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Network Connectedness Analysis on European Corporate and Government Bonds

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Introduction

Quantitative and qualitative branches of economic studies, ranging from pure philosophical or behavioral models and theories to complex econometric frameworks, have in common several assumptions on connectedness among individuals and institutions. The meaning of connectedness in this sentence is wide: market operators' expectations, individual risk aversion, but even heuristics and bank runs phenomena or a financial bubble explosion, are all mechanisms and events connected among themselves, and constituted by an interrelated variety of impulses and realizations.

Financial firms balance sheets and counterparty relations, but also public institutions, pension funds and healthcare systems, literally every socioeconomic and financial system the society has developed, is today more interrelated and co-dependent than yesterday.

"A butterfly flapping its wings in Brazil can produce a tornado in Texas."[1], this famous sentence of Edward Lorenz, progenitor of chaos theory, highlighted a basic but fundamental concept: with the right tools, events that appear as completely unrelated can be not only linked but even measured in their reciprocal influences. In other words, deterministic or stochastic that is, a system interrelation study is the first step to be made to understand its provenience, its status, and its relative importance.

Economic theory and a variety of empirical findings state that financial systems are among the most interrelated in the social-economic panorama. Financial bubbles formations and explosions, economic cycles turnovers, and stock market capitalization shortfalls are all characterized by two main features: the centrality of some institutions (public or private they are), and the positive or negative, but

[1] Edward Norton Lorenz (1972); Session of the annual meeting of the AAAS (American Association for the advancement of Science).

always high, correlation among economic actors. The main idea inherited from the theory and empirical applications is so that during crisis times, or high market volatility periods, connectedness of financial systems rises, and the objective chased by the following analysis is to prove and measure this interrelation change. Historically speaking is clear that a single institution can not cause global economic earthquakes: the Lehman Brothers holding operations were not the cause of the subprime crisis, Greek government behaviour did not erase creditworthiness of a vast majority of Euro area countries, and the global undervaluation of the Coronavirus emergency was not caused by a single country poor first reaction to the disease spread. However, correlation among actors and the magnitude of both, the leading agent and the event suffered in a crisis, surely serves as propellent for shocks propagation and crisis ignitions. These considerations make reasonable the assumption that polarization in connectedness exists, and determines how impulses are spread in the system, on a directional and on a magnitude level.

One of the key objectives of the thesis is the investigation of this polarization phenomenon and the description of it. The scope of the analysis is to evaluate the framework of connectedness channels at a granular level, in order to understand if there exist drivers for interrelation directionality. Then I studied how polarization in connectedness frameworks changes by observing if a polarized structure exists and if it changes under stress conditions. At the same time, I investigated if it conforms in standard or peculiar ways depending on historical economic occurrences.

The thesis focuses on the European bond market and measures its total-wide dynamics, together with granular pairwise relations evolution. This will support the main idea that connectedness changes in structure and level, depending on financial and economic environment variations and, in particular, an increase in connectedness is expected to be measured under crisis periods. Meanwhile, some kind of polarization phenomenon is expected to be observed, giving specific institutions the role of connectedness drivers.

The estimation of connectedness measures will be done by modelling both corporate and governments bonds.

Bonds rather than stocks, credit default swaps, or other assets, have been chosen for two main reasons:

i. one of the latest and serious financial crises (the sovereign debt one) had a central debt component. Moreover, even if the repercussions were globally spread, it was a crisis that started and matured on European "soil";
ii. bond yields contain an interest rate risk component, thus measures based on them can reflect not only current network structures due to financial dynamics but also market operators' expectations.

In addition to (i) and (ii), another factor partially drove the data choice for the analysis. In fact, the empirical literature is richer in applications on stock returns and volatilities, or on financial derivatives, rather than on bonds-related data. Since the former's outcomes reflected very interesting results, I was interested in a further investigation on the efficiency of bonds networks, in explaining connectedness spread and institutions' frameworks, as an alternative to the mainly used stock returns data.

