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ABSTRACT

This paper examines the connectedness of the Eurozone sovereign debt market over the period 2005–2011. By employing measures built from the variance decompositions of approximating models we are able to define weighted, directed networks that enable a deeper understanding of the relationships between the Eurozone countries. We find that connectedness in the Eurozone was very high during the calm market conditions preceding the global financial crisis but decreased dramatically when the crisis took hold, and worsened as the Eurozone sovereign debt crisis emerged. The drop in connectedness was especially prevalent in the case of the peripheral countries with some of the most peripheral countries deteriorating into isolation. Our results have implications for both market participants and regulators.

Key words: European sovereign debt; MTS; Network; Connectedness; Return; Volatility

JEL Classification: G01, G15, H63

1. Introduction

It is important to understand the network structure of systems, especially financial systems. In particular, understanding how financial market systems behave during crises is important for market participants and regulators alike. The implications are felt not just in the markets themselves, but also in the wider economy. This topic is particularly relevant following the recent global financial and European sovereign debt crises where the failure of Lehman Brothers, a mid-sized investment bank, helped turn a local bust into a global financial crisis due to its high levels of connectedness to the rest of the financial system.

The Eurozone provides an excellent opportunity for an analysis of a network during a period of market turbulence. The Eurozone is a monetary union of a subset of EU member states that have adopted the Euro as their common currency. While bound together geographically, by common currency and by EU laws and regulations, each member state retains independence over its own economy.

Several studies have already attempted to address the Eurozone crisis (Barrios et al., 2009; De Santis, 2012; Fontana and Scheicher, 2010; Beetsma et al., 2012; Bai et al., 2012; Pellizon et al., 2013; Darbha and Dufour, 2013) however little emphasis has been put on connectedness, the interdependence of the Eurozone countries and the impact of these relationships. This paper uses high-frequency bond market data to address the network element of the Eurozone crisis question. We find that connectedness in the Eurozone was extremely high during the calm market conditions preceding the global financial crisis but decreased dramatically when the crisis took hold, and worsened as the Eurozone sovereign debt crisis emerged. The drop in connectedness was especially prevalent in the case of the peripheral countries with some of the most peripheral countries deteriorating into isolation.

To understand network connectedness first we have to be able to quantify the relationships within the networks. A new branch of literature opens up the possibility to study the structure of networks both statically and dynamically. The study of networks in finance and economics is a relatively new field. Measuring connectedness has been attempted by many researchers, and most successfully by Diebold and Yilmaz (2014). In their seminal paper they use an approach, closely linked to network models, which is used to understand causal links measure connectedness using dynamic predictive modelling under misspecification. Specifically, their approach is based on 'assessing shares of forecast error variation in various locations […] due to shocks arising elsewhere.' An attractive feature of this approach is that the forecast error variance decompositions are computed directly and are subject to no additional restrictions beyond those required for estimation and identification; as such they provide an untouched reflection of the connections embedded in the model. This is the framework we follow in this paper.

Other relevant literature includes Schwendner et al. (2015) who use partial correlation networks to analyse European government bond dynamics from 2004-2015. They find contagion risks decreased since the European rescue and stability mechanisms in 2012. Billio et al. (2012) employ both principal component analysis and Granger-causality networks to investigate the connectedness and systemic risk in the finance and insurance sectors. They find an increase in the connectedness between banks, hedge funds, broker/dealers and insurance companies over the past decade.

Other attempts include Engle and Kelly's (2012) equicorrelation approach with a focus on average pairwise correlation, Adrian and Brunnermeier's (2011) CoVaR approach which goes beyond the pairwise association, and Acharya et al. (2010) and their use of marginal expected shortfall (MES) which again goes further than pairwise association.

Unlike with networks, literature on the Eurozone is abundant. The early literature focused on the introduction of the single currency and the subsequent impact this had on the markets in the years following. McCauley (1999) discusses the liquidity of European fixed income markets with a focus on the impact of the introduction of the Euro, concluding that this accelerated the concentration of liquidity in German futures contracts, increasing integration to the Eurozone government bond market. Codogno, Favero and Missale (2003) analyse the yield spreads on Eurozone debt, and determined that movements in yield differentials are explained in the most part by international risk factors. They find that liquidity factors are less important in explaining movements, but still account for some movement.

Recent Eurozone literature focuses on the various crises that have engulfed the markets. In particular, several papers discuss reasons for movements in the yields of Eurozone government debt. Barrios, Iversen, Lewandowsk and Setzeos (2009) study Eurozone government bond yield spreads during the global financial crisis and find that international factors, particularly risk, played a major role in explaining yield differentials. Domestic factors, such as liquidity, were smaller but non-negligible drivers of yield spreads and the impact increased significantly during the crisis. Similarly, De Santis (2012) conducts an analysis on the sovereign spreads on Eurozone government debt using daily data from September 2008 until August 2011. He concludes that three factors explain spread developments: aggregate regional risk factors, country-specific credit risk, and the spillover effect from Greece. Beetsma, Giuliodori, de Jong and Widijanto (2012) consider the impact of news on Eurozone government bond spreads over Germany since September 2009, finding that an increase in news announcements regarding the peripheral nations raised the domestic interest spreads of these nations. It also affected the other peripheral countries, with the magnitude of movement related cross-border bank holdings. There was some spillover from peripheral to non-peripheral.

Based on the above discussion, a number of studies have empirically examined the Eurozone crisis. This paper is unique in adopting a network approach to analyse the recent turbulence in the Eurozone market. By focusing on network connectedness, both statically and dynamically, it is possible to gain a perspective on various intricacies and inefficiencies with the aim of formulating recommendations for optimal design and regulation of financial markets. Understanding the network structure for the countries in the Eurozone will help to answer many questions, including the question of mutual monitoring. For example, was the early trauma suffered by Greece a prelude to the problems in Ireland and Portugal? Was the robustness of Germany and France a sign of a potential split into weak and strong nations?

Our study extends and compliments the existing Eurozone crisis literature by providing a novel perspective on the Eurozone countries during recent crises using sovereign debt returns and realised volatilities as proxies for economic health. To quantify the structural properties of the network of Eurozone countries, we follow the method of Diebold and Yilmaz (2014). Specifically, connectedness as measured by the variance decompositions of approximating models. As they point out ‘connectedness features prominently in key aspects of market risk (return connectedness and portfolio concentration), credit risk (default connectedness), counter-party and gridlock risk (bilateral and multilateral contractual connectedness), and not least, systemic risk (system-wide connectedness). It is also central to understanding underlying fundamental macroeconomic risks, in particular business cycle risk (intra- and intercountry real activity connectedness).’

Sovereign debt market data provide an excellent basis for the analysis in this study; since they are actively traded on liquid and transparent markets they reflect forward-looking assessments of many thousands of smart, strategic and often privately-informed agents as regards precisely the relevant sorts of connections and, as such, can be used to measure connectedness and its evolution through time.

Previewing our results, we document a very high level of connectedness within the Eurozone during the calm market conditions, with no distinguishable differences between the countries. Connectedness began to breakdown in early 2008 and worsened throughout the sample period to varying degrees depending on the country’s position within the European economy. We performed the analysis on both returns and volatilities and found similar results, but with subtle, important differences.

Overall, our results imply that the Eurozone countries, and actors within these countries, saw the worsening conditions of the peripheral nations and acted on this information. The slow onset of the Eurozone crisis, as well as the vast support afforded by international governing bodies, gave the countries time to disassociate themselves, and this isolation is reflected in the connectedness numbers.

The layout of the rest of this paper is as follows: Section 2 provides a description of the employed data and methodology. Section 3 discusses the main findings and Section 4 concludes the paper.

2. Data and methodology

2.1. Data description

Our study is based on a high-frequency data sample from the MTS electronic trading platform. MTS is the largest interdealer market for Eurozone government debt, with a share of interdealer trading in Eurozone government bonds of considerably more than 50% (Dunne et al., 2006). Access is granted to large institutions and investment banks with traders acting as professional market makers. The role of market makers in these markets is to provide stable price formation and reliable liquidity. Architecturally the MTS platform has a fragmented structure with two different market segments for trading: EuroMTS and MTS Domestic Markets. EuroMTS is the reference electronic market for Euro benchmark bonds; bonds with an outstanding value of at least €5 billion. The MTS Domestic Markets list the whole yield curve of the government bond market of the respective European country. The two segments operate as independent limit order books. The data used in this paper consist of the most competitive tick-by-tick quoted prices across both market segments for benchmark Eurozone government bonds from July 2005 until December 2011.

Eleven countries were using the Euro for the entirety of this 78-month period (Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, and Spain) and they are the subject of this analysis. Each of the eleven countries in the sample had multiple benchmark bonds actively traded in the secondary markets during the period of interest. In order to get a single representative time series for each country, we construct a country-specific bond index. The index is constructed as a simple linear-weighted representation of all benchmark bonds available on both MTS segments for the entire period.

This method was preferable to other options such as, for example, using a single ‘benchmark’ bond since there is no single bond that acts as a benchmark in the European market. Similarly, unlike the U.S. Treasury market, there is no concept of liquidity concentration into on-the-run and off-the-run bonds. Table 1 presents the bonds, identified by ISIN code, that were used to construct the indices.

Table 1

Bonds used in the indices for each of the eleven Eurozone countries.

