Gold	Precious Metals	Mines	Non-Metallic and Industrial Metal Mining
Coal	Coal	Oil	Petroleum and Natural Gas
Util	Utilities	Telcm	Communication
PerSv	Personal Services	BusSv	Business Services
Hardw	Computers	Softw	Computer Software
Chips	Electronic Equipment	LabEq	Measuring and Control Equipment
Paper	Business Supplies	Boxes	Shipping Containers
Trans	Transportation	Whlsl	Wholesale
Rtail	Retail	Meals	Restaurants, Hotels, Motels
Banks	Banking	Insur	Insurance
RlEst	Real Estate	Fin	Trading
Other	Almost Nothing		

Table 4.3: Definitions of 5 Industry Portfolios

Name	Definition
Cnsmr	Consumer Durables, NonDurables, Wholesale, Retail, and Some Services
Manuf	Manufacturing, Energy, and Utilities
HiTec	Business Equipment, Telephone and Television Transmission
Hlth	Healthcare, Medical Equipment, and Drugs
Other	Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment, Finance

Table 4.4: Summary Statistics of 49 Industry Portfolio Returns

The table represents the mean (Mn), median (Med), maximum (Max), minimum (Min), standard deviation (Sd), skew (Skw) and kurtosis (Krt) of 49 industry portfolio returns. Statistics in the left part are for value-weighted portfolios and statistics in the right part of the table are for equally-weighted portfolios. The summary statistics are based on observations between July 1969 and July 2018.