Regarding the choice of the type of corporations for the empirical analysis, I selected major European financial institutions. The role of those types of corporations related to the subprime crisis makes the study of connectedness measures based on them, very interesting from a risk management and regulatory policy perspective. Furthermore, due to counterparty relations and balance sheet interdependencies, financial corporations are likely to be more interrelated than industrial ones, making the study of connectedness more interesting and potentially more fruitful.

Another important aspect of the European bonds markets regards the link between government bonds and economic and monetary policies since the start of the QE program in 2015. The QE made bonds an interesting possible channel of connectedness spread across European countries.

For these reasons the thesis also investigates connectedness in government bonds separating short-term (2-year) from long-term (10-year) bonds. This last discrimination has the purpose of chasing dynamics reflected in a different way according to the yield tenor. In fact, for example, interest rate risk and inflation expectations are linked to long-term treasury yields, while consumption trends impacts of economic policies are linked to short-term rates.

The empirical work in the thesis shows some very interesting results, which confirm the potential of bond yields in reflecting connectedness' dynamics, coherently with recent global economic history. Variations in every system's overall connectedness measure have been observed and analysed, proving the rise in connectedness supposed at first, concurrently to crisis periods. In fact, the latest economic relevant happenings can be read through interrelation measures patterns, with high degrees of systems' connectedness, observed in concomitance to economic crises. Solely one system out of the three, the long-term government one, showed connectedness resilience in relation to crisis events, reflecting a cyclical behaviour stronger than any sort of dependence on financial markets shocks. This outcome in addition to reflecting an interesting and unexpected independence feature of the relative system, at first labelled its connectedness' measure as useless for risk management applications, since apparently unrelated to market shocks manifestations. However, further analysis will show interesting applications of these system-derived measures in phenomena evaluation, under a joint perspective with other systems' connectedness estimates. Specifically, the relative level of the system overall interrelation measure, compared with the one of the short-term government framework, showed great explanatory power for market operators' expectations and for the understanding of the relevance of a crisis.

Historically speaking the long-term government bond system has been always observed as the most interrelated. Regrading the short-term and the corporate framework, an interesting result will be presented: an exchange in relative level has been observed after the sovereign debt crisis, marking the corporate system as constantly more interrelated than the government one (inverse situation with respect to times prior to the crisis).

Polarization in connectedness frameworks has also been observed. This confirms the supposed dynamics and reflects a peculiar hierarchy of institutions in influencing specific actors in the system. Furthermore, I observed that this phenomenon changes dynamically under crisis circumstances, reflecting idiosyncratic contributes of few entities in the spread of shocks consequences.

On a corporate level, a clear role of influencers is detained by UniCredit Bank and Deutsche Bank, connectedness is in fact polarized around these institutions, heavily influencing the others in the system. The role of these corporations was observed as central also for two recent economic crises. UniCredit acted in fact as a protagonist in connectedness spread, during the sovereign debt crisis, while Deutsche Bank played the same role during market crashes following the pandemic explosion. As opposed, among the institutions mainly suffering influence from others, we can see the Dutch ABN Amro and Rabobank, and the Danish Nordea Bank.

On a government level, strong evidence supports the role of Portugal and Ireland as main influencers, with the strongest connections directed to Spain and Italy. In this latter system, an interesting role is played by Belgium, acting as an intermediate node: it is heavily influenced by the just mentioned four countries, but it also presents important connections towards the residual actors in the system.

Main drivers of connectedness polarization have been so identified in economic size and creditworthiness, a dynamic proper of all three systems analysed. However, an interesting difference in the functioning of these drivers, between government and corporate systems, will be presented.

Final considerations were so able to address concrete drivers for shocks dissipation, discovering an unexpected marginal role of geographical components in connectedness spread.

