# Was a deterioration in ‘*connectedness*’ a leading indicator of the European sovereign debt crisis?

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## 1. Introduction

Policy makers, regulators and practitioners understand the central role of ‘*connectedness*’ and its importance in modern risk measurement and management encompassing areas such as counter-party and gridlock risk, market, credit and systemic risks, *inter-alia*. The global financial crisis led to renewed interest in crisis prediction models and highlighted the importance of financial connectedness as a source of systemic risk and macroeconomic instability (Minoiu, Kang, Subrahmanian and Bera, 2015). From a policy perspective incorporating connectedness is viewed as an important pre-requisite to develop forward-looking monitoring programmes to identify and track sources of systemic risk overtime, and to facilitate the development of pre-emptive policies to support financial stability (Diebold and Yilmaz, 2014; Adrian, Covitz and Liang, 2015; Bostanci and Yilmaz, 2020). Using high-frequency data from the Mercato dei Titoli di Stato (MTS) this paper investigates returns connectedness in the eurozone sovereign debt market from 2005 to 2011 which encompasses both the global and European sovereign debt crises for the eleven countries using the Euro over this time frame: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal and Spain. Sovereign debt market instruments provide an excellent basis for the analysis of connectedness; as they are actively traded on liquid and transparent markets, they reflect forward-looking assessments of many thousands of market participants, and often privately-informed agents, to measure connectedness and its evolution through time.

The importance of networks and their connectedness is well established in the academic literature (Minoiu *et al*., 2015; Anand et al., 2015; Gaffeo and Molinari, 2015; Halaj and Kok, 2015; Bargigli *et al*., 2015; Schwendner *et al*., 2015; Billio *et al*., 2012). However, empirically a range of approaches have been adopted which rely on a variety of assumptions and techniques. Correlation based measures are limited as they deal with pairwise relationships underpinned by Gaussian assumptions which are of limited use in financial markets. Alternative approaches include equi-correlation, the CoVar approach and marginal expected shortfall (Engle and Kelly, 2012; Adrian and Brunnermeier, 2011; Acharya *et al*., 2012). This paper uses the connectedness methodology proposed by Diebold and Yilmaz (2014). They argue that connectedness had previously been incompletely defined and poorly measured. In response they propose a *‘…unified framework for conceptualizing and empirically measuring connectedness at a variety of levels, from pairwise to system-wide’* (p. 119). Their methodology relies on variance decompositions from approximating models. Diebold and Yilmaz (2014) use the variance decomposition proposed by Pesaran and Shin (1998). Chan-Lau (2017) point out that the nature of these networks and their implied rankings depend on the choice of decomposition method. In the standard approach of Pesaran and Shin (1998) the shares of forecast error variation do not add to unity making it difficult to compare risk ratings and risks contributions at two points in time. Chan-Lau (2017) employ Lanne and Nyberg (2016) decomposition to overcome this weakness and show that for the global financial system from 2001 to 2016 the different decomposition methods lead to significantly different systemic risk and vulnerability rankings which had important implications for advising financial regulation and economic policy. We also employ the Lanne and Nyberg (2016) decomposition to investigate if these alternative approaches have a material effect in the specific context of estimating the connectedness methodology for the European sovereign debt markets through a period of crisis.

This paper contributes to the literature encompassing the economic link between banking and sovereign debt crises, and early-warning-systems. Across countries and time, the theoretical and empirical evidence supports the view that banking crisis are economically linked to sovereign debt crisis and can increase the likelihood of sovereign default (Diaz-Alejandro, 1985; Velasco, 1987; Arellano, 2008; Reinhart and Rogoff, 2010, 2011, and 2014; Yan *et al*., 2015). More specifically, one strand of literature focuses on connectedness of global banking networks, contagion and systemic risk during banking crisis (Minoiu, *et al*. 2015; Gai, Haldane and Kapadia, 2011; Cont, Moussa and Santos, 2013; Allen, Babus and Carletti, 2012). Minoiu *et al.* (2015) investigate connectedness in the global network of financial linkages to predict systemic banking crises from 1978-2010. They conclude that financial interconnectedness had early-warning potential, especially for the 2007-2010 wave of systemic banking crises. Fernández-Rodrígues, Gomez-Puig and Sosvilla-Rivero (2016) focus on connectedness in EMU sovereign debt markets volatility. They use the Diebold and Yilmaz (2014) methodology to examine volatility connectedness in Eurozone sovereign debt market between April1999 and January 2014. Using annualized daily variance derived from data of 10-year indicative bond prices they document a significant decrease in connectedness during the crisis period, and conclude that peripheral countries imported credibility from central countries during the first ten years of the monetary union[2].

We contribute to this literature in a number of ways. Fernández-Rodrígues *et al*. (2016) point out that there is a dearth of literature specifically examining connectedness and spillover effects within the euro area sovereign debt markets. *Ex-ante*, this paper complements Fernández-Rodrígues *et al*. (2016) by analysing daily returns connectedness and contributes to the relatively limited extant empirical evidence. Together, our paper and theirs helps build a better understanding of volatility and returns dynamics for the European sovereign debt markets over periods of financial crisis which is important for a range of stakeholders. Our second contribution is methodological. Application of Diebold and Yilmaz (2014) system-wide and pair-wise connectedness methodology has not been employed extensively. It is evident from the current literature that it is a useful tool for defining, measuring, and monitoring connectedness in financial markets, *inter-alia*, and for risk management (Diebold and Ylimaz, 2015). Chan-Lau (2017) provide theoretical justification, and show, that the Lanne-Nyberg (2016) variance decomposition improves upon the Pesaran and Shin (1998) which was adopted by Fernández-Rodrígues *et al*. (2016). Any inconsistency reported in our results is important for this paper, and for and subsequent applications. Post-financial crisis there was a focus by regulators on enhancing our understanding of systemic risk and how financial networks propagate and amplify shocks which subsequently influenced policy, with the identification of

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[2] The examine daily 10-year bond yields for Austria, Belgium, Finland, France, Germany, Netherlands and five peripheral countries of Greece, Ireland, Italy, Portugal and Spain.

systemically-important financial institutions which are subject to higher capital requirements and enhanced oversight in the US and Europe, which used connectedness as an assessment criteria (FSB, 2009; Chan-Lau, 2017; Capital Requirements Regulation and Directive IV[3]). A key aim of this paper is to provide analysis and insights for European sovereign debt markets from applying Diebold and Ylimaz (2014) unified connectedness framework which allows for ranking of countries by their systemic importance[4].

As expected Eurozone is connected during the pre-crises period, with no distinguishable differences between the countries. Connectedness began to breakdown in early 2008 and continued to decrease throughout the sample period to varying degrees depending on the country's position within the European economy. The analysis with both Pesaran-Shin and Lanne-Nyberg decompositions provide similar results at the network level, but with subtle, important differences at the country level. Overall, the results imply that global financial and European sovereign debt crises altered the sentiment of the Eurozone countries, and actors within these countries. They witnessed the worsening conditions of the peripheral nations throughout the crises and acted on this information. The decrease in connectedness witnessed in the Eurozone sovereign debt markets implies that contagion was not considered a major concern. The slow onset of the Eurozone crisis, as well as the support afforded by the Troika (International Monetary Fund, European Union, European Central Bank) gave the countries time to disassociate themselves and the isolation is reflected in the connectedness numbers.

For the global financial crisis period both methods again give similar results at the macro level and we conclude that the markets were beginning to identify, and action, a breakdown in the Eurozone network and the isolation of some countries. There are however important differences between the findings of the two methods for the global financial crisis period, more significant than the pre-crisis period. Specifically, the Lanne-Nyberg decomposition implies that there was a substantial amount of systemic risk spillover from Greece, whereas the Pesaran-Shin decomposition does not. Finally, we provide evidence that the Lanne-Nyberg decomposition led the Pesaran-Shin approach over the period from early 2008 to July 2009. While total connectedness experienced a visible reduction for the Lanne-Nyberg it remained relatively constant for Pesaran-Shin over the same period. This result suggests that modelling dynamic connectedness using the methodology of Diebold and Yilmaz (2014) with Lanne-Nyberg variance decomposition provided an early-warning signal. There is considerable scope for further research in this area.

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[3] Regulation (EU) No.575/2013 was directly applicable in Member States when the legislation entered into force in January 2014 but Directive 2013/36/EU required transposition into national law.

[4] This analysis is linked to the literature on contagion which has been classified as spillovers/interdependence /fundamental-based contagion, or pure contagion. Fernández-Rodrígues *et al*. (2016) point out Diebold and Yilmaz's (2014) methodology can be considered as a 'bridge' between these two classifications which allows for avoiding defining and the presence of '*fundamentals-based*' or '*pure contagion*'. This paper and its accompanying references provides a useful starting point for readers interested in the contagion literature.

The remainder of this paper is structured a follows. Section 2 reviews the literature focusing on the theoretical and empirical relationship between banking and sovereign debt crises, and the literature covering network connectedness with a focus on empirical literature for European sovereign debt markets. Section 3 explains the structure of the MTS electronic trading platform, the dataset and the chronology of significant events spanning the sample period, while section 4 provides a parsimonious outline of the connectedness methodology of Diebold and Yilmaz (2014) modified for the Lanne-Nyberg (2016) variance decomposition. Our connectedness results are reported in section 5, which is followed by a general discussion, possible limitations and opportunities for further research in section 6, and a conclusion in section 7 summarising key findings and recommendations.