	Value-Weighted Portfolios							Equally-Weighted Portfolios						
	Mn	Med	Max	Min	Sd	Skw	Krt	Mn	Med	Max	Min	Sd	Skw	Krt
Agric	0.99	0.86	28.88	-29.06	6.41	0.01	4.88	0.76	0.52	51.97	-30.59	7.45	0.66	8.52
Food	1.09	1.02	19.59	-17.88	4.49	0.19	5.10	1.14	1.32	20.88	-25.46	4.44	-0.52	6.78
Soda	1.13	1.40	38.27	-26.26	6.50	0.20	7.07	1.34	1.31	51.06	-23.04	6.73	1.03	10.15
Beer	1.14	1.12	26.09	-19.76	5.23	0.04	5.48	1.23	0.93	32.31	-19.43	5.34	0.46	6.71
Smoke	1.43	1.82	32.47	-24.93	6.18	0.11	5.68	1.83	1.42	53.51	-24.76	7.45	1.52	10.49
Toys	0.76	1.03	26.88	-34.41	7.05	-0.33	4.52	0.72	1.10	36.99	-29.77	7.43	0.18	5.90
Fun	1.37	1.44	38.77	-31.86	7.75	-0.08	5.95	1.03	1.05	40.99	-32.69	7.22	0.18	6.67
Books	0.88	0.50	30.74	-25.19	5.89	-0.01	5.08	1.11	1.15	53.15	-33.86	6.69	0.75	13.40
Hshld	0.84	1.06	18.54	-21.64	4.68	-0.37	5.05	0.94	0.82	39.68	-29.72	6.21	0.09	7.96
Clths	1.08	1.08	32.37	-30.90	6.60	-0.00	5.48	1.01	0.65	40.04	-30.35	6.74	0.27	7.13
Hlth	1.04	1.08	36.47	-39.11	8.11	-0.03	5.65	1.30	1.43	38.32	-38.48	7.88	0.02	6.33
MedEq	1.07	1.33	21.03	-20.56	5.28	-0.34	4.37	1.27	0.85	30.63	-30.07	7.03	0.13	5.15
Drugs	1.09	1.06	31.80	-19.11	5.04	0.22	5.85	1.57	1.41	63.36	-32.86	8.22	0.91	9.25
Chems	1.04	1.10	22.05	-28.00	5.65	-0.12	5.30	1.19	1.10	23.74	-30.73	5.95	-0.44	6.03
Rubbr	1.02	1.29	31.95	-30.57	6.00	-0.23	5.90	1.17	1.07	36.62	-30.56	6.62	0.06	6.21
Txtls	1.00	1.14	59.04	-32.51	7.30	0.50	12.29	0.85	0.66	50.95	-31.50	7.38	0.48	8.83
BldMt	1.01	1.21	35.51	-30.67	6.23	-0.02	6.88	1.20	1.21	39.00	-28.88	6.38	0.20	6.94
Cnstr	0.88	0.80	24.01	-31.10	7.23	-0.17	3.93	0.88	0.49	51.63	-30.16	7.71	0.56	7.72
Steel	0.76	0.67	30.67	-32.91	7.58	-0.27	5.12	1.03	0.61	34.00	-31.19	7.29	-0.04	5.42
FabPr	0.77	0.72	30.38	-26.67	7.28	-0.23	4.32	0.90	1.00	43.97	-26.90	7.17	0.06	6.12
Mach	0.99	1.33	23.05	-31.19	6.33	-0.41	5.43	1.21	1.31	24.46	-31.61	6.39	-0.38	5.43
ElcEq	1.14	0.93	23.21	-32.20	6.30	-0.14	4.71	1.04	0.91	33.04	-30.38	6.85	-0.10	4.95
Autos	0.83	0.72	49.57	-36.41	6.93	0.15	8.86	0.98	0.88	39.39	-35.09	7.16	-0.09	7.16
Aero	1.22	1.49	25.33	-30.23	6.66	-0.27	4.81	1.44	1.19	36.91	-30.04	7.02	0.37	6.21
Ships	1.11	1.13	29.15	-32.27	7.34	0.04	4.56	1.16	0.76	40.04	-43.12	7.94	0.14	6.79
Guns	1.30	1.40	32.64	-30.08	6.50	-0.05	5.35	1.61	1.26	27.75	-29.04	7.12	0.45	4.35
Gold	0.88	0.54	78.68	-33.57	10.85	0.74	7.58	1.04	-0.21	59.66	-43.23	12.06	0.86	5.55
Mines	1.02	0.59	26.91	-34.75	7.57	-0.29	4.89	1.10	0.31	37.42	-35.23	8.39	0.34	5.33
Coal	1.09	0.71	46.06	-37.94	10.83	0.19	4.68	0.80	0.15	80.02	-40.04	11.48	0.68	8.12
Oil	1.01	0.91	24.66	-18.21	5.61	0.08	4.11	1.05	1.11	27.28	-32.88	8.23	-0.06	4.29
Util	0.89	1.02	18.84	-12.65	4.07	-0.20	4.05	1.08	1.05	22.76	-13.07	3.61	0.02	5.75
Telcm	0.93	1.12	21.36	-16.36	4.74	-0.26	4.17	1.28	1.45	53.13	-27.39	7.46	0.49	8.47
PerSv	0.64	0.94	24.47	-28.25	6.68	-0.45	4.82	0.87	0.78	26.76	-30.68	6.63	-0.17	4.99
BusSv	0.96	1.46	25.34	-27.67	5.69	-0.46	5.41	1.23	1.33	33.38	-30.58	6.68	-0.07	5.77
Hardw	0.90	0.76	25.16	-33.50	7.18	-0.22	4.77	1.15	0.98	49.30	-33.25	9.03	0.54	5.95
Softw	1.03	1.45	73.65	-35.94	10.66	0.65	7.93	1.01	1.48	73.65	-51.76	10.84	0.45	9.34
Chips	1.07	1.57	27.27	-32.23	7.53	-0.35	4.65	1.44	1.24	45.22	-32.90	8.74	0.40	5.62
LabEq	1.05	1.19	21.56	-30.15	7.10	-0.16	4.23	1.43	1.43	37.24	-30.33	7.30	0.22	5.02
Paper	0.99	1.12	24.27	-26.35	5.54	0.09	5.34	1.06	1.23	35.03	-28.04	5.87	-0.08	7.26
Boxes	0.99	1.08	20.87	-28.24	5.71	-0.43	4.99	1.18	1.25	24.22	-27.35	6.24	-0.26	5.09
Trans	0.98	1.24	19.02	-27.90	5.81	-0.26	4.27	1.05	1.22	25.38	-29.82	6.20	-0.21	5.24
Whlsl	0.94	1.22	18.12	-28.65	5.47	-0.38	5.57	0.99	1.00	32.39	-29.22	6.33	-0.03	6.11
Rtail	1.08	0.82	27.07	-29.14	5.51	-0.14	5.12	1.04	0.90	36.41	-31.44	6.60	0.20	7.40
Meals	1.04	1.37	27.96	-31.33	6.04	-0.51	5.80	0.88	1.25	36.51	-28.60	6.49	-0.04	7.46
Banks	1.00	1.12	25.06	-27.24	6.07	-0.30	5.04	1.16	1.20	29.43	-20.53	4.97	0.01	6.35
Insur	1.07	1.50	26.84	-26.46	5.53	-0.25	5.13	1.33	1.73	39.01	-23.04	5.14	0.26	9.54
RlEst	0.55	0.61	69.23	-39.42	7.79	0.73	16.04	0.66	0.60	53.26	-32.97	7.40	0.50	9.67
Fin	1.11	1.44	19.57	-25.91	6.27	-0.38	4.29	1.12	1.49	27.19	-21.98	5.30	-0.15	5.53
Other	0.47	0.70	21.22	-27.20	6.85	-0.72	4.86	0.77	0.65	26.32	-32.62	6.75	-0.43	5.72