Chapter I. On connectedness measures

1.1 The spill-over lookout

The centrality of connectedness is one of the main aspects of modern risk measurement and management discipline. It is, for example, a key aspect of market risk management. As a first example, one can think about returns connectedness or concentration risk. All the sources and channels from which risks arise and spill-over can be described and quantified through connectedness analysis. Also systemically speaking, system-wide connectedness measures have a growing importance in modelling market conjunctural phenomena and responses to shock or innovations in macroeconomics fundamentals. Connectedness measures can help analysts to understand and predict how and why there will be a shortfall in defaults between economic actors (credit risk), as well as point out mainlines to understand fundamental macroeconomics risks impact on business cycles.

So far, the description of networks bonds at a qualitative and quantitative level, seem to have had a powerful enrichment impact on the overall academic and practice risk management world, touching a wide range of different fields.

The wide known unsuitability of standard correlation-based measures, for non just pairwise applications, have led academics to concentrate on developing more general frameworks to describe the magnitude and structure of connectedness. However, a consistent portion of the literature still overlooks several fundamental properties of connectedness and hence possible sources of risk and tools for describing the dynamics of it.

1.2 Empirical works

A relatively modern thread of studies had started and enriched the academic literature providing tools and researches analysing shocks spill-over effects.

One notable first step in the direction of connections discrimination was done by Forbes & Rigobon in 2002 ("*No Contagion, Only Interdependence: Measuring Stock Market Comovements*"), in a research aimed to mark the differences between contagion and interdependence in a pre-structural meaning form, the so-called *correlation breakdown* (a statistically significant increase in correlation during crashes periods). In order to do so, the authors tried to measure correlation from a dynamic point of view (approach re-proposed and analysed by many other researchers then), finding out estimation problems related to heteroscedasticity, proper of financial markets. Although Forbes et al. proposed a method of correcting for cross-market correlation estimators bias, that was far from the more recent elaborate attempt to assess, not only changes in co-movements but also specific forms of contagion.

Another notable step ahead in the field should be addressed to Rodriguez's works of 2007 ("*Measuring financial contagion: A Copula approach*"), this paper studied financial contagion using a methodology that went beyond the simple analysis of correlation breakdowns and, at the same time, was careful in the characterization of nonlinearity and asymptotic dependence, some notorious features translated by the common conscience that extremely bad events lead to irrational outcomes. Copulas contain information about the joint behaviour of the random variables in the tails of the distributions. The research outcome on the study cases examined, found out contagion in the sense of Forbes and Rigobon's (2002) definition. However, although overall dependence was seen increasing after a main shock spreading, patterns of change in tail behaviour differed widely across markets, with tail dependence being more prevalent in times of financial turmoil. This paper made the case that structural breaks in tail dependence are an actual dimension of the contagion phenomenon.

In reviewing empirical works of the related literature, attention should be paid also to the work of Billio, Getmansky, Lo and Pelizzon of 2012 ("*Econometric measures of connectedness and systemic risk in the finance and insurance sectors*"), where a wide range of connectedness estimation approaches was revied by empirical applications. Since the final approach on network bonds evaluation used in the current thesis project, it is not one of the proposed there, I will limit to a presentation of the mentioned work, without entering into quantitative details of all the proposed tools. They used several econometric measures of connectedness based on Principal Components Analysis (PCA) and Granger-causality networks, applying them to the monthly returns of hedge funds, banks, broker/dealers, and insurance companies. The authors found out that all the mentioned sectors were becoming strongly interconnected over the last few years. This was likely increasing the level of systemic risk in the finance and insurance industries through a complex and time-varying network of relationships. The authors found out that PCA provided a broad view of connections among all four groups of financial institutions, while Granger-causality efficiently captured the complex framework of pairwise relations among individual firms in the finance and insurance industries. An important result in term of field applications and research path was the conclusive suggestion that the banking and insurance sectors may be even more important sources of connectedness than other parts, consistently with evidence from recent financial crises (2008 & 2010).