## 2. Literature

The aim of this paper is to examine the dynamic time-varying connectedness between European sovereign bond markets over a period of time spanning a banking crisis which is followed by a sovereign debt crisis. There is a significant literature examining the theoretical connection between banking and sovereign debt crisis, with an accompanying empirical literature indicating a causal, leading, link from banking crisis to sovereign default[5]. In general, prior to a banking crisis private debts – external debt, broader private capital inflows, domestic bank debt - accumulate and also display a repeated cycle of boom and bust with the run-up in debts accelerating as the crisis point is reached. Subsequent bank collapses and large-scale government bailouts increase sovereign indebtedness and their propensity to default increases as subsequent decreases (post-bailout recession) in economic activity reduces government tax revenue and their ability to service debts which in turn increases the propensity for Sovereign default (Diaz-Alejandro, 1985; Velasco, 1987; Arellano, 2008). Arellano and Kockerlakota (2014) develop a model which incorporates a self-fulfilling belief that if all debtors know that all other debtors are going to default, then they all know that they will be subject to a small sanction. Consequently, '*strategic*' defaults by those who could pay but chose not to exacerbate sovereign default. Underpinning this model is weak bankruptcy mechanisms which favour debtors over creditors. Ireland is offered as an example of this phenomena where banks suffered widespread mortgage defaults, became insolvent, and were bailed out by the government with fiscal support of approximately 40% of GDP. One estimate put strategic mortgage defaults at 25%[6]. Further economic analysis of the Irish experience redefines the definition of strategic

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[5] The focus of our paper is connectedness between European sovereign bond markets over the recent global financial crisis period in the context of the preceding banking crises. A considerable literature has been developed in response to this crisis period. It is beyond the scope of this paper to review this entire body of literature. We refer interested readers to Meier, Gonzalez and Kunze (2020) who provide a systematic literature review of 455 papers examining the global financial crisis and the European sovereign debt crisis. For readers interested in a detailed narrative of the European banking and sovereign debt crises, and the accompanying policy response, see Reichlin (2014).

[6] (2012), *Strategic arrears – bank-made myth or harsh economic reality?,* The Irish Times. Viewed on 29th December 2020 <https://www.irishtimes.com/business/strategic-arrears-bank-made-myth-or-harsh-economic-reality-1.498406>.

default and provides a more complex analysis, and explanation, of the phenomena (O'Malley, 2018). Reinhart and Rogoff (2010, 2011, 2014) show that, for a sample of 70 countries over two-hundred years, increases in external debts systematically predict countries in default and systemic banking crises. In the ten-year period running up to the global financial crisis in 2007 they report a surge in public and private debts for 22 advanced economies with the average external/debt to GDP ratio doubling over this period. Furthermore, domestic credit increases sharply prior to banking crisis and unwinds afterwards. Reinhart and Rogoff (2011) conclude that, irrespective of sample period '*…systemic banking crises in financial centres help explain domestic banking crises, and domestic banking crises help explain sovereign default'* (p. 1699).

A significant body of literature examines interlinkages between firms and markets and systemic risk. Minoiu *et al*. (2015) investigate the degree of connectedness in the global network of financial interlinkages and suggest that interconnectedness can be used as an early warning sign for crises. Interbank connectedness is discussed by Anand *et al*. (2015), Gaffeo and Molinari (2015), Halaj and Kok (2015), and Bargigli *at al*. (2015). Other relevant connectedness literature includes Schwendner *et al*. (2015) who use partial correlation networks to analyse European government bond dynamics from 2004 to 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. Engle and Kelly (2012) use equi-correlation with a focus on average pairwise correlation, while Adrian and Brunnermeier (2011) use a CoVaR approach which goes beyond the pairwise association, and Acharya *et al*. (2012) use marginal expected shortfall (MES) which again goes further than pairwise association. As discussed in the introduction, Diebold and Yilmaz (2014) provide a unified framework for empirically measuring connectedness from pair-wise to system-wide.

The early Euro 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 and increased integration to the Eurozone government bond market. Codogno *et al*. (2003) analyses the yield spreads on Eurozone debt and find that movements in yield differentials are explained in the most part by international risk factors. They report that liquidity factors are less important in explaining movements, but still account for some movement. More recent Eurozone literature focuses on the various crises that have engulfed the markets. Barrios *et al*. (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 *at al*. (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 to cross-border bank holdings. There was some spillover from peripheral to non-peripheral.

Antonakakis and Vergos (2013) examine spillovers between 10 Eurozone government yield spreads during the period 2007 to 2012 and find an increased vulnerability of the Eurozone following destabilising shocks originating mostly from Eurozone countries in the periphery. Glover and Richards-Shubik (2014) use a network model of credit risk to measure market expectations of the potential spillovers from a sovereign default. Using data on a set of European sovereigns from 2005 to 2011, they conclude that credit markets did not demand a significant premium for the interconnectedness of European sovereign debt. Nguyen (2014) examines the propagation of volatility and liquidity shocks across several major sovereign bond markets during the European sovereign crisis, finding increased spillovers around major crisis events and specifically that liquidity is the most important source of shocks transmitted across borders. Claeys and Vašicek (2014) examine the linkages, both strength and direction, between 16 European sovereign bonds spreads during the period 2000 to 2012 and document substantial spillover. Canofari *et al*. (2015) investigate the perceived risk of a Eurozone break-up, using a sustainability index as a proxy for market expectations. They find that the market expectation of a break-up was a fundamental driver of Eurozone government bond spreads. Fernandez-Rodrigues *et al*. (2016) use the Diebold and Yilmaz (2014) methodology to examine volatility connectedness in Eurozone sovereign debt market between 1999 and 2014. Using annualized daily variance derived from data of 10-year indicative bond prices collected from Thompson Reuters Datastream they document a significant decrease in connectedness during the crisis period, and conclude that peripheral countries imported credibility from central countries during the first ten years of the monetary union.

## 3. Data

This paper analyses high-frequency data from the Mercato dei Titoli di Stato (MTS) electronic trading platform which is the largest interdealer market for eurozone government bonds (Dunne *et al*., 2006). Access is granted to large institutions and investment banks with traders acting as professional market makers. 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. 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 1st July 2005 until 31st 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 which are analysed in this paper.

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 using a group of benchmark bonds. We select the benchmark bonds using two criteria: (1) the bond is traded in both EuroMTS and MTS Domestic Markets, and (2) the bond exists throughout our sample period. Table 1 presents the International Securities Identification Number (ISIN) codes of the bonds that are selected as benchmarks in our study. Since there are more than one benchmark bond in each of the countries, we take the average value of daily return or daily volatility of these bonds when constructing a single bond index. This method is preferable to other options such as, for example, using just one single ‘benchmark’ bond since this captures all market activity without focusing on a maturity benchmark. Similarly, unlike the US Treasury market, there is no concept of liquidity concentration into on-the-run and off-the-run bonds. Where Fernandez-Rodriguez *et al.* (2016) analyze volatility connectedness, we focus on daily returns 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.). Table 2 presents the bond duration, coupon rate, and trading volume of the benchmark bonds. The coupon rates are quite similar among the benchmarks across countries. The durations of the benchmark bonds are long with more than 10 years on average for all countries, with the shortest average duration of 11.2 years for Finland and the longest average duration of 17.9 for France. This is not surprising since the sample period is around 7 years and one of the criteria for a bond to be included in the index is that it's available for the whole period, then no bonds with maturity less than 7 years would make the index. The trading volume is also large since these bonds are available on both market segments they are available to more participants[7].

**INSERT TABLE 1 AND 2 ABOUT HERE**

In general, we examine the level, variation, paths, patterns and clustering in the 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 of 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.

**INSERT FIGURE 1 ABOUT HERE**

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[7] For a discussion of the various aspects of the issues when measuring corporate and sovereign bond liquidity in terms of price versus quantity-based measures, and the relationship between proxies for benchmark liquidity see Langedijk, Monokroussos, and Papanagiotou, (2018) and Hameed, Helwege, Li, and Packer (2018). Given the level of trading volume reported in table 2 and the fact that we are analysing high-frequency benchmark bond data, as opposed to proxies which can lead to erroneous conclusions, the impact of illiquidity skewing our results is mitigated.

It is evident from figure 1 that the country indices begin to diverge from around September 2008 and by September 2009 the peripheral countries begin to diverge and decline over the rest of the sample period. The dataset spans several important financial market episodes which allows for an analysis of how the dynamics of the market changed from a period of calm through the global financial crisis and finally into the European sovereign debt crisis. Consequently, the entire sample period from 1st July 2005 to 31st December 2011 was sub-divided into three sub-periods. Similar to previous studies we adopt a chronological approach based on events to identify crises periods for banking and debt crisis (Reinhart and Rogoff, 2011)[8].

- **Pre-Crisis Period (PRE):** 1st July 2005 to 31st May 2007.
- **Global Financial Crisis (GFC): 1st** June 2007 to 31st December 2008.

  Banks stopped lending to each other in July 2007 due to market fears that counterparts were exposed to the emerging US sub-prime crisis. Also, in July, Bear Sterns informed investors that they would get little, if any, money back from two hedge funds with large holdings of sub-prime mortgages. LIBOR rates spike. Following a BBC report on the 13th September, Northern Rock experienced a bank-run on the 14th. It was subsequently nationalised on 22nd February 2008.

- **European Sovereign Debt Crisis (ESDC):** 1st January 2009 to 31st December 2011.

  On 15th January 2009, the Irish government announced that it would nationalize Anglo Irish Bank. Fall 2009 Greece's budget was revised highlighting that the deficit for that year would be significantly higher than previously predicted. On May 2nd, 2010 the EU endorsed the IMF announce an €85bn first European financial rescue plan for Greece. Problems persisted and Greece and a second rescue package was negotiated with Greece in 2011. On 28th November 2010 the Trokia (European Commission, European Central Bank and International Monetary Fund agreed an €85bn bailout deal with the Irish Government. On 5th May 2011 Portugal agrees with the EU and IMF on a €78bn bailout in exchange for an austerity programme.

## 4. Methodology

This paper applies the approach introduced by Diebold and Yilmaz (2014) to quantify Eurozone network connectedness in conjunction with Chan-Lau's (2017) method as a robustness check. The empirical framework for this approach is to use variance decompositions of approximating models; by assessing the shares of forecast error variation in

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[8] In contrast, Reinhart and Rogoff (2011) point out that quantitative approaches are typically used for identifying crisis episodes for inflation and exchange rate crisis. The events approach in our study is consistent with the results from the quantitative approach employed by Cronin, Flavin and Sheenan (2016) who identify a structural break around mid-2007.

various countries due to shocks arising elsewhere we can define a weighted, directed network that is linked to the key measures of connectedness used in the network literature. There are three steps in the construction of the variance decomposition networks. First, estimate the Vector Autoregression (VAR) model. Second, generate the generalised forecast error variance decompositions. Finally, use the generalised forecast error variance decompositions to determine the network structure. When applying the two different methods, the difference happens in step two. For the variance decomposition, Diebold and Yilmaz (2014) use the approach proposed by Pesaran and Shin (1998), whereas Chan-Lau (2017) uses the approach proposed by Lanne and Nyberg (2016). We also report connectedness results using the same schematic as Diebold and Yilmaz (2014)[9]. Table 3 parsimoniously summarises how the connectedness schematic is reported.