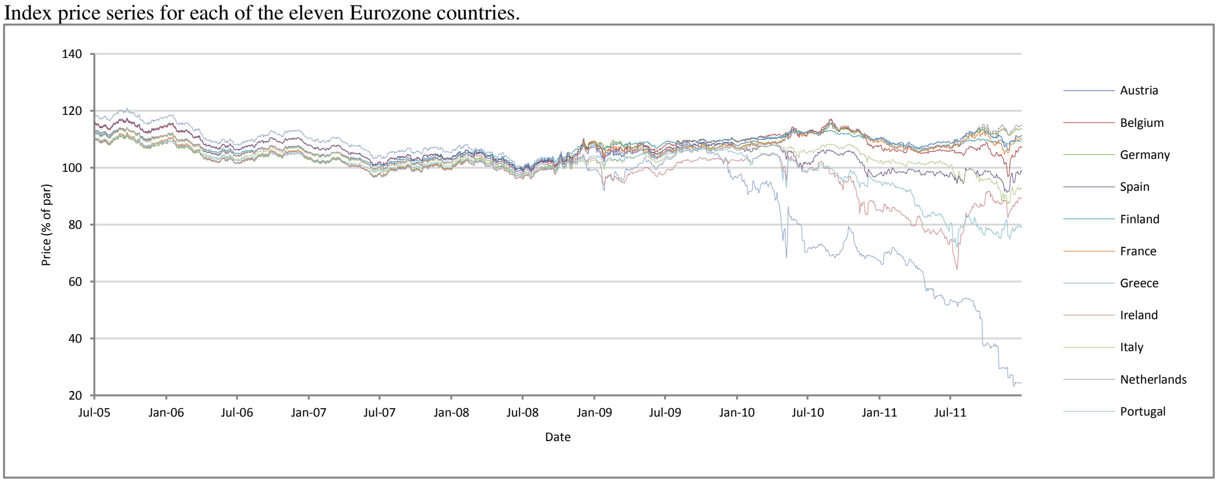
Austria	Belgium	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain
AT0000383864	BE0000291972	FI0001005407	FR0000187361	DE0001135176	GR0124026601	IE0006857530	IT0003242747	NL0000102234	PTOTE1OE0019	ES0000012098
AT0000385356	BE0000298076	FI0001005704	FR0000187635	DE0001135200	GR0128002590	IE0031256328	IT0003256820	NL0000102242	PTOTEGOE0009	ES0000012411
AT0000385745	BE0000300096		FR0000188690	DE0001135218	GR0133001140	IE0034074488	IT0003357982	NL0000102317	PTOTEKOE0003	ES0000012783
AT0000385992	BE0000301102		FR0000188989	DE0001135234	GR0133002155		IT0003472336	NL0000102325	PTOTEYOE0007	ES0000012791
AT0000386073	BE0000303124		FR0000189151	DE0001135242	GR0138001673		IT0003493258	NL0000102671		ES0000012866
AT0000386115	BE0000304130		FR0010011130	DE0001135259			IT0003535157	NL0000102689		ES0000012916
AT0000386198	BE0000306150		FR0010061242	DE0001135267			IT0003618383			ES0000012932
			FR0010070060	DE0001135275			IT0003644769			
			FR0010112052	DE0001135283			IT0003719918			
			FR0010163543				IT0003844534			
			FR0010171975							
			FR0010216481							

Notes: This table shows the ISIN codes for each of the bonds used to construct the country-specific indices. To be included in the country index the bond must have been listed and available to trade on both the MTS domestic and EuroMTS market segments, and available for the whole period July 2015 – December 2011.

We study daily return and volatility connectedness. Returns provide a direct relation to the market’s assessment of a country’s economic and financial health (credit worthiness, ability to sustain and manage debt, interest rates, etc.). Volatility tracks investor fear, and so volatility connectedness can be considered the ‘fear connectedness’ expressed by market participants as they trade. In addition, volatility connectedness is of special interest because we are examining in crises, and volatility is particularly crisis-sensitive. We calculate daily realized volatility as the sum of squared log price changes over 5 minute intervals during trading hours. Realized volatility is treated as the object of direct interest, as in Andersen et al. (2003). Five-minute sampling is frequent enough largely to eliminate measurement error, yet infrequent enough such that microstructure noise (e.g., due to bid–ask bounce) is not a concern.

In general, we examine the level, variation, paths, patterns and clustering in both connectedness measures. Constructing these bond indices for each country makes it possible to accurately monitor and characterize the evolution of price dynamics for the sovereign debt of each the eleven countries in the Eurozone during the sample period. The bond index price series of the eleven countries can be seen in Figure 1.

Figure 1
Index price series for each of the eleven Eurozone countries.



Notes: This table shows the price series of the bond indices for each country included in the study.

The dataset spans several important financial market episodes, which allows us to examine how the dynamics of the market changed from a period of calm, through the global financial crisis and finally into the Eurozone sovereign debt crisis. To this end, to aid the analysis the full period of July 2005 to December 2011 was sub-divided into three phases according to the macro-economic environment at the time.

The early part of the last decade was characterised by high growth and stable conditions in the market for European sovereign debt – the first period in our data sample is from July 2005 to May 2007 and is considered calm, or normal, market conditions.

The growth in the financial markets in the last decade occurred in tandem with huge inflation in the U.S. housing market before it slowed and subsequently collapsed in early 2007. The financial stress of the subprime crisis spread from the U.S. to the rest of the world; the period being characterised by bank runs, bankruptcies and nationalisations – the second period in our data sample is from June 2007 to December 2008 and is considered the global financial crisis.

Finally, first evidenced by the nationalisation of the Anglo Irish Bank by the Irish government in January 2009, the Eurozone crisis emerged. The Eurozone crisis affected all countries in the Eurozone, but with varying severity most easily seen in the bond markets. Due to the interconnectedness of the countries in the Eurozone, the resulting lack of confidence in the governments' abilities to pay their outstanding debts was revealed in the markets by a lack of willingness to hold the debt and a subsequent drop in liquidity and trading volume – the third and final period in our data sample is from January 2009 to the end of the dataset at December 2011 and is considered the Eurozone crisis.

It is worth noting at this stage that we focus on returns and volatility, and not liquidity. Liquidity is a key aspect of the bond markets but, as illustrated in other studies, the decrease in liquidity was uniform across all the Eurozone countries and therefore missing the idiosyncratic nature of the returns and volatilities that make this study interesting.

2.2. Methodology

This paper applies the approach introduced by Diebold and Yilmaz (2014) to the problem of quantifying Eurozone network connectedness. The empirical framework for this approach is to use variance decompositions of approximating models; by assessing the shares of forecast error variation in various countries due to shocks arising elsewhere we can define a weighted, directed network that is intimately linked to the key measures of connectedness used in the network literature.

In the overview of the analysis technique that follows, the following notation is used: $\mathrm{d}_{\mathrm{ij}}^{\mathrm{H}}$ is the ij$^{\mathrm{th}}$ H-step variance decomposition component. In words, this is the fraction of variable i's H-step forecast error variance due to shocks in variable j. A key point in the method is that all connectedness measures are based on cross variance decompositions, i.e. $\mathrm{d}_{\mathrm{ij}}^{\mathrm{H}},\ \mathrm{i},\mathrm{j} = 1,2,3,\ldots,\mathrm{N},\ \mathrm{j} \neq \mathrm{i}$. In this way, it is possible to determine the bilateral relationship between two variables.

2.2.1. Population connectedness

The analysis starts from an N-dimensional covariance-stationary data generating process with orthogonal shocks: $x_t = \Theta(L)u_t$, $\Theta(L) = \Theta_0 + \Theta_1 L + \Theta_2 L + \cdots$, $E(u_t u_t') = I$, where Θ_0 need not be diagonal. This general process can be considered to contain all aspects of connectedness: contemporaneous aspects are summarised in Θ_0 and dynamic aspects are summarised in $\{\Theta_1, \Theta_2, \ldots\}$. However, trying to understand connectedness by analysing the potentially hundreds of coefficients in $\{\Theta_1, \Theta_2, \ldots\}$ is computationally impractical and better approached by transformation into a form that compactly summarises all aspect – enter variance decompositions.

Results are displayed in a Diebold and Yilmaz (2014) connectedness table in order to aid understanding and allow intuitive visualisation. Table 2 outlines the key aspects of this table.