An even more recent ring of the literature chain, treating a parallel approach compared to the one just mentioned, is the work of Hautsch, Schaumburg and Schienle of 2014 ("*Financial Network Systemic Risk Contributions*"). The authors used a realized systemic risk *Beta* as a measure of financial companies' contribution to systemic risk, given network interdependence between firms' tail risk exposures. They defined the *Beta* as the total time-varying marginal effect of a firm's Value-at-risk (VaR) on the system's VaR, conditionally on a pre-identified network of spill-over effects, market and balance sheet information. The approach was mainly aimed to monitor companies' systemic importance, enabling transparent macroprudential supervision. Based on relevant company-specific risk drivers, the researchers measured firm's idiosyncratic tail risk by explicitly accounting for its interconnectedness with other institutions. Their empirical results showed the interconnectedness of the US financial system marking channels of relevant potential risk spill-overs. Specifically, they classified companies into major risk producers, transmitters, or recipients within the system, driving to a principal feature of connectedness measurement besides dynamics: directional weighted effects.

Others very important and more recent contributions to the literature are the works of Diebold et al. (2014)[2], Demirer et al. (2016)[3], Buse et al. (2019)[4]. Flying over the empirical findings, the quantitative and methodological approaches will be explained later in details, since the current thesis project is inspired by their methods (i.e. use of connectedness measure based on forecast error variance decomposition (FEVD)).

1.3 On network topology

Network theory is defined as the study of either symmetric or asymmetric relations between discrete objects. In network science and computer science, network theory is a part of graph theory: a network can be defined as a graph in which nodes and/or edges have attributes.

The applications of Network theory touch many disciplines including statistics, physics, computer science, engineering, biology, climatology, sociology, and of course economics and finance.

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[2] Diebold F.X. & Yilmaz K. (2014); "On the network topology of variance decomposition: Measuring the connectedness of financial firms"; *Journal of Econometrics.*

[3] Demirer M., Diebold F.X., Liu L. & Yilmaz K. (2016); "Estimating global bank network connectedness"; *Journal of Applied Econometrics.*

[4] Buse R. & Schienle M. (2019); "Measuring connectedness of euro area sovereign risk"; *International Journal of Forecasting.*

Topologically speaking a network $\mathbf{N}$ can be defined as a collection of N nodes (or vertices) connected by L links (or edges). The distance $\boldsymbol{S_{ij}}$ between two nodes $\boldsymbol{i}$ and $\boldsymbol{j}$ is the smallest number of links that have to be crossed to go from $\boldsymbol{i}$ to $\boldsymbol{j}$. The network $\mathbf{N}$ is defined as connected, if $\boldsymbol{S_{ij}} \leq \boldsymbol{N-1}\ \forall\, \boldsymbol{i,j}$.

Once defined, the main aspect of a network that needs to be analyzed is the strength of connections and their capillarity. A multitude of questions arise also thinking on which prospective connections have to be considered in order to evaluate a network, for example, is a pairwise or a system-wide concept of links that better measures the strength of a network's connections?

In order to better clarify these concepts, is useful to think of $\mathbf{N}$ simply as an $\boldsymbol{N}$ x $\boldsymbol{N}$ adjacency matrix A of zeros and ones ($\boldsymbol{A} = [\boldsymbol{A}_{ij}]$), where $\boldsymbol{A}_{ij} = 1$ if nodes $\boldsymbol{i}$ and $\boldsymbol{j}$ are connected while $\boldsymbol{A}_{ij} = \mathbf{0}$ otherwise. The so defined A matrix is a symmetric matrix because, obviously, if $\boldsymbol{i}$ and $\boldsymbol{j}$ are connected also $\boldsymbol{j}$ and $\boldsymbol{i}$ are.

Since algebraically speaking the network is the matrix A, all the network properties are contained in A, and so all connectedness measures have to be based on A. Anyway, there is not a universal defined measure of them, and a lot have been proposed. The most popular measures, and so far, the most important for the purposes of the following econometric analysis, are based on the concept of node degree ad diameter.