**INSERT TABLE 3 ABOUT HERE**

The connectedness table shows how disaggregated connectedness measures can be aggregated to obtain macroeconomic economy-wide total directional and total connectedness measures. Different market participants may be more focused on one or another of the measures. For example, prudential regulators would be interested in identifying systemically important institutions (micro-prudential regulation) in the context of large total directional connectedness to other institutions, and would also be concerned with monitoring total system-wide (systemic) connectedness (macro-prudential regulation)[10]. Consequently, this methodology provides a useful econometric tool for regulators tasked with implementing micro- and macro-prudential regulation which need to be assessed in tandem to promote financial stability. Applying the connectedness methodology to financial markets has the potential to provide investors and regulators with a better understanding of how, and why, financial shocks are transmitted across assets which could lead to preventative action to minimize damage (Osinski, Seal, Hoogduin; 2013; Diebold and Yilmaz, 2014; Bostanci and Yilmaz, 2020; Meier, Gonzales and Kunze, 2020).

Empirically we start with the moving average representation of the VAR (Hamilton, 1994):

$$x_t = \sum_{j=0}^{\infty} A_j \varepsilon_{t-j} \qquad (1)$$

where $x_t$ is the $n \times 1$ vector of endogenous variables, $A_j$ are $n \times n$ matrices, and $\varepsilon_t$ is an independently and identically distributed error term with zero mean and covariance matrix $\Sigma =$

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[9] In the interest of parsimony, the methodology section provides an explanation of the main empirical aspects required for executing the connectedness methodology proposed by Diebold and Yilmaz (2014). We refer those interested in gaining a comprehensive understanding of theoretical and empirical aspects of the methodology to this paper Bostanci and Yilmaz (2020).

[10] The notes to table 1 explain how to interpret directional flows and where the single total connectedness measure is reported.

$\{\sigma_{ij}, i, j = 1, \dots, n\}$. Once the VAR has been estimated the next step is to calculate the generalised forecast error variance decomposition of the system using either the Pesaran-Shin or Lanne-Nyberg decomposition. Before calculating either, we calculate the generalised impulse response function of Koop et al. (1996):

$$\begin{aligned} & GI(H, \delta_t, \Omega_{t-1}) \\ &= E(Y_{t+H} | \varepsilon_t = \delta_t, \Omega_{t-1}) \\ &\qquad - E(Y_{t+H} | \Omega_{t-1}) \end{aligned} \qquad (2)$$

In a linear model the generalise impulse response function is independent of the history of shocks. Pesaran and Shin (1998) simplify it by restricting the shock to a single element:

$$GI(H, \delta_t, \Omega_{t-1}) = A_H \Sigma \mathrm{e_j} \sigma_{jj}^{-1} \delta_j \qquad (3)$$

where $\mathrm{e_j}$ is an $n \times 1$ vector with all entries set to zero except for the $j^{th}$ entry.

Diebold and Yilmaz (2014) opt for generalised variance decomposition.[11] The H-step generalised variance decomposition matrix $\mathrm{D^{gH}} = \left[\mathrm{d_{ij}^{gH}}\right]$ has entries as follows:

$$d_{ij}^{gH} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} (e_i' \mathrm{A}_h \Sigma \mathrm{A}_h' e_i)} \qquad (4)$$

where $\mathrm{e_j}$ is a selection vector with jth element unity and zeroes elsewhere, $\mathrm{A_h}$ is the coefficient matrix multiplying the h-lagged shock vector in the infinite moving-average representation of the non-orthogonalised VAR, $\Sigma$ is the covariance matrix of the shock vector in the non-orthogonalised VAR, and $\sigma_{\mathrm{jj}}$ is the jth diagonal element of $\Sigma$. Because shocks are not necessarily orthogonal in the generalised variance decomposition environment, sums of forecast error variance contributions are not necessarily unity (that is, row sums of $\mathrm{D^g}$ are not necessarily unity). Hence, convention is to base the generalised connectedness indexes not on $\mathrm{D^g}$, but rather on $\tilde{\mathrm{D}}^{\mathrm{g}} = \left[\tilde{\mathrm{d}}_{\mathrm{ij}}^{\mathrm{g}}\right]$, where $\tilde{\mathrm{d}}_{\mathrm{ij}}^{\mathrm{g}} = \frac{\mathrm{d_{ij}^g}}{\sum_{\mathrm{j=1}}^{\mathrm{N}} \mathrm{d_{ij}^g}}$. 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 $\tilde{\mathrm{D}}^{\mathrm{g}}$ it is possible to immediately calculate generalised connectedness measures. The Lanne-Nyberg alternative generalised variance decomposition is based on the partial contribution of variable $j$ to the total generalised impulse response function of variable $i$:

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[11] 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, assumptions are required. 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.

$$d_{ij}^{gH} = \frac{\sum_{k=0}^{H} GI\left(H, \delta_{jt}, \Omega_{t-1}\right)^2}{\sum_{j=1}^{n} \sum_{k=0}^{H} GI\left(H, \delta_{jt}, \Omega_{t-1}\right)^2} \qquad (5)$$

This alternative generalised variance decomposition sums to unity, and so the interpretation as the relative contribution of a variable is direct.

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 as $C(x, H, A(L))$. Consistent with the recommendation of Diebold and Yilmaz (2014), the connection outlined in table 3 and all its elements are allowed to vary over time. Consequently, $C_t(x, H, A_t(L), M(\theta_t))$. The methodology to this point refers to the population, whereas in practise 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 $t = 1, \ldots, T$. Empirically, we need to specify the 'x object', the 'x choice', and the 'x frequency' (Diebold and Yilmaz, 2014). Our 'x' object is the natural log of bond returns, 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 calculated as an average over the day using 5 minute snapshots from market open at 08:15 to market close at 17:30. The choice of connectedness horizon, H, in the limit as $H \rightarrow \infty$, we obtain an unconditional variance decomposition. In this paper we use a horizon of $H = 12$ days and employ a VAR(3) approximating model with a one-sided rolling estimation window of $W = 100$ days.

## 5. Results

### 5.1. Static connectedness

This section reports the static (full sample, unconditional) connectedness results for each sub-period for the Eurozone sovereign bond returns using Pesaran-Shin (P-S) and Lanne-Nyberg (L-N) variance decompositions. Table 3, and its accompanying notes, explain each element of the results reported in the connectedness static empirical results tables 4 and 5. Table 4 reports results for return series connectedness calculated using the L-N decomposition, while table 5 reports results from P-S variance decompositions. $C_{i \leftarrow j}^{H}$ does not have to equal $C_{j \leftarrow i}^{H}$, so there will be $N^2 - N$ separate pairwise directional connectedness measures; for the 11 countries in the sample that equals 110 pairwise directional connectedness measures as well as 11 measures for '*own connectedness*'. Total connectedness, bottom right-hand cell in the table, of the network is 89.0%. The spread of the '*from others*' (right-hand column panel A) ranges from 79.1% for Greece to 99.0% for Portugal contrasts with the '*to others*' (second last row panel A) which ranges from 56.2% for Finland to 138.5% for Greece. The highest pairwise directional connectedness is from Greece to the Netherlands at 18.6%, and the lowest pairwise directional connectedness is from Finland to both the Netherlands and Belgium at 3.7% which gives a spread of 14.9% between the highest and lowest pairwise directional connectedness. The diagonal elements - own connectedness - are 11.0%, on average whereas the average of the off-diagonal elements at 8.9% implying that variation in bond returns during this phase is driven by both internal and external factors.

**INSERT TABLES 4 AND 5 ABOUT HERE**

The results reported in Table 5 Panel A for L-N decomposition are consistent with those reported for Panel A in table 4. Total connectedness of the network is marginally higher at 90.3% with the spread of the '*from others*' degree distribution ranging from 86.9% for Finland to 91.6% for Germany. The '*to others*' degree distribution ranges from 81.0% for Germany to 108.1% for Ireland. The highest pairwise directional connectedness is from Greece to Italy at 12.1%, and the lowest pairwise directional connectedness is from Germany to Greece at 7.8% which gives a spread of 4.3%. The diagonal elements (own connectedness) are 9.71% on average, which is again similar to the average of the off-diagonal elements. These results are consistent with our previous assertion that variation in bond returns is driven by both internal and external factors and that over the pre-crisis period the Eurozone countries were connected in the eyes of market participants and that there were no major factors isolating any one country.

Table 6 reports, and ranks, countries by systemic vulnerability ('*from others*') and systemic risk ('*to others*') for the L-N and P-S decompositions. It is evident from table 6 that the rankings for systemic vulnerability are inconsistent depending upon the choice of variance decomposition. The left side of the rank column in the centre of the table refers to rankings for '*from others'*. GR (Greece) is ranked 1 the most systemically vulnerable at 79.1% using L-N, whereas Finland is ranked 1 at 86.8% using P-S, with Greece now ranked 2 at 87.3%. We also see that whereas Germany is ranked 6 for L-N it is ranked 11, least vulnerable, for P-S.

**INSERT TABLE 6 ABOUT HERE**

The right-hand column of ranks '*to others'* for systemic risk reverses the rank ordering. Germany (DE) is ranked 11th for P-S indicating lowest risk and ranked 8 for L-N which also puts it at the lower end of the systemic risk spectrum.

Table 4 Panel B reports the results for the global financial crisis period. Total connectedness, compared to the calm period, has decreased to 79.5%. There is a significant increase in the variation, especially in the systemic risk from Greece '*to*' others. The highest pairwise directional connectedness is from Greece to Finland at 52.6%, and the lowest pairwise directional connectedness is from Germany to Finland at 3.7%. The total variation '*to others*' from Greece has increased significantly from 138.5% in the period of calm to 259.4% implying that by this stage the markets were already considering Greece as a high source of systemic risk. The variation of '*to others*' for the other ten countries remains similar to the calm figures.