Table 2
Connectedness table schematic.

	x_1	x_2	$\cdots$	x_N	From others	
x_1	d_{11}^H	d_{12}^H	$\cdots$	d_{1N}^H	$\sum_{j=1}^N d_{1j}^H$,	$j \neq 1$
x_2	d_{21}^H	d_{22}^H	$\cdots$	d_{2N}^H	$\sum_{j=1}^N d_{2j}^H$,	$j \neq 2$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	
x_N	d_{N1}^H	d_{N2}^H	$\cdots$	d_{NN}^H	$\sum_{j=1}^N d_{Nj}^H$,	$j \neq N$
To others	$\sum_{j=1}^N d_{i1}^H$,	$\sum_{j=1}^N d_{i2}^H$,	$\cdots$	$\sum_{j=1}^N d_{iN}^H$,	$\frac{1}{N}\sum_{i,j=1}^N d_{ij}^H$,	
	$i \neq 1$	$i \neq 2$		$i \neq N$	$i \neq j$	

Notes: The off-diagonal entries of the main $N \times N$ matrix will contain the parts of the N forecast error variance decomposition of relevance from a connectedness perspective; unsurprisingly it is named the 'variance decomposition matrix', and denoted $D^H = [d_{ij}^H]$. The 'From others' column displays the off-diagonal row sums. The 'To others' row displays the off-diagonal column sums. And the intersection of these in the bottom right contains the grand average of all off-diagonal entries. The variance decomposition matrix provides measures of pairwise directional connectedness. Pairwise directional connectedness from j to i is defined as $C_{i\leftarrow j}^H = d_{ij}^H$. There is no reason why $C_{i\leftarrow j}^H$ should be equal to $C_{j\leftarrow i}^H$, so there will be $N^2 - N$ separate pairwise directional connectedness measures. Moving on from the individual elements of the variance decomposition matrix, the off-diagonal row and column sums also provide useful insight at a less granular level. The sum of the off-diagonal elements of a row gives the share of the H-step forecast error variance of the row variable coming from shocks arising in other variables, $C_{i\leftarrow \cdot}^H = \sum_{j=1, i\neq j}^N d_{ij}^H$. Similarly the sum of the off-diagonal elements of a column give the amount of the H-step forecast error variance that the column variable contributes to others, $C_{\cdot\leftarrow j}^H = \sum_{i=1, i\neq j}^N d_{ij}^H$. Finally, the total sum of the off-diagonal elements measures the total connectedness, $C^H = \frac{1}{N}\sum_{i,j=1, i\neq j}^N d_{ij}^H$. This single total connectedness measure distils the connectedness of the entire system into a single number.

In the model orthogonal reduced-form system, the variance decompositions are easily calculated because orthogonality guarantees that the variance of a weighted sum is simply an appropriately-weighted sum of variances. However, reduced-form shocks are rarely orthogonal, and so to identify uncorrelated structural shocks from correlated reduced-form shocks we have to make assumptions.

Some example assumptions from the literature are Sims (1980) Cholesky-factor vector autoregression (VAR) identifications, Koop et al. (1996) and Pesaran and Shin (1998) generalised variance decomposition (GVD) framework, and Del Negro and Schorfheide (2011) survey of structural dynamic stochastic general equilibrium environments. The benefits and short comings of these assumptions are well documented and not discussed here.

In this paper we follow the lead of Diebold and Yilmaz (2014) and opt for generalised variance decomposition. The H-step GVD matrix $D^{gH} = \left[d_{ij}^{gH}\right]$ has entries as follows

$$d_{ij}^{gH} = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e_i'\Theta_h\Sigma e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i'\Theta_h\Sigma\Theta_h' e_i\right)} \tag{1}$$

where e_j is a selection vector with jth element unity and zeroes elsewhere, Θ_h is the coefficient matrix multiplying the h-lagged shock vector in the infinite moving-average representation of the non-orthogonalised VAR, Σ is the covariance matrix of the shock vector in the non-orthogonalised VAR, and σ_{jj} is the jth diagonal element of Σ.

Because shocks are not necessarily orthogonal in the GVD environment, sums of forecast error variance contributions are not necessarily unity (that is, row sums of D^g are not necessarily unity). Hence we base the generalised connectedness indexes not on D^g, but rather on $\widetilde{\mathrm{D}}^{\mathrm{g}} = \left[\tilde{\mathrm{d}}_{\mathrm{ij}}^{\mathrm{g}}\right]$, where $\tilde{\mathrm{d}}_{\mathrm{ij}}^{\mathrm{g}} = \frac{\mathrm{d}_{\mathrm{ij}}^{\mathrm{g}}}{\sum_{\mathrm{j}=1}^{\mathrm{N}} \mathrm{d}_{\mathrm{ij}}^{\mathrm{g}}}$. By construction $\sum_{\mathrm{j}=1}^{\mathrm{N}} \tilde{\mathrm{d}}_{\mathrm{ij}}^{\mathrm{g}} = 1$ and $\sum_{\mathrm{i,j}=1}^{\mathrm{N}} \tilde{\mathrm{d}}_{\mathrm{ij}}^{\mathrm{g}} = \mathrm{N}$. Using $\widetilde{\mathrm{D}}^{\mathrm{g}}$ it is possible to immediately calculate generalised connectedness measures.

2.2.2. Empirical methodology

All measures of connectedness (C) depend on the set of variables whose connectedness is to be examined (x), the predictive horizon for variance decompositions (H), and the dynamics ($A(L)$). As such, C is more accurately written $C(x, H, A(L))$. Further, in reality $A(L)$ is unknown and must be approximated, using a finite-ordered vector auto-regression. Recognising the centrality of the approximating model adopted this is refined further to $C(x, H, A(L), M(L; \theta))$, where $M(L; \theta)$ is a dynamic approximating model with finite-dimensional parameter θ.

In addition, in order to be able to extend the analysis from the static, unconditional perspective to a dynamic, conditional perspective, time-varying connectedness must be allowed for. Time-varying dynamics $A(L)$, and by extension time-varying connectedness, may arise for a variety of reasons. As Diebold and Yilmaz (2014) point out, $A(L)$ may evolve 'slowly with evolving tastes, technologies and institutions, or it may vary with the business cycle, or it may shift abruptly with financial market environment. Whether and how much $A(L)$ varies is ultimately an empirical matter and will differ across applications, but in any event it would be foolish to assume it is constant'. As such the connection table and all its elements are allowed to vary over time. Finally, this leaves $C_t(x, H, A_t(L), M(\theta_t))$.

Everything written so far refers to the population, whereas in reality we have only a finite data sample available. That is, we must estimate approximating models, so we write $\tilde{C}_t(x, H, A_t(L), M(\tilde{\theta}_t))$, where the data sample runs from $t = 1, \ldots, T$. Connectedness measurements are defined only with respect to a reference universe, namely the set of x's defining the object of interest to be studied. Choice of x has important implications for the appropriate approximating model; for example, x may (or may not) be strongly serially correlated, conditionally heteroskedastic, or highly disaggregated. Connectedness measurements generally will not, and should not, be robust to choice of reference universe.

Three sub-issues arise, which Diebold and Yilmaz (2014) refer to as the 'x object', the 'x choice', and the 'x frequency'. The x object is the type of x variable studied, the x choice refers to precisely which (and hence how many) x variables are chosen for study, and the x frequency is the observational frequency of the x variables.

In this paper there are two separate x objects studied: the natural log of bond returns and the natural log of bond return volatility, in both cases the x choice is the 11 Eurozone countries whose debt is traded on MTS for the entire sample period, and the x frequency is daily observations.

The choice of connectedness horizon, H, can be context driven. For example, in risk management contexts, one might focus on H values consistent with risk measurement considerations, for example portfolio rebalancing periods. As Diebold and Yilmaz (2014) point out, the connectedness horizon is important because it is related to issues of dynamic connectedness (in the fashion of contagion) as opposed to purely contemporaneous connectedness. To take a simple pairwise example, shocks to j may impact the forecast error variance of i only with a lag, so that $C_{i \leftarrow j}$ may be small for small H but nevertheless larger for larger H. Intuitively, as the horizon lengthens there may be more chance for connectedness to appear. Thus, in a sense, varying H allows the breaking of connectedness into 'long-run', 'short-run', etc. More precisely, as H lengthens the corresponding sequence of conditional prediction error variance decompositions are obtained for which the conditioning information is becoming progressively less valuable. In the limit as $H \rightarrow \infty$, we obtain an unconditional variance decomposition. In this paper we use a horizon of $H = 12$ days.

There are two issues to consider when choosing the approximating model. The first issue is choice of approximating model class. Many options are possible, such as traditional data-driven VAR approaches, to 'structural' VARs, to fully-articulated dynamic stochastic general equilibrium (DSGE) models. The second issue is how to allow for time-varying connectedness. Since connectedness is simply a transformation of model parameters, allowance for time-varying connectedness effectively means allowance for time-varying parameters in the approximating model. Linear models with time-varying parameters are actually very general nonlinear models, as emphasized in White's Theorem (Granger, 2008). As with choice of approximating model class, many choices are possible to allow for time-varying parameters. A simple and popular scheme, used by Diebold and Yilmaz (2014) involves use of a rolling estimation window. To track time-varying connectedness in real-time, for example, they use a uniform one-sided estimation window of width W, sweeping through the sample, at each period using only the most recent W periods to estimate the approximating model and calculate connectedness measures. This means C is written as $\tilde{C}_t(x, H, M_{t-w:t}(\tilde{\theta}))$. The rolling-window approach has the advantages of tremendous simplicity and coherence with a wide variety of possible underlying time-varying parameter mechanisms. Rolling windows do, however, require choice of window width W, in a manner precisely analogous to bandwidth choice in density estimation. In this paper we focus on a VAR(3) approximating model with a one-sided rolling estimation window of $\mathrm{W} = 100$ days.

3. Empirical results

In this section, we report the main findings from the empirical analysis. It was evident from the literature and data sections that the global financial crisis and Eurozone crisis had profound effects on the dynamics of the Eurozone sovereign debt. This section attempts to add some additional colour to the earlier findings by giving the results of the network connectedness analysis and an interpretation of the results.

We begin with the static analysis, split by the three sub-periods defined in the data section: calm, global financial crisis and Eurozone crisis. We then examine the dynamic elements of connectedness. Finally, we discuss the economic significance of the findings, and how they can help regulators and market participants alike.