1.3.1 Degree and Diameter

A node's *degree* can be defined as its number of links L connecting it to other nodes, so for example the degree of the node $\boldsymbol{i}$ is:

$$\delta_i = \sum_{j=1}^{N} \boldsymbol{A}_{ij} = \sum_{j=1}^{N} \boldsymbol{A}_{ji} \tag{1.1}$$

The degree distribution is the probability distribution of degrees across the nodes and is a discrete univariate distribution, with all parameters describing its shape contained into the network characteristics. The one that we are more concerned for the carried analysis, are obviously the network behavior aspects that define the location parameter of the degree distribution: the mean. So, the mean of the degree distribution has been taken as the benchmark measure from the literature developed so far in network connectedness analysis for econometrics applications. Another important aspect of a network is closely related to the previously introduced concept of distance between nodes: the *diameter*. In fact, the diameter of a network is defined as the maximum distance between two nodes, so:

$$S_{max} = max_{ij} S_{ij} \tag{1.2}$$

This is another diffused benchmark measure of overall network connectedness and of course, the relation with the degree is that the smaller is $\mathbf{N}$ diameter, the greater is the overall connectedness.

1.4 Forecast error variance decomposition

In the field of econometrics and other applications of multivariate time series analysis, the Forecast Error Variance Decomposition (FEVD) is used to aid in the interpretation of a Vector Autoregressive (VAR) model once it has been fitted, and it is derived from the Impulse Response Function (IRF). This latter explains the response of one variable to an impulse in another variable in a system, that involves several further variables as well (a VAR(p) model for instance). It manages to do this, tracing out the effect of an exogenous shock or innovation in one of the variables on some or all the other variables. This feature allows to trace the transmission of a single shock within an otherwise noisy system of equations and, thus, makes them very useful tools in the assessment of economic policies for example.

Variance decomposition indicates the amount of information each variable contributes to the other variables in the (auto)-regression (a vector form one for the current analysis). It determines so how much of the forecast error variance of each of the variables can be explained by exogenous shocks to the other variables. Letting the quantitative specification and derivation of FEVD and IRF for *Appendix A.1-A.2*, it follows the exploration of FEVD implementation in network analysis.

1.4.1 FEVD in network analysis

Given the definition and the econometric meaning of FEVD, it is not surprising that some of the main authors in econometric network analysis chose it to develop a unified framework for conceptualizing and empirically measuring connectedness, from a pairwise through a system-wide level. It is in fact the approach proposed by Diebold and Yilmaz (2014), from which this thesis project is inspired under a methodological and quantitative point of view.

This approach is based on assessing shares of forecast error variance in the objects of analysis, due to shocks arising elsewhere.

From now on it will be denoted by $\boldsymbol{d_{ij}^H}$ the $\boldsymbol{ij}$-th H-step variance decomposition element, so the fraction of the variable $\boldsymbol{i}$'s H-step forecast error variance due to shock in variable $\boldsymbol{j}$. For obvious reasons all the so defined FEVD-based connectedness measures, rely only on "non-own" variance decomposition fractions, basically where $\boldsymbol{i \neq j}$.

In order to better summarize the various connectedness measures of this methodology and their relationships, a good approach is to analyze the representation given by Diebold et al. (2014), with the connectedness table provided in *Table 1*[5] below:

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

Table 1 - Connectedness table.

The portion delimited in red is the *variance decomposition matrix*, denoted by $\boldsymbol{D^H} = [\boldsymbol{d_{ij}^H}]$. The rest of the table simply integrates the information with rows and columns sums, and the grand average (for $\boldsymbol{i \neq j}$).