The diagonal elements are 20.5% on average, and there is a maximum of 51.7% for Spain; this indicates an increase in the importance of internal factors for many countries in general and Spain in particular. Total directional connectedness ('*from others*' or '*to others'*) is lower than own connectedness, but overall connectedness remains relatively high due to the spillover from Greece.

Next, we compare the result for the same period using P-S decomposition reported in Table 5 Panel B. Total connectedness is higher than the L-S decomposition at 86.9%. The highest pairwise directional connectedness is from Italy to Portugal at 15.1%, and the lowest pairwise directional connectedness is from Belgium to Greece at 5.0%. Total variation '*from others*' to Greece has dropped from 87.3% (right-hand column panel A) in the period of calm to 77.3% (right-hand column panel B). This indicates that by this stage the markets had started to treat Greece differently from the rest of the Eurozone and it was becoming isolated. The variation of '*from others*' for the other ten countries remains similar to the calm period 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, which indicates that the results for the P-S decomposition also indicates that internal factors had become increasingly important for the peripheral countries in general, and for Greece in particular.

However, overall total directional connectedness '*from others*', which ranges from 77.3% for Greece to 91.9% for Austria (right-hand column panel B), or '*to others*' which ranges from 67.3% for Germany to 114.8% for Italy (second last row panel B) is relatively larger than own connectedness reported along the diagonal with the largest value of 22.7% for Greece followed by Italy at 19.2%. For Italy this level of own connectedness is relatively higher having increased from 10% in the calm period. Finland also experiences what appears to be a significant marginal increase from 13.1% to 18.2%. When we compare own connectedness of the remaining countries reported in panel A and B, the change in values is relatively marginal. For example, Austria changes from 8.6% in panel A to 8.2% in panel B. Overall, for the global financial crisis period, both decomposition methods provide similar insights at the macro level. This analysis suggests that the markets were beginning to identify, and action, a breakdown in the Eurozone network and the isolation of some countries including Greece, Italy and Finland.

However, when we compare the results for the L-S and P-S decompositions for the crisis period for Greece an important anomaly emerges. As highlighted earlier, the total variation '*to others*' from Greece increased significantly from 138.5% in the period of calm to 259.4% for L-N with '*from*' Greece to Finland at 52.6%, France 42.2%, Ireland 46.4% and the Netherlands 46.9%. In contrast, for P-S in table 5 panel B, the equivalent results were for Finland at 5.5%, France 6.7%, Ireland 11.2% and the Netherlands 11%. This finding implies that while the results from the L-N decomposition show significant systemic risk spillover from Greece the P-S decomposition do not. It therefor appears that the theoretical and empirical justification for using the L-N approach advocated by Chan-Lau (2017) is warranted. From a regulatory toolkit perspective this leads to the concrete recommendation that application of the Diebold and Yilmaz (2014) connectedness methodology should be employed in conjunction with L-N decomposition. From an economic perspective, the P-S method would not have identified the potential systemic vulnerability of Finland, France, Ireland and the Netherlands at this point and flagged the need for policy options to mitigate risk.

This finding has important consequences when countries are ranked by systemic vulnerability ('*from others*') and systemic risk ('to others') reported in Table 7.

**INSERT TABLE 7 ABOUT HERE**

It is evident that there is inconsistency in the rankings. To highlight this point we focus on Greece and Germany which could be regarded as two extremes. For systemic risk Germany is ranked 9 at 53.2% whereas Greece is ranked 1 at 259.4% for L-N. For P-S Germany is ranked 11 (lowest risk) at 67.3% while Greece is ranked 9 at 72.2%. This variation in the ranking is also consistent with the finding of Chan-Lau (2017).

Table 5 Panel C reports the results for the sample period spanning the European sovereign debt crisis. Total connectedness decreases to 42.0%. The highest pairwise directional connectedness is from Greece to Finland at 24.7%. There is significant variation '*from others*' (right-hand column panel C). For Greece it is 1.3%, Ireland 5.3% and Portugal at 22.8% which indicates that the general economic environment of the Eurozone was driving returns less than their own internal factors. For panel C the diagonal elements are the largest individual elements of the table. During the sovereign debt crisis core countries' own connectedness increased. For example Germany increased from 3.7% in the initial crisis period to 98.7%. This suggests that they were being influenced less by the other countries as the crisis deepened.

Table 5 Panel C reports the results for P-S decomposition. Total connectedness is 58.9% and the highest pairwise directional connectedness is from the Netherlands to Germany is 31.6%. Total '*from others*' for what could be regarded as the peripheral countries is relatively 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 relatively 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 affected each other. The diagonal elements, especially those of the peripheral countries, are the largest individual elements of the table, with core countries' own connectedness increasing. This suggests that that they were being influenced less by the other countries as the crisis depended. During the European sovereign debt crisis period, both methods highlight the same results at the network level, showing the almost total breakdown of the Eurozone network. There was a reduction in system-wide connectedness, an increase in own connectedness and the isolation of many countries.

To conclude this static connectedness section we examine the ranking reported in table 8. For consistency, we again compare Greece with Germany. For systemic vulnerability there is very little variation between the L-N and P-S decomposition methods: Greece is ranked least, and Germany as most, systemically vulnerable.

**INSERT TABLE 8 ABOUT HERE**

In contrast, there is substantial variation in the systemic risk ranking. The L-N ranks Greece as the second largest systemic risk after Ireland at number 1, whereas P-S rank Greece in 11th place as the lowest systemic risk. In summary, Eurozone government bond returns connectedness was at its highest during the period of calm and decreased over successive crises periods. 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 increasingly connected during the crisis period (Diebold and Yilmaz, 2014), investors segmented the Eurozone into core, semi-core and peripheral countries, thus creating multiple sub-networks within the major network. These results complement the work of Fernández-Rodrígues *et al*. (2016). Comparing the L-N and P-S variance decompositions provides similar the same conclusions at the network level, but, as highlighted by Chan-Lau (2017), caution must be exercised when examining micro details as there are significant, important differences.

## 5.2. Dynamic connectedness

Static connectedness analysis provides characterization of the unconditional aspects of each of the connectedness measures. However, it provides limited insight into connectedness dynamics. This section reports the results for the dynamics of connectedness using a rolling estimation window. We begin with total connectedness before moving to various levels of disaggregation. Figures 2 and 3 show the total returns connectedness for the Eurozone network over 100-day rolling-sample windows using the L-N and P-S decompositions, respectively.

**INSERT FIGURES 2 AND 3 ABOUT HERE**

Figures 2 and 3 have the same overriding patterns at the macro level. However, there is clearly more variation in Figure 2 and the dynamics are more extreme. There is a long stable period of high connectedness from the start of the sample until early 2008 where a substantial dip leads to total connectedness decreasing from around 90% in January to approximately 85% by June. In contrast, figure 3 remains relatively constant over the same period. This early dip, although relatively small, is not insignificant as it correlated with the collapse of Bear Stearns, implying that the overall problems in the wider financial environment are beginning to be felt by investors in the Eurozone sovereign debt market and the potential results anticipated. Following this short dip, there is a recovery in the total connectedness to back over 90.0% by both measures, where it remains until late 2008 at which time there is an obvious downward trend that continues until the end of the sample period. Interestingly, the beginning of this downward trend precedes the beginning of the European sovereign debt 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 has two sub-periods. The first sub-period is a big cycle (dip and rise) starting in late 2008 and ending in late 2009. Following this there is a long volatile downward trend throughout the end of the sample period as the European sovereign debt crisis takes hold. These dips both occur during the European sovereign debt crisis; as the crisis takes hold and the countries are affected differently the total connectedness decreases over time. Although the trends are similar across both methods the drops in connectedness are more extreme when using the L-N decomposition. This finding contrasts with Diebold and Yilmaz (2014) where the total connectedness of US financial institutions 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 GIIPS (Greece, Ireland, Italy, Portugal and Spain) as peripheral, troubled countries, in comparison to the relative health of Germany and France. The dynamic analysis of the total connectedness of returns gives 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 Figures 4 and 5 for L-N and P-S decompositions. Although, by definition, the mean '*to others*' and '*from others*' directional connectedness measures are both equivalent to the total connectedness measure presented in Figures 2 and 3, each country has significantly 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.

**INSERT FIGURES 4 AND 5 ABOUT HERE**

The first point, common across both Figures 4 and 5, 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 also reported by Diebold and Yilmaz (2014). When there is a shock to the returns of an individual country (or a number of countries) the 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 central country, which has strong connections with other countries, that received the returns shock, then one can expect this shock to have an even larger spill-over effect on the 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 explains 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 Figures 4 and 5 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 Figures 4 and 5. The '*from others*' plots for the core countries of Austria, Germany, Finland, France and Netherlands indicate that these countries were for the most part unaffected by the global financial and European sovereign debt crises, while Belgium is showing signs of '*from others*' dropping as the European sovereign debt crisis deepens. The semi-peripheral countries of Spain and Italy '*from others*' drop to around 70% during the European sovereign debt crisis. The peripheral countries of Ireland, Greece and Portugal drop significantly to lows of under 50% during the European sovereign debt crisis showing a severe deterioration into isolation in the eyes of investors. The L-N decomposition results are far more extreme than the P-S decomposition results, with the '*from others*' measure for Greece, Ireland and Portugal decreasing to below 20% during the European sovereign debt crisis. The '*to others*' plots for the Lanne-Nyberg decomposition show clearly the increase in systemic risk emanating from Greece, Ireland and Portugal. The same results using the P-S decomposition are not observed.

## 6. Discussion, limitations and further research

Our findings have implications for a range of sovereign bond market stakeholders. From an investment perspective the decrease in connectedness and changes in correlations affects passive and active portfolio managers. Excepting hedge funds which pursue absolute returns and some mutual funds without a specified performance objective, the vast majority of fund managers are subject to a defined performance benchmark (Chevalier and Ellison, 1999; Lo, 2008). Dramatic changes in the European sovereign benchmark bonds market's returns make rebalancing for indexing, or enhanced indexing strategies more problematic, and also has the potential to significantly affect the execution of dynamic bond portfolio optimization strategies and impact portfolio performance (Calderia, Moura and Santos, 2016). However, financial cries are not all bad news for investors. During the financial crises dedicated short bias hedge funds outperformed and provided a source of diversification (Connolly and Hutchinson, 2012). Investigating further how the connectedness methodology can be used for investment strategies across firms, markets, assets and countries is an important avenue of research for investors and regulators.