3.1. Static (full-sample, unconditional) analysis

In this sub-section, we investigate the static (full sample, unconditional) connectedness between Eurozone countries in the period July 2005 – December 2011, specifically looking in turn at each of the three sub-periods of calm (July 2005 to May 2007), global financial crisis (June 2007 to December 2008), and Eurozone crisis (January 2009 to December 2011).

As explained earlier, the primary method is the variance decompositions of approximating models first introduced in this context by Diebold and Yilmaz (2014). We examine both returns and realised return volatilities. Results of the static analysis are presented in connectedness tables, as described in Table 1. There is no reason why $C^H_{i \leftarrow j}$ should be equal to $C^H_{j \leftarrow i}$, so there will be $N^2 - N$ separate pairwise directional connectedness measures; for the 11 countries in our sample that equals 110 pairwise directional connectedness measures (as well as 11 measures for 'own connectedness') that need to be analysed. To facilitate interpretation, we place heat-maps over the connectedness tables.

Table 3 reports the results for return series connectedness. Looking first at Table 3 Panel A it is clear that there is very little variation between the numbers, meaning the share of forecast error variation due to shocks arising elsewhere was evenly spread amongst the countries, both own and external. Accordingly, total connectedness of the network is extremely high at 90.3%. The spread of the 'from others' degree distribution (which ranges from 86.9% for Finland to 91.6% for Germany) is noticeably less than that of the ‘to others’ degree distribution (which ranges from 81% for Germany to 108.1% for Ireland). The highest pairwise directional connectedness is from Greece to Italy (12.1%), and the lowest pairwise directional connectedness is from Germany to Greece (7.8%). That is a spread of only 4.3% between the highest and lowest pairwise directional connectedness, and there is no discernible pattern amongst the countries. The diagonal elements (own connectedness) have an average of 9.71%, which is lower than the average of the off-diagonal elements, implying that most variation in bond returns was driven by external factors. From this finding we conclude that the Eurozone countries are tightly linked in the eyes of investors and that there are no major factors isolating any one country.

Looking next at Table 3 Panel B there is a significant increase in the variation. Total connectedness is still very high at 86.9%, but has decreased from the period of calm. The highest pairwise directional connectedness is from Italy to Portugal (15.1%), and the lowest pairwise directional connectedness is from Belgium to Greece (5.0%). More specifically, the total variation ‘from others’ to Greece has dropped from 87.3% in the period of calm to 77.3% implying that the markets have already started to treat Greece differently from the rest of the Eurozone and it is already becoming isolated. The variation of ‘from others’ for the other ten countries remains similar to the calm figures. The diagonal elements have an average of 13.06%, driven mostly by an increase for the peripheral countries, and there is a maximum of 22.7% for Greece; this indicates a move to internal factors for the peripheral countries in general and Greece in particular. However overall total directional connectedness (‘from others’ or ‘to others’) remains much larger than own connectedness, and the own connectedness of the core countries doesn’t change from the calm period.

Finally looking at Table 3 Panel C there is a marked difference from the previous periods. Total connectedness has dropped significantly to 58.9%. The highest pairwise directional connectedness is from the Netherlands to Germany (31.6%) and, in general, the total ‘from others’ for the core countries remains high. Contrastingly, the total ‘from others’ for the peripheral countries is very low with Greece at 25.7%, Ireland at 42.6% and Portugal at 44.9% indicating that the general economic environment of the Eurozone was driving returns less than their own internal factors. One noteworthy point is that of the low amount of variation ‘from others’ to the peripheral countries, the majority comes from other peripheral countries. For example, consider Greece: of the 25.7% variation coming from others, 17.5% comes from the three countries of Spain, Portugal and Ireland. Consider Ireland: of the 42.6% variation coming from others, 25.0% comes from three countries of Spain, Portugal and

Greece. Consider Portugal: of the 44.9% variation coming from others, 33.5% comes from the three countries of Spain, Ireland and Greece. This implies that the peripheral countries strongly affect other peripheral countries. The diagonal elements, especially those of the peripheral countries, are the largest individual elements of the table. In this period even core countries' own connectedness has increased, implying that they are being influenced less by the other countries as the crisis worsened.

To summarise, Eurozone government bond returns connectedness was at its highest during the period of calm and dropped significantly when the crisis set in. Given the nature of the network in question, and the relatively slow onset of the crises, this is to be expected. Unlike the financial industry, which became more highly connected during the crisis period (Diebold and Yilmaz, 2014), investors segmented the Eurozone into core, semi-core and peripheral – thus creating multiple sub-networks within the major network.

One anomaly to note is Finland which, judging by the price series, was firmly amongst the core nations. However, the connectedness was significantly lower than the other core countries, and this low connectedness remained quite consistent and was not so much affected by the crisis. This reflects Finland's position within the Eurozone as the lone Scandinavian country.

Table 3

Panel A: Returns series connectedness table for July 2005 – May 2007.

	AT	BE	DE	ES	FI	FR	GR	IE	IT	NL	PT	FRO
AT	8.6%	8.5%	8.2%	8.5%	10.6%	8.6%	10.0%	10.9%	8.9%	8.7%	8.6%	91.4%
BE	8.6%	8.5%	8.2%	8.6%	10.4%	8.7%	9.9%	10.8%	9.0%	8.8%	8.5%	91.5%
DE	8.5%	8.5%	8.4%	8.5%	10.1%	8.7%	10.3%	10.7%	8.9%	8.8%	8.6%	91.6%
ES	8.6%	8.5%	8.2%	8.8%	10.5%	8.5%	10.0%	10.6%	9.0%	8.8%	8.5%	91.2%
FI	8.1%	8.0%	8.1%	8.0%	13.1%	8.8%	9.5%	10.8%	8.4%	8.3%	9.0%	86.9%
FR	8.6%	8.6%	8.2%	8.7%	10.1%	8.5%	9.9%	10.9%	9.0%	8.8%	8.5%	91.5%
GR	8.2%	8.4%	7.8%	8.4%	9.2%	8.4%	12.7%	11.0%	9.2%	8.6%	8.1%	87.3%
IE	8.4%	8.4%	8.2%	8.4%	11.4%	8.6%	9.9%	10.4%	8.8%	8.6%	8.8%	89.6%
IT	8.1%	8.4%	7.9%	8.3%	9.3%	8.4%	12.1%	10.8%	10.0%	8.6%	8.1%	90.0%
NL	8.6%	8.6%	8.2%	8.7%	10.3%	8.6%	9.9%	10.7%	8.9%	9.0%	8.5%	91.0%
PT	8.1%	8.2%	8.1%	8.2%	11.3%	8.7%	10.4%	10.8%	8.8%	8.5%	8.8%	91.2%
TO	83.6%	83.9%	81.0%	84.5%	103.4	86.1%	101.9	108.1	88.9%	86.4%	85.2%	**90.3%**
NET	-7.8%	-7.6%	-10.6%	-6.7%	16.5%	-5.3%	14.6%	18.5%	-1.1%	-4.6%	-5.9%	

Panel B: Returns series connectedness table for June 2007 – December 2009.

	AT	BE	DE	ES	FI	FR	GR	IE	IT	NL	PT	FROM
AT	8.2%	7.6%	7.1%	8.1%	13.0%	7.7%	6.5%	11.3%	11.8%	7.6%	11.3%	91.9%
BE	9.1%	8.2%	7.4%	9.8%	10.2%	9.1%	6.9%	8.9%	12.2%	8.2%	10.0%	91.8%
DE	8.9%	8.1%	8.3%	8.3%	7.6%	10.0%	9.3%	10.4%	10.5%	8.4%	10.1%	91.5%
ES	8.8%	7.8%	7.1%	12.3%	10.1%	8.4%	7.0%	8.9%	11.4%	8.1%	10.2%	87.9%
FI	7.3%	7.7%	6.5%	6.0%	18.2%	6.4%	5.5%	11.3%	10.7%	7.1%	13.3%	81.8%
FR	9.2%	8.2%	7.6%	9.5%	9.6%	10.4%	6.7%	9.2%	11.4%	8.6%	9.6%	89.6%
GR	7.8%	5.0%	5.8%	8.5%	7.8%	7.6%	22.7%	8.6%	9.5%	8.9%	7.9%	77.3%
IE	7.3%	6.9%	5.9%	7.8%	15.1%	6.5%	6.3%	13.0%	11.2%	8.6%	11.4%	87.0%
IT	6.5%	5.8%	5.9%	7.8%	9.8%	7.0%	10.7%	7.8%	19.2%	8.4%	11.1%	80.8%
NL	9.7%	8.2%	7.7%	9.2%	10.2%	9.7%	6.8%	9.5%	11.0%	8.4%	9.6%	91.6%
PT	7.4%	6.6%	6.2%	7.5%	12.1%	6.5%	6.6%	9.7%	15.1%	7.5%	14.8%	85.2%
TO	82.0%	71.9%	67.3%	82.5%	105.4%	78.9%	72.2%	95.7%	114.8%	81.2%	104.6%	**86.9%**
NET	-9.9%	-19.8%	-24.3%	-5.4%	23.7%	-10.7%	-5.2%	8.6%	34.0%	-10.4%	19.4%	

Panel C: Returns series connectedness table for January 2010 – December 2011.