The off-diagonal elements of the $\boldsymbol{D^H}$ express a measure of *pairwise directional connectedness* that can so be expressed (from $\boldsymbol{i}$ to $\boldsymbol{j}$), as:

$$C_{i \leftarrow j}^H = d_{ij}^H \tag{1.3}$$

The first point of attention is on the fact that generally $\boldsymbol{C_{i \leftarrow j}^H \neq C_{j \leftarrow i}^H}$, and so that there are $\boldsymbol{N^2 - N}$ different pairwise directional connectedness measures.

It now follows the presentation of a variety of measures definitions, that aim to describe a network from a granular, to a system-wide level. This, in order to understand and evaluate degree, diameter and all the important aspects that make network analysis an appealing study approach for a system of variables.

[5] Diebold F.X. & Yilmaz K. (2014); "On the network topology of variance decomposition: Measuring the connectedness of financial firms"; *Journal of Econometrics*.

Starting from pairwise directional connectedness, it can be defined as *net pairwise directional connectedness,* the following:

$$C_{ij}^{H} = C_{j\leftarrow i}^{H} - C_{i\leftarrow j}^{H} \tag{1.4}$$

Moving now to a wider point of view, *total directional connectedness* from others to $\boldsymbol{i}$, is defined as:

$$C_{i\leftarrow *}^{H} = \sum_{\substack{j=1 \\ j\neq i}}^{N} d_{ij}^{H} \tag{1.5}$$

and on the other hand, *total directional connectedness* to others, from $\boldsymbol{j}$, is:

$$C_{*\leftarrow i}^{H} = \sum_{\substack{i=1 \\ i\neq j}}^{N} d_{ij}^{H} \tag{1.6}$$

Just as done for pairwise connectedness it follows the definition of *net total directional connectedness:*

$$C_{i}^{H} = C_{*\leftarrow i}^{H} - C_{i\leftarrow *}^{H} \tag{1.7}$$

In the end, a grand total connectedness measure comes from the sum of the off-diagonal elements of $\boldsymbol{D^H}$, divided by $\boldsymbol{N}$:

$$C^{H} = \frac{1}{N} \sum_{\substack{i,j=1 \\ i\neq j}}^{N} d_{ij}^{H} \tag{1.8}$$

Leaving again more sophisticated specifications and derivation for *Appendix A*, Diebold et al. (2014) chose to use Generalized Variance Decomposition (GVD) as introduced by Pesaran et al. (1998)[6], as opposed to Cholesky-based Variance Decomposition. This choice was supported by the useful properties of GVD outcomes, which are invariant to ordering in estimation. In fact, the shocks are not orthogonalized but are allowed for correlation, while simultaneously accounting for the correlation among them observed historically (under normality assumptions). On the other hand, Cholesky-based decomposition orthogonalized the errors, via Cholesky factorization, and this last technique is dependent on the order of the equations in the system.

It follows the mathematical expression of *H*-step GFEVD matrix $\boldsymbol{D^{gH}} = [\boldsymbol{d_{ij}^{gH}}]$ elements:

$$d_{ij}^{gH} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \theta_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' \theta_h \Sigma \theta_h{}' e_i)} \tag{1.9}$$

Where $\boldsymbol{e_j}$ is a selection vector with the element equal to 1 and zero elsewhere, $\boldsymbol{\theta_h}$ is the coefficient matrix of the *h*-lagged shock vector, in the infinite moving average representation of the non orthogonalized original VAR(p) model, Σ is the covariance matrix of the shock vector in the same model, and $\boldsymbol{\sigma_{jj}}$ is the $\boldsymbol{j}$-th diagonal element in Σ.