Time-varying illiquidity within the longer duration bonds which, by necessity, comprise our benchmark indices could be a limitation of our study which span both domestic and Euro MTS market segments. To be included in the country index the bond must have been listed and available to trade on both the MTS Domestic Markets and EuroMTS market segments, and available for the whole period July 2005 to December 2011. O'Sullivan and Papavassiliou (2020) provide a comprehensive analysis of the domestic MTS benchmark across four time-to-maturity segments: 2-, 5-, 10-, and 30 year and report evidence of flight-to-liquidity to shorter duration benchmarks during periods of market stress. Understanding if benchmark bonds which span both the domestic and EuroMTS market segments concentrated in the longer duration range affects dynamic connectedness is an important extension of this paper.

At the heart of this paper is the concept of indebtedness. Our findings of connectedness evolving over time from a banking crisis to a sovereign debt crisis are consistent with this literature (Diaz-Alejandro, 1985; Velasco, 1987; Arellano, 2008; Reinhart and Rogoff (2010, 2011, and 2014). The spectre of Covid-19 in 2020 has again highlighted the important issue of sovereign indebtedness.  The Covid-19 crisis has been described as distinctive and is expected to dwarf the financial crisis from 2008. A number of recent papers have highlighted the issue of government indebtedness to finance support programmes introduced to mitigate the economic impact of the Covid-19 pandemic (see, Baldwin and Weder di Mauro, 2020). Prior to the onset of this health crisis public debt ratios had increased due to the global financial crisis and the European sovereign debt crisis with the pandemic increasing government budget deficits, with a number of macroeconomic economic indicators pointing toward an economic downturn (Taskinsoy, 2018; Meier *et al*, 2020; Fornaro and Wolf, 2020; Taskinsoy, 2020; Beetsma, Giuliodori, Hanson and de Jong, 2021).  Empirical evidence suggests that public debt in excess of 90 percent typically leads to a reduction in growth across both advanced countries and emerging markets, with a 60% threshold for emerging markets when external debt is considered (public and private) leading to a significant deterioration in growth (Reinhart and Rogoff, 2010; Reinhart and Rogoff, 2011). The evolution of household income, consumption and savings are important to policy makers given their role in determining an economic recovery. During the pandemic savings ratios increased in some countries and decreased in others[12]. An assessment of how consumers' financial behavior, and how it impacts upon the financial sector and its interaction with fiscal policy is an important research area.

An important extension of this paper would be to assess the fiscal impact of these measure and the implication for sovereign debt connectedness to help regulators navigate this period effectively.

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[12] Heffernan, T., Saupe, S., and Maria, W., 2020. Investigating household deposits during COVID-19. Central Bank of Ireland. Viewed on 29th December 2020 < https://www.centralbank.ie/statistics/statistical-publications/behind-the-data/investigating-household-deposits-during-covid-19>.

## 7. Conclusion

This paper uses high-frequency MTS sovereign bond market data to investigate connectedness for Eurozone countries from 2005 to 2011 which allows for analysis of sub-periods reflecting periods of relative calm, the global financial, and European debt, crises. This involved constructing country-specific bond indices for the eleven countries in the Eurozone and employing the methodology proposed by Diebold and Yilmaz (2014) which provides a comprehensive framework to empirically estimate from pairwise connectedness to system-wide statically and dynamically.

We find that Eurozone sovereign bond markets were, as expected, connected during the pre-crisis period preceding the onset of the global financial crisis mid-2007. Over the two subsequent sub-periods spanning the global financial crisis and European sovereign debt crisis connectedness decreased. Connectedness began to breakdown in early 2008 and deteriorated throughout the sample period to varying degrees depending on the country's position within the European economy. The drop in connectedness was especially prevalent in the case of the peripheral countries with some deteriorating into isolation by the end of the sample period in January 2011.

We estimate connectedness using the methodology proposed by Diebold and Yilmaz (2014) to overcome the well documented weakness of alternative approaches. In addition, we also incorporate the recommendation of Chan-Lau (2017) to use the Lanne-Nyberg decomposition method, as opposed to variance decompositions method of Pesaran-Shin, which can lead to significantly different systemic risk and vulnerability rankings and influence any subsequent financial regulation advice and economic policy. We find that this is in fact the case. With conflicting results. Analysis of the crisis period showed that for the Lanne-Nyberg decomposition indicated significant systemic risk spillover from Greece to Finland, France, Ireland, and the Netherlands while the Pesaran-Shin decomposition did not, and provided inconsistent systemic risk and vulnerability rankings.

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 that the connectedness of US financial institutions increased, which is expected, during the crisis period for financial institutions. To some extent, the other financial institutions were blind-sighted by the Lehman Brothers' bankruptcy and did not have the time, or were unable, to unwind the connections and distance between themselves from Lehman Brothers and this is reflected in the connectedness numbers. In contrast, Eurozone network connectedness experienced a deterioration over a relatively long period of time. The slow onset of the European sovereign debt crisis, as well as the vast support afforded by Trokia (IMF, European Union and the European Central Bank) gave the countries time to disassociate themselves. Consequently, European sovereign bond markets went from being highly connected in 2005 to a significant reduction to the extent that some counties including Greece, Portugal and Ireland were isolated by 2011.

Finally, argue that the connectedness analysis reported in this paper is of significant value and provides useful guidance for regulators and policy makers. First, more generally, we recommend the connectedness methodology as a useful tool to monitor the individual, and aggregate, levels of risks and their transmission in a connected network to aid micro- and macro-prudential regulation of the financial system. From a technical perspective the approach of Diebold and Yilmaz (2014) should be employed with the Lanne-Nyberg decomposition which significantly improves static connectedness analysis and, as our study suggests, provided a leading indicator of financial crisis. In hindsight, and in context of our dynamic connectedness results, we conjecture that if these findings had been available to regulators and policy makers the sudden deterioration in connectedness in early 2008 could have provided an indication of systemic vulnerability and amplified a red flag for action. This early dip correlated with the collapse of Bear Stearns, implying that the overall problems in the wider financial environment are beginning to be felt by investors in the Eurozone sovereign debt market. Obviously in a financial crisis actions takes place within a political economy context. Very often regulation, and regulatory actions, lag what’s happening in practice. In a study such as this using returns data the dynamic connectedness methodology provides a real-time monitor of market behaviour and health. The financial equivalent of an ECG. Fixed income portfolio managers, both active and passive, would have had access to an objective data analytics approach which would have given them insights to individual markets and the system as a whole which could have influenced their decision making.

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**Table 1. Bonds used to construct the indices for the eleven Eurozone countries.**

| Austria | Belgium | Finland | France | Germany | Greece | Ireland | Italy | Netherlands | Portugal | Spain |
|---|---|---|---|---|---|---|---|---|---|---|
| AT000038 | BE000029 | FI0001005 | FR000018 | DE000113 | GR012402 | IE0006857 | IT0003242 | NL000010 | PTOTE1O | ES000001 |
| AT000038 | BE000029 | FI0001005 | FR000018 | DE000113 | GR012800 | IE0031256 | IT0003256 | NL000010 | PTOTEGO | ES000001 |
| AT000038 | BE000030 | | FR000018 | DE000113 | GR013300 | IE0034074 | IT0003357 | NL000010 | PTOTEKO | ES000001 |
| AT000038 | BE000030 | | FR000018 | DE000113 | GR013300 | | IT0003472 | NL000010 | PTOTEYO | ES000001 |
| AT000038 | BE000030 | | FR000018 | DE000113 | GR013800 | | IT0003493 | NL000010 | | ES000001 |
| AT000038 | BE000030 | | FR001001 | DE000113 | | | IT0003535 | NL000010 | | ES000001 |
| AT000038 | BE000030 | | FR001006 | DE000113 | | | IT0003618 | | | ES000001 |
| | | | FR001007 | DE000113 | | | IT0003644 | | | |
| | | | FR001011 | DE000113 | | | IT0003719 | | | |
| | | | FR001016 | | | | IT0003844 | | | |
| | | | FR001017 | | | | | | | |
| | | | FR001021 | | | | | | | |

Notes: This table shows the International Securities Identification Number (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 Markets and EuroMTS market segments, and available for the whole period July 2005 to December 2011. In subsequent tables we use the first two digits from ISIN codes to identify individual countries: Austria (AT), Belgium (BE), Germany (DE), Spain (ES), Finland (FI), France (FR), Greece (GR), Ireland (IE), Italy (IT), Netherlands (NL), and Portugal (PT).

**Table 2. Descriptive statistics of bonds used to construct the country-specific indices**

| | Number of bonds | Average of duration (yrs) | Average coupon (%) | Total vol traded in the period (million €) |
|---|---|---|---|---|
| Austria | 7 | 14.1 | 4.5 | 55,777 |
| Belgium | 7 | 16.8 | 4.75 | 162,759 |
| Finland | 2 | 11.2 | 4.8 | 47,118 |
| France | 12 | 17.9 | 4.3 | 102,848 |
| Germany | 9 | 14.7 | 4.3 | 105,385 |
| Greece | 5 | 12.6 | 5.2 | 79,460 |
| Ireland | 3 | 13.6 | 4.7 | 29,801 |
| Italy | 10 | 16.1 | 4.6 | 769,898 |
| Netherlands | 6 | 16.9 | 4.3 | 109,448 |
| Portugal | 4 | 12.6 | 4.7 | 127,582 |
| Spain | 7 | 17.6 | 4.8 | 100,196 |

*Notes:* This table contains reference information for the benchmark instruments of the eleven countries included in the analysis. The number of bonds for each country is reported along with the average duration in years, the average coupon in percentage of par, the total volume traded for the period in millions of euro.