	AT	BE	DE	ES	FI	FR	GR	IE	IT	NL	PT	FROM
AT	35.3%	6.4%	7.1%	2.4%	13.5%	12.4%	0.4%	2.7%	3.3%	15.0%	3.1%	66.3%
BE	11.2%	31.8%	4.3%	9.8%	8.2%	10.5%	1.3%	4.5%	10.6%	7.5%	2.5%	70.4%
DE	15.9%	6.0%	16.2%	0.7%	7.0%	9.2%	10.5%	0.9%	1.2%	31.6%	1.1%	84.0%
ES	3.8%	7.7%	2.6%	48.7%	0.8%	6.6%	2.8%	11.8%	12.3%	1.7%	4.1%	54.2%
FI	17.1%	4.3%	8.3%	1.0%	37.4%	6.2%	0.3%	2.1%	1.0%	20.7%	1.6%	62.6%
FR	20.6%	9.8%	6.0%	2.5%	9.7%	23.7%	1.0%	1.4%	3.1%	20.6%	1.5%	76.3%
GR	0.8%	0.8%	0.8%	5.0%	2.0%	1.0%	74.3%	1.9%	1.7%	1.2%	10.6%	25.7%
IE	1.3%	1.6%	1.8%	9.2%	6.7%	1.7%	5.5%	57.4%	3.4%	1.1%	10.3%	42.6%
IT	1.9%	11.2%	2.4%	19.7%	1.1%	1.8%	3.0%	8.0%	44.7%	0.3%	6.0%	55.3%
NL	15.9%	6.4%	12.4%	1.0%	11.7%	11.5%	2.3%	1.1%	1.7%	34.7%	1.3%	65.3%
PT	0.6%	2.4%	1.0%	6.2%	2.6%	1.6%	12.1%	15.2%	2.7%	0.5%	55.1%	44.9%
TO	89.2%	56.6%	46.8%	57.5%	63.3%	62.5%	39.2%	49.5%	40.9%	100.1%	42.0%	**58.9%**
NET	22.8%	-13.8%	-37.2%	3.4%	0.7%	-13.8%	13.5%	6.9%	-14.4%	34.8%	-2.9%	

Notes: Full sample connectedness tables for each sub-period. The predictive horizon is 12 days. The ijth entry of the upper-left 11×11 firm sub-matrix gives the ijth pairwise directional connectedness. The rightmost column gives total directional connectedness 'from others'. The second-from-bottom row gives the total directional connectedness 'to others'. And the bottom row gives the difference in total directional connectedness. The bottom-right element is total connectedness for the entire network.

Table 4 reports the results for realised volatility series connectedness. Looking first at Table 4 Panel A there is significantly more variation than there was in the same period for the returns series. Total connectedness is again extremely high at 80.8%, and again the spread of the 'from others' degree distribution is noticeably less than that of the 'to others' degree distribution. The highest pairwise directional connectedness is from France to Belgium (12.0%), and the lowest pairwise directional connectedness is from Greece to Finland (5.1%). The diagonal elements have an average of 19.5% and are, on average, lower than the 'from others' elements implying that most variation in bond volatility is driven by external factors. The diagonal elements (own connectedness) are the largest individual elements of the table, but total directional connectedness ('from others' or 'to others') tends to be much larger.

Looking next at Table 4 Panel B there is a significant increase in the variation. The diagonal elements are again the largest individual elements of the table, but total directional connectedness (from others or to others) continues to be much larger. Total connectedness is still very high at 78.9%, but has dropped slightly from the period of calm. The highest pairwise directional connectedness is from France to Belgium (16.9%), and the lowest pairwise directional connectedness is from Austria to Greece (3.6%). In general, the total 'from others' Greece has dropped from 81.1% in the period of calm to 53.7% implying that the markets have already started to treat Greece differently from the rest of the Eurozone. The diagonal elements average 21.4%, with a max of 46.3% for Greece; this indicates a move to internal factors.

Finally looking at Table 4 Panel C there is a big difference from the previous periods. Total connectedness has dropped significantly to 53.4%. The highest pairwise directional connectedness is from the Netherlands to Germany (23.7%) and, in general, the total variation 'From others' for Germany remains high at 84.0%. The total variation 'From others' for the peripheral countries is very low with Greece at 32.2%, Ireland at 23.9% and Portugal at 38.7% indicating that the general economic environment influences them less than their own internal factors. The diagonal elements have increased significantly, especially for the peripheral countries. Germany and France are the only two that have kept pre-crisis levels of 'own connectedness'. This is in contrast to the returns series where all the core countries have low 'own connectedness' in the Eurozone crisis period, implying that volatility connectedness is a better indicator of the financial environment.

Similar to the returns series, Eurozone government bond volatility connectedness is at its highest during the period of calm and actually drops significantly when the crisis set in. However, unlike the connectedness measured derived from the returns, the connectedness measures derived from the volatility show a significant drop in connectedness also for the semi-peripheral countries. This is indicative of volatility being particularly crisis sensitive.

Table 4

Panel A: Volatility series connectedness table from July 2005 – May 2007.

	AT	BE	DE	ES	FI	FR	GR	IE	IT	NL	PT	FROM
AT	18.0%	8.2%	10.3%	7.4%	9.4%	8.8%	7.0%	6.8%	9.7%	8.7%	6.4%	82.6%
BE	10.8%	13.7%	9.6%	7.6%	5.6%	12.0%	7.4%	6.9%	9.2%	10.5%	7.1%	86.8%
DE	11.9%	8.0%	18.1%	7.3%	5.7%	10.3%	8.1%	6.0%	10.1%	9.1%	6.1%	82.6%
ES	10.3%	8.0%	10.9%	14.8%	6.2%	9.4%	7.1%	8.0%	10.9%	8.3%	6.7%	85.9%
FI	8.7%	5.9%	8.6%	6.1%	32.9%	6.0%	5.1%	6.2%	7.8%	6.0%	6.8%	67.1%
FR	11.2%	8.3%	10.4%	7.3%	5.8%	20.0%	6.4%	6.2%	9.1%	9.3%	6.0%	80.0%
GR	10.1%	8.3%	9.1%	7.3%	5.6%	10.0%	18.9%	6.3%	8.7%	9.0%	6.7%	81.1%
IE	8.7%	7.1%	7.9%	6.6%	5.8%	8.8%	7.0%	24.0%	7.4%	9.2%	7.6%	76.0%
IT	11.5%	7.7%	10.2%	8.8%	6.2%	10.3%	6.9%	6.1%	18.0%	7.7%	6.8%	82.0%
NL	9.2%	9.0%	9.8%	7.3%	5.3%	11.9%	7.5%	7.4%	8.5%	17.6%	6.6%	82.4%
PT	8.1%	7.7%	8.9%	7.0%	6.6%	8.3%	8.0%	9.4%	8.5%	9.2%	18.3%	81.7%
TO	100.3%	78.2%	95.8%	72.7%	62.2%	95.7%	70.5%	69.1%	89.9%	87.0%	66.8%	**80.8%**
NET	17.7%	-8.6%	13.2%	-13.3%	-4.9%	15.7%	-10.6%	-6.9%	7.9%	4.6%	-14.9%	

Panel B: Volatility series connectedness table for June 2007 – December 2009.

	AT	BE	DE	ES	FI	FR	GR	IE	IT	NL	PT	FROM
AT	14.0%	6.2%	6.6%	4.8%	8.4%	13.0%	9.3%	10.1%	8.1%	8.1%	11.8%	86.3%
BE	6.5%	13.5%	6.8%	5.0%	4.9%	16.9%	8.7%	10.3%	8.8%	10.3%	8.7%	86.8%
DE	6.1%	8.0%	13.2%	4.2%	4.9%	13.2%	13.8%	10.3%	8.3%	9.2%	9.1%	87.1%
ES	6.9%	10.2%	7.8%	16.4%	5.1%	14.8%	9.0%	8.2%	7.1%	9.6%	6.5%	85.1%
FI	4.1%	5.3%	6.6%	3.8%	28.4%	8.8%	8.3%	8.9%	7.4%	8.9%	9.5%	71.6%
FR	6.1%	8.3%	7.2%	4.3%	5.6%	22.5%	10.6%	10.4%	6.4%	10.4%	8.3%	77.5%
GR	3.6%	4.3%	4.2%	2.5%	6.3%	11.3%	46.3%	5.4%	3.7%	5.9%	6.6%	53.7%
IE	5.8%	6.5%	6.8%	4.0%	6.6%	14.6%	11.0%	21.6%	5.3%	8.5%	9.3%	78.4%
IT	6.4%	6.5%	6.6%	3.7%	7.1%	12.9%	7.3%	12.4%	21.7%	6.6%	8.6%	78.3%
NL	6.2%	9.0%	6.9%	4.5%	5.7%	16.0%	7.7%	11.3%	7.4%	17.2%	8.2%	82.8%
PT	6.7%	6.4%	6.2%	4.2%	9.1%	11.3%	7.2%	11.9%	9.2%	7.6%	20.2%	79.8%
TO	58.3%	70.7%	65.6%	40.9%	63.7%	132.8%	93.0%	99.3%	71.6%	85.1%	86.5%	**78.9%**
NET	-28.1%	-16.1%	-21.5%	-44.2%	-7.9%	55.3%	39.3%	20.9%	-6.7%	2.3%	6.7%	

Panel C: Volatility series connectedness table for January 2010 – December 2011.