Table 4.5: Summary Statistics of 5 Industry Portfolio Returns

The table represents the mean (Mn), median (Med), maximum (Max), minimum (Min), standard deviation (Sd), skew (Skw) and kurtosis (Krt) of 5 industry portfolio returns. Statistics in the left part are for value-weighted portfolios and statistics in the right part of the table are for equally-weighted portfolios. The summary statistics are based on observations between July 1969 and July 2018.

	Value-Weighted Portfolios							Equally-Weighted Portfolios						
	Mn	Med	Max	Min	Sd	Skw	Krt	Mn	Med	Max	Min	Sd	Skw	Krt
Cnsmr	1.01	1.13	21.74	-25.02	4.55	-0.37	5.83	1.00	1.15	33.29	-29.43	5.92	-0.09	7.50
Manuf	0.95	1.21	17.28	-20.81	4.37	-0.45	5.18	1.06	1.24	25.31	-26.19	5.53	-0.45	6.07
HiTec	0.95	1.28	19.98	-22.62	5.56	-0.40	4.69	1.33	1.34	47.34	-31.00	8.16	0.36	6.23
Hlth	1.06	1.11	29.52	-20.46	4.89	0.09	5.56	1.42	1.11	42.84	-32.67	7.35	0.29	5.71
Other	0.93	1.30	20.22	-23.60	5.30	-0.51	4.97	1.08	1.28	29.02	-24.85	5.28	-0.25	6.23

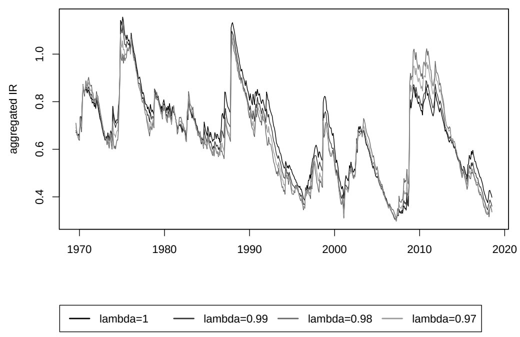
4.6.2 Robustness

While in our setup, Q is constant for both estimation approaches, Koop and Korobilis (2013) allow for time-varying Q_t for the Kalman filter approach. More precisely, the updating formula for the variance of $\beta_t|y^{t-1}$ is given by $var(\beta_t|y^{t-1}) = V_{t|t-1} = V_{t-1|t-1} + Q_t$. This equation is replaced by $V_{t|t-1} = \frac{1}{\lambda}V_{t-1|t-1}$, an EWMA estimator updated with forgetting factor λ. Since this implies $Q_t = (\lambda^{-1} - 1)V_{t-1|t-1}$, the values for Q_t can be easily computed from $V_{t-1|t-1}$. We compare results obtained for constant coefficients[14] with time varying coefficients for $\lambda \in \{0.97, 0.98, 0.99\}$. As illustrated in Figure 4.9, the choice of λ barely affects the spillover measure results.

For the robustness to alternative specifications of the priors for the Gibbs sampler, we refer to Primiceri (2005) and Cogley and Sargent (2005).

Figure 4.9: Comparison IRs for different lambdas.

The figure illustrates the network density based on estimates from the Kalman filter for different choices of $\lambda \in \{0.97, 0.98, 0.99, 1\}$.



[14] This occurs if $\lambda = 1$.

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