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

**Table 3.** ***Connectedness table schematic:*** 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 $D^H = [d^H_{ij}]$. 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 $C^H_{i \leftarrow j} = d^H_{ij}$. 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. 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, $C^H_{i \leftarrow \cdot} = \sum_{j=1, i \neq j}^{N} d^H_{ij}$. 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, $C^H_{\cdot \leftarrow j} = \sum_{i=1, i \neq j}^{N} d^H_{ij}$. Finally, the total sum of the off-diagonal elements measures the total connectedness, $C^H = \frac{1}{N}\sum_{i,j=1, i \neq j}^{N} d^H_{ij}$. This single total connectedness measure distils the connectedness of the entire system into a single number.

| | AT | BE | DE | ES | FI | FR | GR | IE | IT | NL | PT | FROM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **AT** | 12.1% | 9.2% | 6.6% | 8.8% | 4.1% | 9.4% | 17.1% | 7.2% | 11.0% | 9.1% | 5.4% | 87.9% |
| **BE** | 7.7% | 6.8% | 8.4% | 10.3% | 3.7% | 11.5% | 17.3% | 6.6% | 13.2% | 9.8% | 4.7% | 93.2% |
| **DE** | 7.3% | 10.1% | 12.0% | 10.4% | 4.0% | 11.5% | 13.2% | 6.2% | 11.0% | 9.7% | 4.6% | 88.0% |
| **ES** | 9.0% | 9.9% | 7.7% | 14.1% | 6.8% | 9.3% | 9.9% | 9.2% | 7.0% | 9.6% | 7.4% | 85.9% |
| **FI** | 8.2% | 9.6% | 8.6% | 9.8% | 10.1% | 9.6% | 11.5% | 8.6% | 8.8% | 8.9% | 6.3% | 89.9% |
| **FR** | 8.9% | 9.0% | 7.3% | 9.7% | 8.1% | 5.7% | 14.7% | 8.7% | 11.0% | 9.1% | 7.8% | 94.3% |
| **GR** | 7.5% | 9.0% | 7.5% | 9.3% | 5.4% | 9.4% | 20.9% | 7.2% | 10.0% | 8.5% | 5.2% | 79.1% |
| **IE** | 8.9% | 9.5% | 7.8% | 9.1% | 7.9% | 9.6% | 13.2% | 6.0% | 10.4% | 8.8% | 8.7% | 94.0% |
| **IT** | 8.6% | 8.9% | 7.9% | 9.1% | 8.3% | 8.2% | 7.6% | 9.2% | 17.2% | 8.2% | 6.8% | 82.8% |
| **NL** | 6.0% | 7.0% | 6.9% | 8.1% | 3.7% | 7.5% | 18.6% | 4.2% | 17.1% | 15.5% | 5.2% | 84.5% |
| **PT** | 7.8% | 11.0% | 9.0% | 11.7% | 4.1% | 12.0% | 15.1% | 7.0% | 9.7% | 11.5% | 1.0% | 99.0% |
| **TO** | 79.8% | 93.2% | 77.8% | 96.3% | 56.2% | 98.0% | 138.5% | 74.0% | 109.4% | 93.3% | 62.1% | **89.0%** |
| **NET** | 8.0% | 0.0% | 10.2% | -10.4% | 33.7% | -3.7% | -59.3% | 20.0% | -26.6% | -8.8% | 36.9% | |

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

| | AT | BE | DE | ES | FI | FR | GR | IE | IT | NL | PT | FROM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **AT** | 27.2% | 5.4% | 2.0% | 6.6% | 2.9% | 7.3% | 20.6% | 9.0% | 5.6% | 8.9% | 4.5% | 72.8% |
| **BE** | 5.0% | 28.6% | 5.2% | 4.2% | 3.1% | 6.9% | 25.4% | 5.4% | 7.7% | 6.1% | 2.3% | 71.4% |
| **DE** | 11.0% | 11.2% | 7.3% | 11.8% | 10.4% | 5.8% | 5.0% | 25.1% | 0.9% | 6.4% | 5.0% | 92.7% |
| **ES** | 1.9% | 5.3% | 7.7% | 51.7% | 4.7% | 5.8% | 5.6% | 6.5% | 2.4% | 5.7% | 2.6% | 48.3% |
| **FI** | 5.1% | 3.4% | 0.3% | 2.1% | 19.1% | 4.6% | 52.6% | 1.2% | 4.5% | 6.5% | 0.6% | 80.9% |
| **FR** | 7.5% | 3.5% | 1.7% | 6.1% | 4.7% | 0.8% | 42.2% | 8.2% | 14.5% | 5.5% | 5.3% | 99.2% |
| **GR** | 9.7% | 9.5% | 11.5% | 10.8% | 5.0% | 15.7% | 3.7% | 5.7% | 9.9% | 12.2% | 6.3% | 96.3% |
| **IE** | 1.0% | 2.6% | 10.1% | 3.6% | 6.5% | 6.2% | 46.4% | 14.1% | 2.1% | 1.6% | 6.0% | 85.9% |
| **IT** | 8.2% | 7.9% | 7.3% | 8.6% | 5.2% | 11.2% | 5.5% | 6.9% | 23.7% | 8.8% | 6.7% | 76.3% |
| **NL** | 7.4% | 1.3% | 1.4% | 1.9% | 5.9% | 1.6% | 46.9% | 7.6% | 9.3% | 13.9% | 2.8% | 86.1% |
| **PT** | 5.3% | 10.1% | 5.9% | 6.3% | 2.5% | 9.2% | 9.2% | 1.8% | 8.5% | 6.1% | 35.1% | 64.9% |
| **TO** | 62.2% | 60.1% | 53.2% | 62.0% | 50.9% | 74.3% | 259.4% | 77.4% | 65.2% | 67.7% | 42.3% | **79.5%** |
| **NET** | 10.6% | 11.3% | 39.5% | -13.7% | 29.9% | 24.8% | -163.1% | 8.6% | 11.1% | 18.4% | 22.7% | |

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

| | AT | BE | DE | ES | FI | FR | GR | IE | IT | NL | PT | FROM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **AT** | 61.7% | 0.7% | 2.4% | 3.0% | 0.8% | 0.5% | 8.7% | 17.7% | 0.8% | 1.9% | 1.8% | 38.3% |
| **BE** | 2.9% | 63.1% | 4.0% | 5.5% | 0.2% | 3.1% | 2.6% | 11.1% | 0.3% | 6.6% | 0.6% | 36.9% |
| **DE** | 8.8% | 23.6% | 5.5% | 12.8% | 6.2% | 7.1% | 8.7% | 11.3% | 2.5% | 11.3% | 2.2% | 94.5% |
| **ES** | 0.2% | 5.4% | 0.6% | 76.8% | 0.1% | 0.2% | 2.3% | 8.2% | 3.1% | 1.6% | 1.5% | 23.2% |
| **FI** | 1.7% | 7.7% | 2.4% | 3.6% | 33.3% | 2.0% | 24.7% | 15.2% | 1.6% | 2.7% | 5.0% | 66.7% |
| **FR** | 2.2% | 4.6% | 5.7% | 12.8% | 0.6% | 40.3% | 3.3% | 1.3% | 5.5% | 5.7% | 18.1% | 59.7% |
| **GR** | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 98.7% | 1.1% | 0.0% | 0.0% | 0.1% | 1.3% |
| **IE** | 0.4% | 0.7% | 0.2% | 0.6% | 0.0% | 0.6% | 0.1% | 94.7% | 0.4% | 0.3% | 2.0% | 5.3% |
| **IT** | 0.9% | 9.2% | 4.3% | 12.6% | 0.8% | 0.9% | 0.2% | 10.6% | 43.5% | 10.2% | 6.7% | 56.5% |
| **NL** | 1.2% | 11.1% | 2.8% | 1.4% | 2.7% | 0.3% | 8.0% | 20.4% | 4.8% | 42.9% | 4.5% | 57.1% |
| **PT** | 1.6% | 4.3% | 0.4% | 1.0% | 0.1% | 1.5% | 11.9% | 0.8% | 0.4% | 0.8% | 77.2% | 22.8% |
| **TO** | 19.8% | 67.4% | 22.8% | 53.2% | 11.7% | 16.2% | 70.5% | 97.8% | 19.4% | 41.2% | 42.4% | **42.0%** |
| **NET** | 18.5% | -30.5% | 71.7% | -30.0% | 55.0% | 43.5% | -69.1% | -92.5% | 37.1% | 16.0% | -19.7% | |

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

**Table 4. *Connectedness tables***, *Lanne-Nyberg decomposition:* Full sample connectedness tables for each sub-period. The predictive horizon is 12 days. The ijth entry of the upper-left $11 \times 11$ 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. Austria (AT), Belgium (BE), Germany (DE), Spain (ES), Finland (FI), France (FR), Greece (GR), Ireland (IE), Italy (IT), Netherlands (NL), and Portugal (PT).

| | AT | BE | DE | ES | FI | FR | GR | IE | IT | NL | PT | FROM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **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% | |

(A) Returns series connectedness table for July 2005 to May 2007

| | 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% | |

(B) Returns series connectedness table for June 2007 to December 2009

| | 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% | |

(C) Returns series connectedness table for January 2010 to December 2011

**Table 5.** ***Connectedness tables, Pesaran-Shin decomposition****:* Full sample connectedness tables for each sub-period. The predictive horizon is 12 days. The ijth entry of the upper-left $11 \times 11$ 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. Austria (AT), Belgium (BE), Germany (DE), Spain (ES), Finland (FI), France (FR), Greece (GR), Ireland (IE), Italy (IT), Netherlands (NL), and Portugal (PT).

| Systemic vulnerability (‘from others’) | | | | | Systemic risk (‘to others’) | | | |
|---|---|---|---|---|---|---|---|---|
| **Lanne-Nyberg** | | **Pesaran-Shin** | | **Rank** | **Lanne-Nyberg** | | **Pesaran-Shin** | |
| GR | 79.1% | 86.9% | FI | 1 : 11 | FI | 56.2% | 81.0% | DE |
| IT | 82.8% | 87.3% | GR | 2 : 10 | PT | 62.1% | 83.6% | AT |
| NL | 84.5% | 89.6% | IE | 3 : 9 | IE | 74.0% | 83.9% | BE |
| ES | 85.9% | 90.0% | IT | 4 : 8 | DE | 77.8% | 84.5% | ES |
| AT | 87.9% | 91.0% | NL | 5 : 7 | AT | 79.8% | 85.2% | PT |
| DE | 88.0% | 91.2% | PT | 6 : 6 | BE | 93.2% | 86.1% | FR |
| FI | 89.9% | 91.2% | ES | 7 : 5 | NL | 93.3% | 86.4% | NL |
| BE | 93.2% | 91.4% | AT | 8 : 4 | ES | 96.3% | 88.9% | IT |
| IE | 94.0% | 91.5% | FR | 9 : 3 | FR | 98.0% | 101.9% | GR |
| FR | 94.3% | 91.5% | BE | 10 : 2 | IT | 109.4% | 103.4% | FI |
| PT | 99.0% | 91.6% | DE | 11 : 1 | GR | 138.5% | 108.1% | IE |