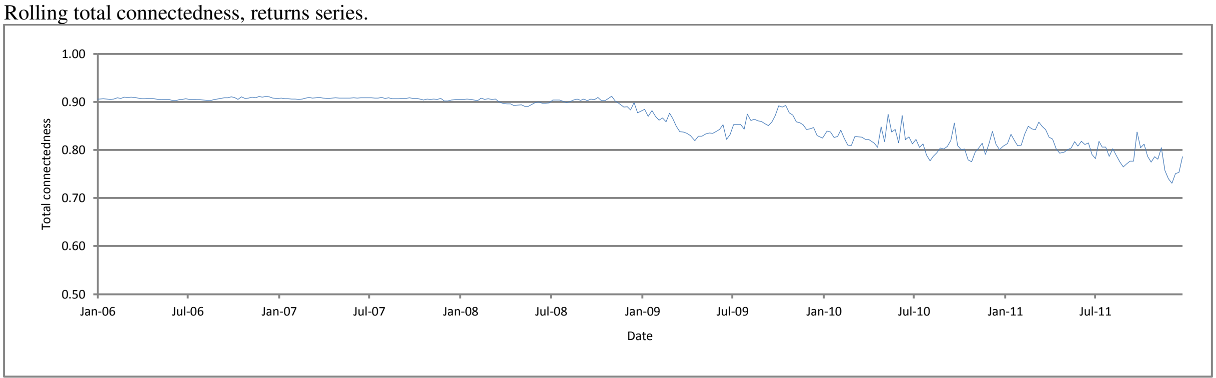
	AT	BE	DE	ES	FI	FR	GR	IE	IT	NL	PT	FROM
AT	50.8%	5.9%	5.8%	1.2%	10.5%	5.9%	3.3%	1.0%	6.0%	12.8%	0.4%	52.7%
BE	13.1%	41.4%	4.6%	1.5%	6.8%	7.8%	3.0%	3.9%	7.0%	12.4%	1.6%	61.9%
DE	9.4%	8.5%	24.7%	1.1%	4.7%	9.4%	10.8%	3.2%	3.5%	23.7%	1.7%	76.1%
ES	3.3%	8.0%	3.3%	48.6%	1.1%	2.6%	1.0%	14.0%	17.9%	1.8%	1.3%	54.3%
FI	10.0%	4.1%	16.6%	0.9%	42.7%	5.3%	5.7%	0.5%	2.0%	10.7%	1.6%	57.3%
FR	10.9%	7.1%	17.8%	1.2%	7.2%	21.4%	4.0%	3.4%	3.7%	21.7%	1.6%	78.6%
GR	1.5%	0.9%	11.8%	2.1%	2.6%	5.5%	67.8%	2.5%	0.7%	1.9%	2.7%	32.2%
IE	1.6%	4.0%	2.5%	1.7%	3.7%	1.5%	1.9%	76.1%	1.7%	1.5%	4.0%	23.9%
IT	6.3%	6.3%	2.0%	19.3%	2.8%	2.3%	1.1%	6.8%	49.3%	2.5%	1.5%	50.7%
NL	8.7%	8.5%	14.9%	0.9%	6.1%	11.1%	3.3%	2.8%	4.0%	39.0%	1.0%	61.0%
PT	4.5%	6.8%	3.8%	2.7%	4.9%	1.4%	1.1%	3.6%	6.1%	3.7%	61.3%	38.7%
TO	69.2%	60.0%	83.1%	32.5%	50.3%	52.8%	35.2%	41.7%	52.7%	92.7%	17.3%	**53.4%**
NET	16.5%	-1.9%	7.0%	-21.8%	-7.0%	-25.8%	3.0%	17.8%	2.0%	31.7%	-21.4%	

Notes: Full sample connectedness tables for each sub-period. The predictive horizon is 12 days. The ijth entry of the upper-left 11×11 firm sub-matrix gives the ijth pairwise directional connectedness. The rightmost column gives total directional connectedness 'from others'. The second-from-bottom row gives the total directional connectedness 'to others'. And the bottom row gives the difference in total directional connectedness. The bottom-right element is total connectedness for the entire network.

3.2. Dynamic (rolling-sample, conditional) analysis

The analysis in the previous section looked at full-sample connectedness which provides a good characterization of the unconditional aspects of each of the connectedness measures. However, it provides limited insight into connectedness dynamics. In this section we look at the dynamics of connectedness using a rolling estimation window. The first thing to look at is the total connectedness, before moving to various levels of disaggregation. Figure 2 shows the total returns connectedness for the Eurozone network over 100-day rolling-sample windows.

Figure 2
Rolling total connectedness, returns series.



Notes: The rolling estimation window width is 100 days, and the predictive horizon for the underlying variance decomposition is 12 days. The sample is from July 2005 – December 2011.

Immediately looking at Figure 2 the overriding patterns are clear. There was a long, stable period of high (>90.0%) connectedness from the start of the sample, until early 2008 where the first dip below 90.0% occurred. This early dip, although small, is not insignificant as it correlated with the collapse of Bear Stearns, implying that the overall problems in the wider financial environment were beginning to be felt by investors in the Eurozone sovereign debt market and the potential results anticipated.

Following this short dip, there was a recovery in the total connectedness to back over 90.0% where it remained until late 2008 at which time there was an obvious downward trend that continued until the end of the sample. Interestingly, the beginning of this downward trend preceded the beginning of the Eurozone crisis (which is generally accepted to have started with the nationalisation of Anglo Irish bank in January 2009) by a few months.

The long, downward trend in connectedness had two sub-periods. The first sub-period was a big cycle (dip and rise) starting in late 2008 and ending in late 2009. Following this, there was a long, volatile, downward trend throughout the end of the sample as the Eurozone crisis took hold. These dips both occurred during the Eurozone crisis; as the crisis took hold and the different countries were affected differently the total connectedness decreased over time to a low of 74%.

This finding contrasts to those of Diebold and Yilmaz (2014) where the total connectedness of select companies in the financial services industry increased during the global financial crisis. This is expected, however, as the health of the financial industry was inherently interlinked, while the health of the Eurozone countries was well understood – for example the emergence of the PIIGS as peripheral, troubled countries, in comparison to the relative health of Germany and France.

The dynamic analysis of the total connectedness of returns gave a clear understanding of the dynamics of connectedness over the full sample period, and provides insight into the system as a whole. The next step is to look at the dynamics of directional connectedness over the same period. To better evaluate the differences between the ‘to others’ and ‘from others’ directional connectedness, the evolution of the entire ‘to others’, ‘from others’ and ‘net’ degree distributions is shown in Figure 3. Although, by definition, the mean ‘to others’ and ‘from others’ directional connectedness measures are both equivalent to the total connectedness measure presented in Figure 2, each country has rather different ‘to others’ and ‘from others’ directional connectedness. This implies that even though their means are the same, ‘to others’ and ‘from others’ connectedness measures are distributed quite distinctively.

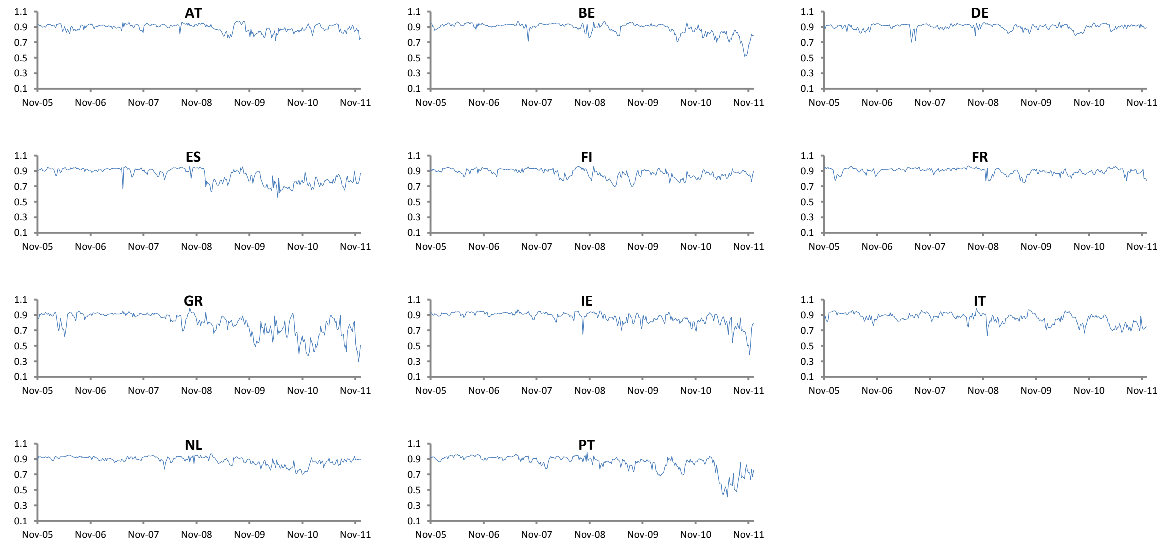
The first stand out point is the difference in smoothness between the ‘from others’ and ‘to others’ plots, presented in Panels A and B respectively. The ‘from others’ plots are much smoother than the ‘to others’ plots. This is equally found and Diebold and Yilmaz (2014), the explanation being that when there is a shock to the returns of an individual country (or couple of countries) this volatility shock is expected to be transmitted to other countries. Since individual country’s bonds are subject to idiosyncratic shocks, some of these shocks are very small and negligible, while others can be quite large. Irrespective of the size of the shock, if it is a larger country or a highly central country (which has strong connections with other countries) that received the returns shock, then one can expect this shock to have even a larger spill-over effect on returns of other countries. As the size of the shocks vary as well as the size and centrality of the countries in the sample, the directional connectedness ‘to others’ varies substantially across stocks over the rolling-sample windows. Given that the Eurozone countries are a relatively small network none of the countries in the sample of eleven countries are insulated from the volatility shocks to other countries’ debt. In other words, they are expected to be interconnected. As a result, each one will receive, in one form or the other, the returns shocks transmitted by other countries. While the returns shocks transmitted ‘to others’ by each individual country may be large, when they are distributed among ten other countries the size of the returns shock received by each stock will be much smaller. That is why there is much less variation in the directional connectedness ‘from others’ compared to the directional connectedness ‘to others’.