**Table 6.** ***Systemic rankings, July 2005 to May 2007:*** This table displays the systemic vulnerability (‘*from others*’) and systemic risk (‘*to others*’) results calculated using both Lanne-Nyberg and Pesaran-Shin variance decompositions for each of the eleven countries, and ranks accordingly. Austria (AT), Belgium (BE), Germany (DE), Spain (ES), Finland (FI), France (FR), Greece (GR), Ireland (IE), Italy (IT), Netherlands (NL), and Portugal (PT). The left side of the rank column in the center of the table refers to rankings for ‘*from others*’. The right-hand column of ranks ‘*to others*’ which reverses the rank ordering with the 11th rank indicating lowest risk.

| Systemic vulnerability (‘from others’) | | | | | Systemic risk (‘to others’) | | | |
|---|---|---|---|---|---|---|---|---|
| **Lanne-Nyberg** | | **Pesaran-Shin** | | **Rank** | **Lanne-Nyberg** | | **Pesaran-Shin** | |
| ES | 48.3% | 77.3% | GR | 1 : 11 | PT | 42.3% | 67.3% | DE |
| PT | 64.9% | 80.8% | IT | 2 : 10 | FI | 50.9% | 71.9% | BE |
| BE | 71.4% | 81.8% | FI | 3 : 9 | DE | 53.2% | 72.2% | GR |
| AT | 72.8% | 85.2% | PT | 4 : 8 | BE | 60.1% | 78.9% | FR |
| IT | 76.3% | 87.0% | IE | 5 : 7 | ES | 62.0% | 81.2% | NL |
| FI | 80.9% | 87.9% | ES | 6 : 6 | AT | 62.2% | 82.0% | AT |
| IE | 85.9% | 89.6% | FR | 7 : 5 | IT | 65.2% | 82.5% | ES |
| NL | 86.1% | 91.5% | DE | 8 : 4 | NL | 67.7% | 95.7% | IE |
| DE | 92.7% | 91.6% | NL | 9 : 3 | FR | 74.3% | 104.6% | PT |
| GR | 96.3% | 91.8% | BE | 10 : 2 | IE | 77.4% | 105.4% | FI |
| FR | 99.2% | 91.9% | AT | 11 : 1 | GR | 259.4% | 114.8% | IT |

**Table 7.** ***Systemic rankings, June 2007 to December 2009:*** This table displays the systemic vulnerability (‘*from others*’) and systemic risk (‘*to others*’) results calculated using both Lanne-Nyberg and Pesaran-Shin variance decompositions for each of the eleven countries, and ranks accordingly. Austria (AT), Belgium (BE), Germany (DE), Spain (ES), Finland (FI), France (FR), Greece (GR), Ireland (IE), Italy (IT), Netherlands (NL), and Portugal (PT). The left side of the rank column in the center of the table refers to rankings for ‘*from others*’. The right-hand column of ranks ‘*to others*’ which reverses the rank ordering with the 11th rank indicating lowest risk.

| Systemic vulnerability (‘from others’) | | | | | Systemic risk (‘to others’) | | | |
|---|---|---|---|---|---|---|---|---|
| **Lanne-Nyberg** | | **Pesaran-Shin** | | **Rank** | **Lanne-Nyberg** | | **Pesaran-Shin** | |
| GR | 1.3% | 25.7% | GR | 1 : 11 | FI | 11.7% | 39.1% | GR |
| IE | 5.3% | 42.6% | IE | 2 : 10 | FR | 16.2% | 40.3% | IT |
| PT | 22.8% | 44.9% | PT | 3 : 9 | IT | 19.4% | 41.8% | PT |
| ES | 23.2% | 52.6% | ES | 4 : 8 | AT | 19.8% | 46.5% | DE |
| BE | 36.9% | 55.3% | IT | 5 : 7 | DE | 22.8% | 49.0% | IE |
| AT | 38.3% | 62.6% | FI | 6 : 6 | NL | 41.2% | 56.2% | BE |
| IT | 56.5% | 65.3% | AT | 7 : 5 | PT | 42.4% | 57.3% | ES |
| NL | 57.1% | 65.3% | NL | 8 : 4 | ES | 53.2% | 61.8% | FR |
| FR | 59.7% | 68.9% | BE | 9 : 3 | BE | 67.4% | 62.9% | FI |
| FI | 66.7% | 76.3% | FR | 10 : 2 | GR | 70.5% | 88.8% | AT |
| DE | 94.5% | 83.8% | DE | 11 : 1 | IE | 97.8% | 99.6% | NL |

**Table 8.** ***Systemic rankings, January 2010 to December 2011:*** This table displays the systemic vulnerability (‘from others’) and systemic risk (‘to others’) results calculated using both Lanne-Nyberg and Pesaran-Shin variance decompositions for each of the eleven countries, and ranks accordingly. Austria (AT), Belgium (BE), Germany (DE), Spain (ES), Finland (FI), France (FR), Greece (GR), Ireland (IE), Italy (IT), Netherlands (NL), and Portugal (PT). The left side of the rank column in the center of the table refers to rankings for ‘*from others*’. The right-hand column of ranks ‘*to others*’ which reverses the rank ordering with the 11th rank indicating lowest risk.

# Figures

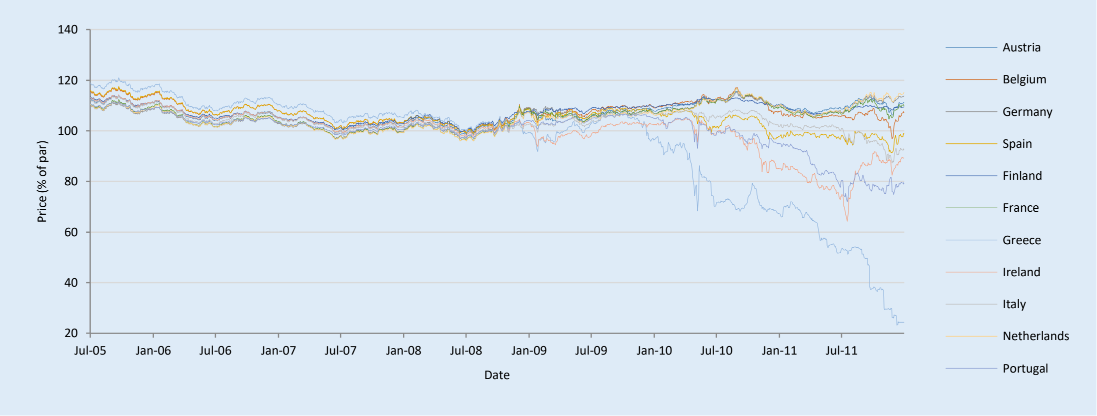


**Figure 1.** ***Index price series for the eleven eurozone countries****:* This table shows the price series of the bond indices quoted on MTS for each country included in the study.

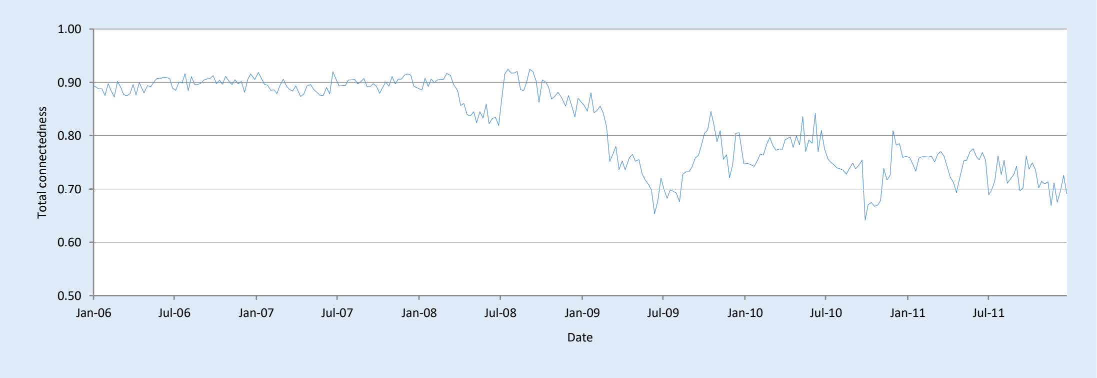


**Figure 2.** ***Rolling total connectedness, Lanne-Nyberg****:* The rolling estimation window width is 100 days, and the predictive horizon for the underlying variance decomposition is 12 days. The sample is from July 2005 to December 2011.