The difference between the directional connectedness ‘to others’ and ‘from others’ is equal to the ‘net’ directional connectedness to others presented in the Figure 4 Panel C. As the connectedness ‘from others’ measure is smoother over the rolling-sample windows, the variation in the plots for ‘net’ connectedness to others over the rolling-sample windows resembles the variation in the plots for connectedness ‘to others’.

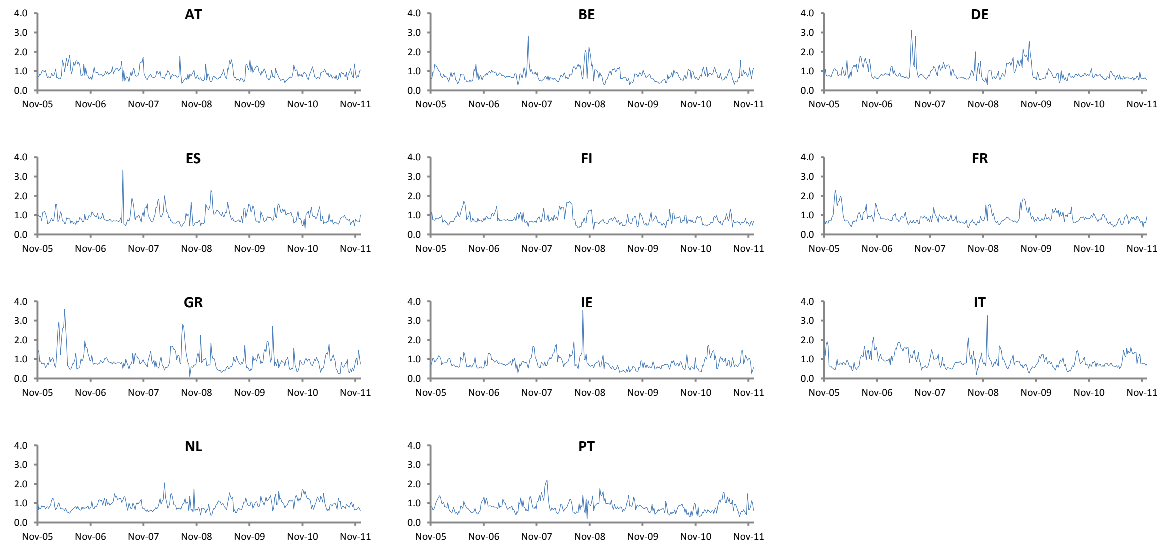
There are several interesting observations from the plots in Figure 4 are as follows. The 'from others' plots for the core countries of Austria, Germany, Finland, France and Netherlands are for the most part unaffected by the financial and Eurozone crises, while Belgium is showing signs of 'from others' dropping the deeper into the Eurozone crisis it gets. The semi-peripheral countries of Spain and Italy 'from others' drop to around 70% during the Eurozone crisis. The peripheral countries of Ireland, Greece and Portugal drop significantly to lows of under 50% during the Eurozone crisis showing a severe deterioration into isolation in the eyes of investors.

Figure 3

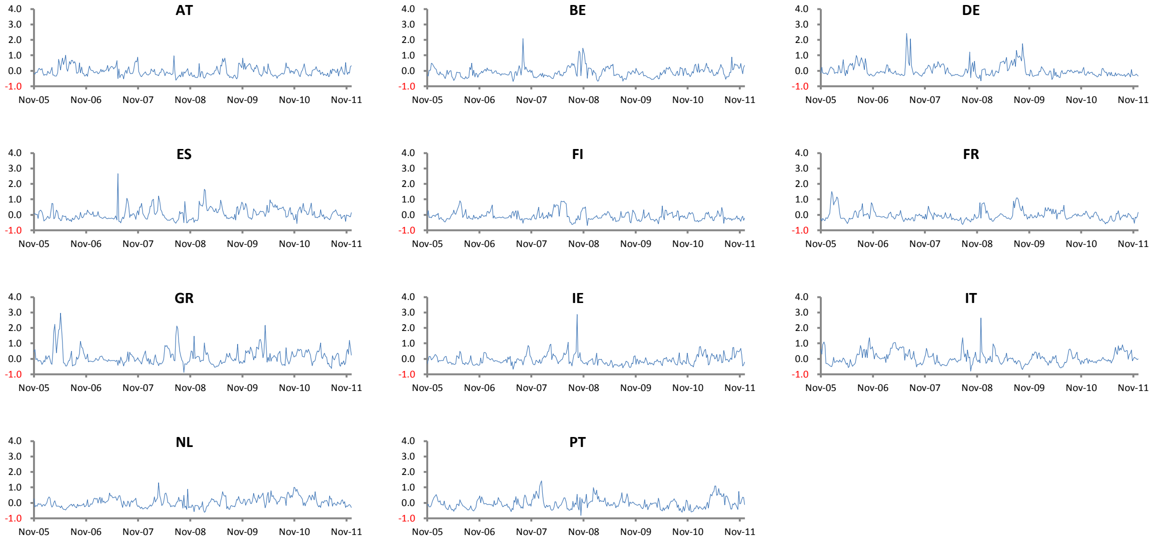
Panel A: Rolling total directional connectedness 'from others', return series.



Panel B: Rolling total directional connectedness 'to others', return series.



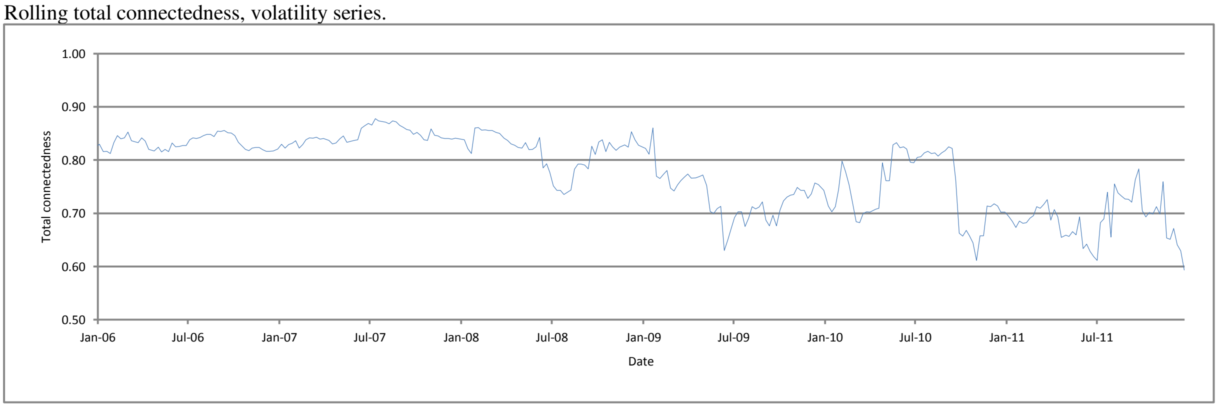
Panel C: Rolling total directional connectedness 'net', return series.



Notes: The rolling estimation window width is 100 days, and the predictive horizon for the underlying variance decomposition is 12 days. The sample is from July 2005 – December 2011.

Following the analysis of the returns series, we move to the volatility series, again beginning with the total connectedness before moving to various levels of disaggregation. Figure 4 shows the total volatility connectedness for the Eurozone network over 100-day rolling-sample windows.

Figure 4
Rolling total connectedness, volatility series.



Notes: The rolling estimation window width is 100 days, and the predictive horizon for the underlying variance decomposition is 12 days. The sample is from July 2005 – December 2011.

Similar to Figure 2, Figure 4 has quite a clear pattern, albeit with more variation. There was a long period of high connectedness from the start of the sample, until mid 2008 where the first dip occurs. This early dip is similar to the early dip experienced by the returns connectedness, although it's larger, longer, and begins a few months later.

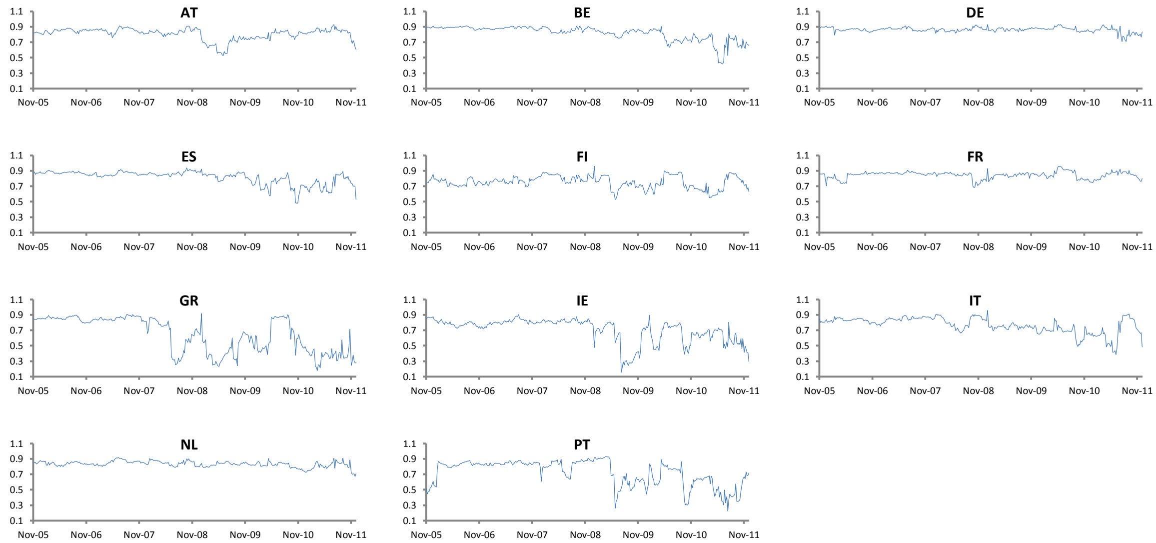
Following this short lived dip, there was a recovery until early 2009, following which there was an obvious downward trend in connectedness that continued until the end of the sample period. During this downward trend, there was a slight recovery in the middle of 2010 where the total connectedness remained over 80.0% for several months.

Again, to better evaluate the differences between the ‘to others’ and ‘from others’ directional connectedness, in Figure 5 we plot the evolution of the entire ‘from others’, ‘to others’ and ‘net’ degree distributions in Panels A, B and C respectively. The findings are similar to that of the returns series again with the difference in smoothness between the ‘to others’ and ‘from others’ plots where the ‘from others’ plots are much more smooth than the ‘to others’ plots.

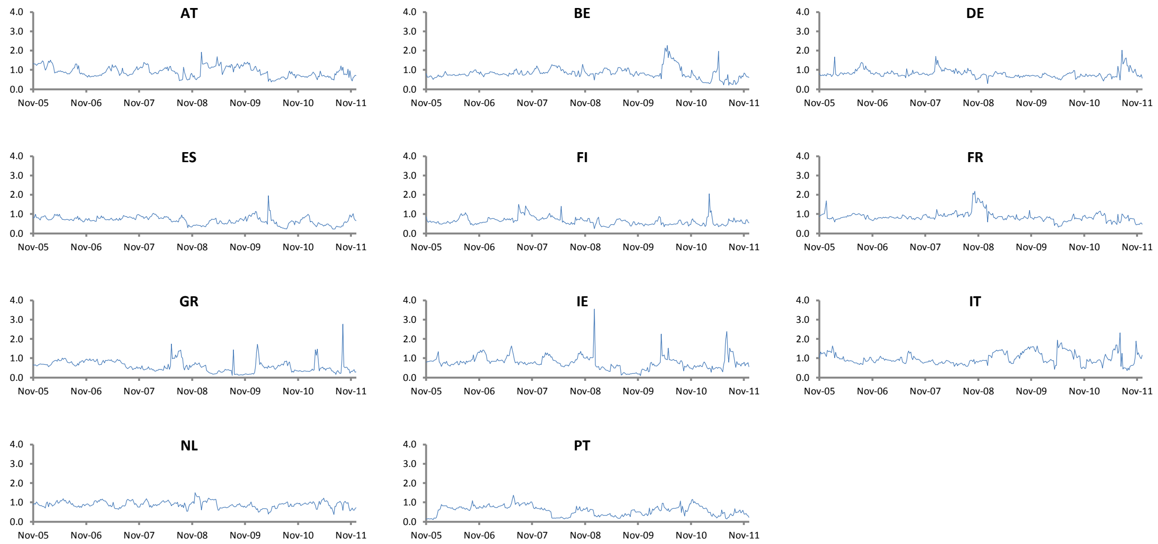
There are several interesting takeaways. The ‘from others’ plots for the core countries of Germany, France and Netherlands are for the most part unaffected by the financial and Eurozone crises – similar to the returns. However, this time Austria and Finland join Belgium in showing signs of decreasing ‘from others’ connectedness as the Eurozone crisis deepens. The semi-peripheral countries of Spain and Italy ‘from others’ drop significantly (more so than for the returns) during the Eurozone crisis. The peripheral countries of Ireland, Greece and Portugal drop significantly to lows of below 20% during the Eurozone crisis. This drop in ‘from others’ is much more severe for the volatility connectedness than it was for the returns connectedness.

Figure 5

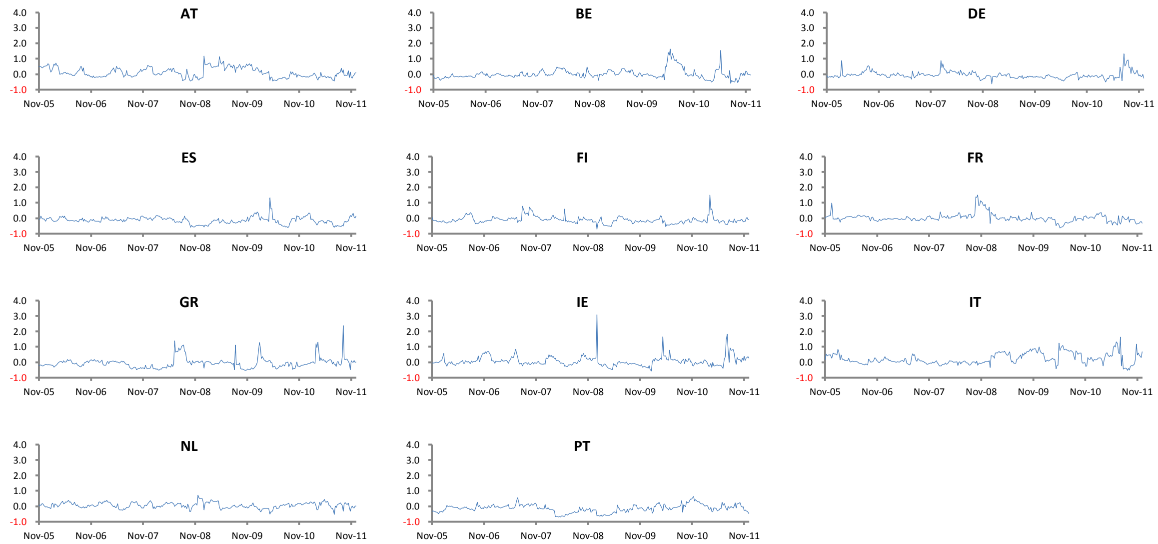
Panel A: Rolling total directional connectedness ‘from others’, volatility series.



Panel B: Rolling total directional connectedness ‘to others’, volatility series.



Panel C: Rolling total directional connectedness ‘net’, volatility series.



Notes: The rolling estimation window width is 100 days, and the predictive horizon for the underlying variance decomposition is 12 days. The sample is from July 2005 – December 2011.

3.3. Discussion

We have shown that the Eurozone network connectedness was extremely high during calm market conditions. This connectedness then decreased during the global financial crisis and decreased further still during the Eurozone crisis. The breakdown in connectedness was driven mainly, although not entirely, by the isolation of the peripheral nations.

When analysing the connectedness of the Eurozone network through these crisis periods, it is useful to draw comparisons with other networks during similar periods. Diebold and Yilmaz (2014) show us that the connectedness of the financial system increased during the crisis period, which is perhaps the main reason why the Lehman Brothers’ bankruptcy had such a profound effect on the financial system, turning a local bust into a global financial crisis. To some extent, the other financial sector companies were blind-sighted by the Lehman Brothers' bankruptcy and didn't have the time, or were unable, to unwind the connections and distance themselves from Lehman Brothers and this is reflected in the connectedness numbers.

Our findings for the Eurozone network are contrary, and imply that the Eurozone countries, and actors within these countries, saw the worsening conditions of the peripheral nations and acted on this information. The slow onset of the Eurozone crisis, as well as the vast support afforded by international governing bodies, gave the countries time to disassociate themselves, which is reflected in the isolation in the connectedness numbers. The conclusion we draw from this is that an increase in communication and transparency would help to prevent similar problems in the future.

4. Conclusion

This paper uses bond market data to address the network element at play during the recent Eurozone crisis. By constructing country-specific bond indices for the eleven countries in the Eurozone between July 2005 and December 2011 we are able to use a variance decomposition approach to build both static and dynamics network connectedness measures.

We find that connectedness in the Eurozone was extremely high during the calm market conditions preceding the global financial crisis but decreased when the crisis took hold, and worsened as the Eurozone sovereign debt crisis emerged. The drop in connectedness was especially prevalent in the case of the peripheral countries with some of the most peripheral countries deteriorating into isolation. We document a very high level of connectedness within the Eurozone during the calm market conditions, with no distinguishable differences between the countries. Connectedness began to breakdown in early 2008 and worsened throughout the sample period to varying degrees depending on the country's position within the European economy. We performed the analysis on both returns and volatilities and found similar results, but with subtle, important differences.

This paper is novel in adopting a network approach to analyse the recent turbulence in the Eurozone market. Understanding the network structure for the countries in the Eurozone will help to answer many questions, including the question of mutual monitoring. Our study extends and compliments the existing Eurozone crisis literature by providing a new perspective on the Eurozone countries during recent crises; using sovereign debt prices and realised volatility as proxies for economic health it was possible to examine the connectedness of the Eurozone network.

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