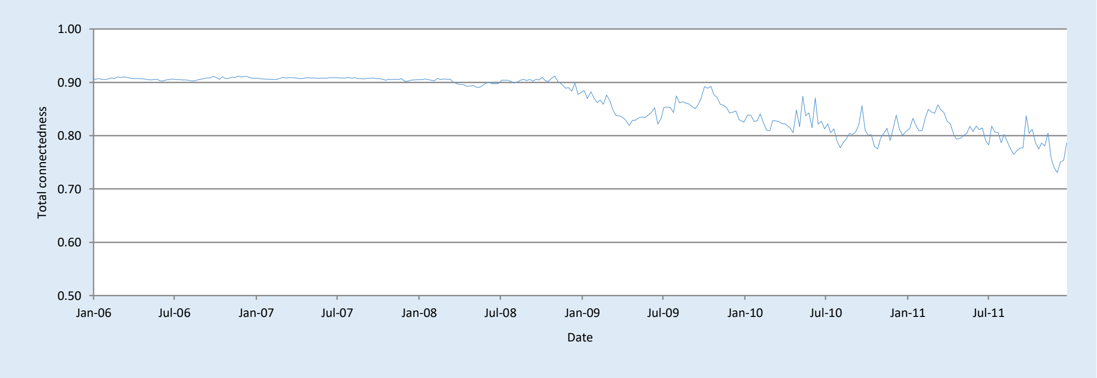
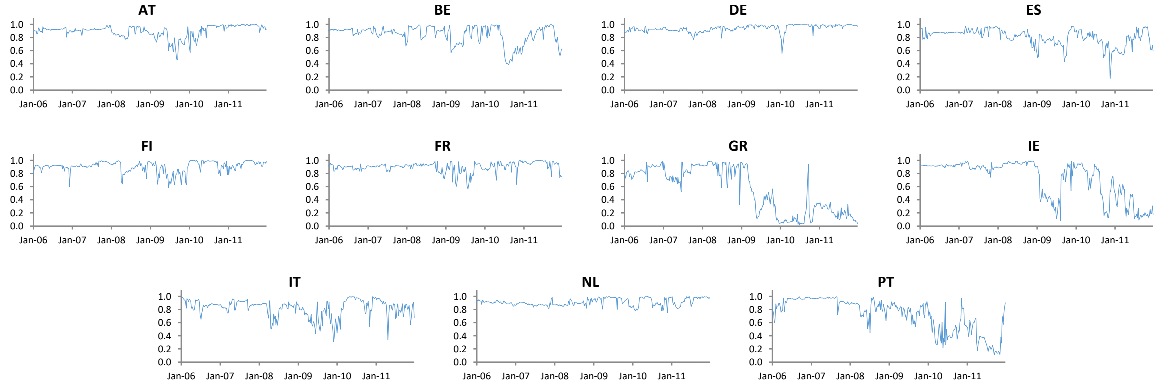
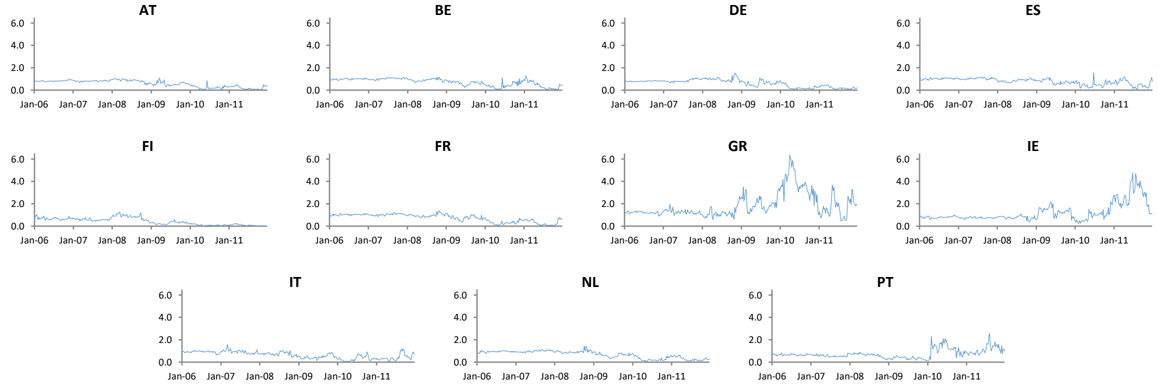


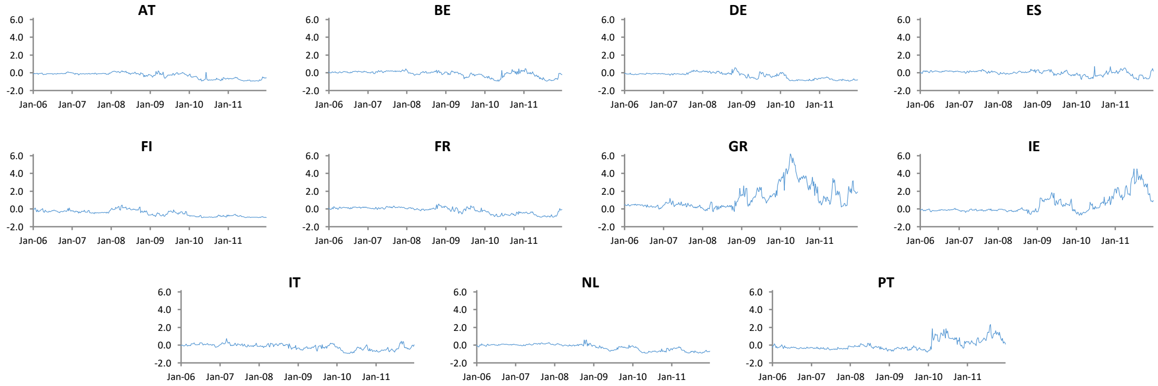
**Figure 3.** ***Rolling total connectedness, Pesaran-Shin:*** The rolling estimation window width is 100 days, and the predictive horizon for the underlying variance decomposition is 12 days. The sample is from July 2005 to December 2011.



(A) Rolling total directional connectedness ‘from others’, return series

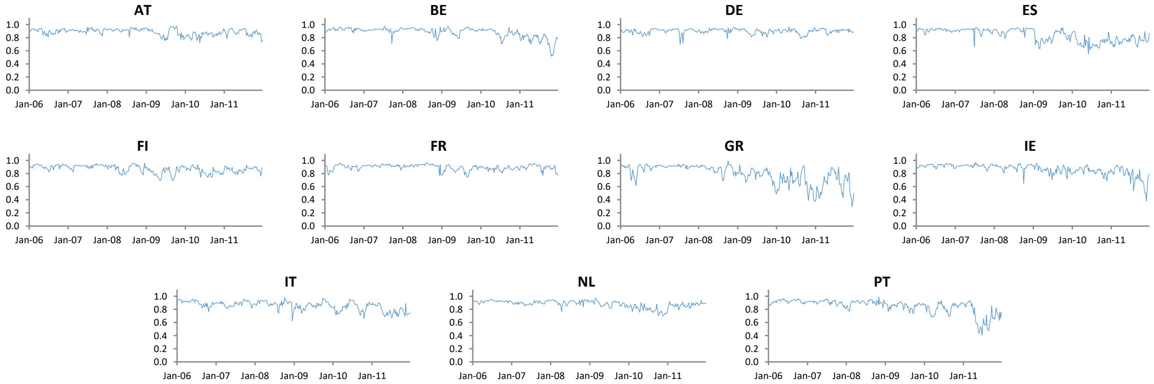


(B) Rolling total directional connectedness ‘to others’, return series

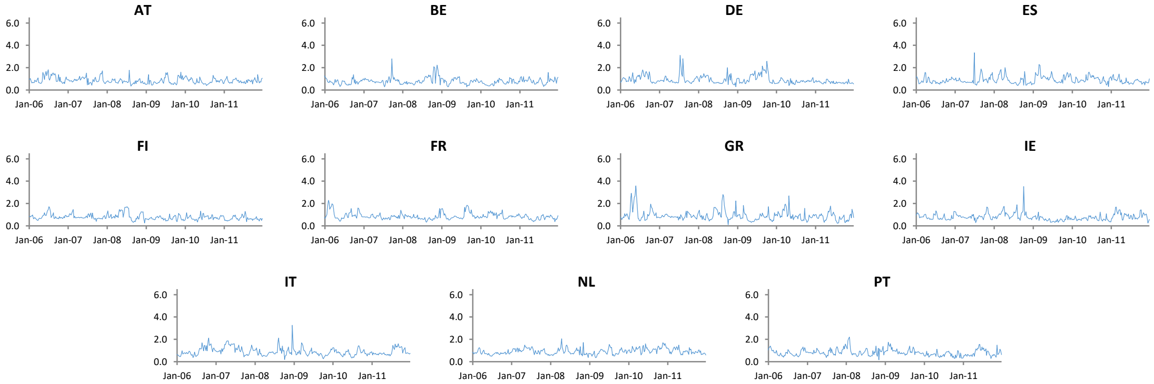


(C) Rolling total directional connectedness ‘net’, return series.

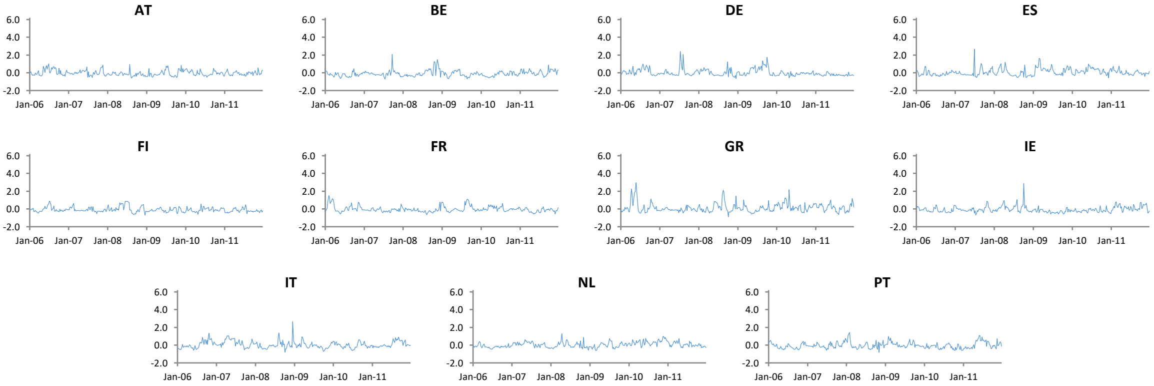
**Figure 4.** ***Rolling total directional connectedness, Lanne-Nyberg****:* The rolling estimation window width is 100 days, and the predictive horizon for the underlying variance decomposition is 12 days. The sample is from July 2005 to December 2011. Austria (AT), Belgium (BE), Germany (DE), Spain (ES), Finland (FI), France (FR), Greece (GR), Ireland (IE), Italy (IT), Netherlands (NL), and Portugal (PT).



(A) Rolling total directional connectedness ‘from others’, return series



(B) Rolling total directional connectedness ‘to others’, return series



(C) Rolling total directional connectedness ‘net’, return series.

**Figure 5.** ***Rolling total directional connectedness, Pesaran-Shin:*** 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 to December 2011. Austria (AT), Belgium (BE), Germany (DE), Spain (ES), Finland (FI), France (FR), Greece (GR), Ireland (IE), Italy (IT), Netherlands (NL), and Portugal (PT).