It should be clear so, since the $\boldsymbol{D^{gH}}$ variance decomposition matrix is an adjacency matrix, that variance decomposition matrices are networks. Moreover, $\boldsymbol{D^{gH}}$ describes a network in a very sophisticated way: the measure introduced in *Section 1.3.1*, concern a matrix (A) filled simply with 1 and 0, but the $\boldsymbol{D^{gH}}$ matrix is composed with non-binary values, that weight connections. That is a measurement system, that describes connections as strong rather than weak ones (in contrast to a simple "present" *vs* "non present" link status). Another good property of this approach is the fact that links are directed, and so that $\boldsymbol{i - j}$ edges are not necessarily equal to the $\boldsymbol{j - i}$ ones. So, in the end, this analysis

[6] Pesaran M.H. & Shin Y. (1997); "Generalized impulse response analysis in linear multivariate models"; *Economics Letters.*

methodology allows for the definition of "*to-degrees*" and "*from-degrees*" and identify the total directional connectedness measure $\boldsymbol{C^H}$ as the mean degree of the network $\boldsymbol{D^{gH}}$.

Because shocks are not necessarily orthogonal in the GFEVD environment, sums of forecast error variance contributions are not necessarily unity. So, in practice row of $\boldsymbol{D^{gH}}$ do not necessarily add to one. Hence the following analysis base the generalized connectedness indexes not on $\boldsymbol{D^{gH}}$, but rather on $\boldsymbol{\widetilde{D}^{gH}} = [\boldsymbol{\widetilde{d}_{ij}^{gH}}]$, where:

$$\tilde{d}_{ij}^{gH} = \frac{d_{ij}^{gH}}{\sum_{J=1}^{N} d_{ij}^{gH}} \tag{1.10}$$

By construction so:

$$\sum_{j=1}^{N} \tilde{d}_{ij}^{gH} = 1 \tag{1.11}$$

and:

$$\sum_{i,j=1}^{N} \tilde{d}_{ij}^{gH} = N \tag{1.12}$$

Chapter II. European bonds market

2.1 Corporate bonds

Corporate bonds generally tend to have a high investment appeal for investors. Financial actors tend to like these due to their shorter maturation timeline and higher yields when compared to government bonds. Furthermore, corporate bonds are generally considered to be safer investments than individual stocks.

Recent years experienced growth in European corporate bond emissions, mainly because of the low borrowing costs. Those latter were driven by an iterated low interest rates policy carried on by the European Central Bank (ECB), that enhanced corporate profitability in capital markets, since the fixed spread reflecting the idiosyncratic risk of each issuer, added to lower risk-free benchmark rates. European bonds are lately increasing in popularity since they have some very attractive benefits for investors. Among these peculiarities, there are: lower regulatory requirements and enhanced flexibility, investors, in fact, are not subject to troublesome paperwork and unnecessary costs. The mentioned lower regulation has been a double-edged sword for investors: simplicity and tax incentives can be quickly offset by the fact that some of these corporate bonds do not have the strict supervision of some others. That builds in an inherent and potentially unforeseeable risk. Anyway, the European bond market holds great potential for sustained, predictable growth.

Corporate bonds can be an important source of funding for European companies, which can use the proceeds from bond sales to invest in growth and job creation. They offer businesses access to alternative, more diverse sources of funding, and they also offer new investment opportunities for European savers. For these reasons, in relation to a chain of general improvement projects of union capital markets, the European Commission, in 2016, launched a review of the functioning of EU corporate bond markets. An expert group of market practitioners examined the functioning of European corporate bond markets and formulated a variety of recommendations to improve their functioning. In addition, a quantitative study on drivers of corporate bond markets' liquidity was conducted. The outcome of these activities clearly contributed to the mentioned growth of corporate bonds emissions during recent years.

Globally speaking the volume of corporate debt reached an all-time high in real terms of 13.5 trillion US dollars at the end of 2019, driven by the return of more expansionary monetary policies early in the year. At the same time, the overall quality of corporate debt has declined, according to a new OECD report[7]. Below, in *Figure 1*[8,] a graph from the mentioned OECD report presents the global corporate bonds issuance path.

"Structural reforms and monetary policy have promoted the use of corporate bonds markets as a viable source of long-term funding for non-financial companies since the global financial crisis" said OECD Secretary-General Angel Gurría (2020).

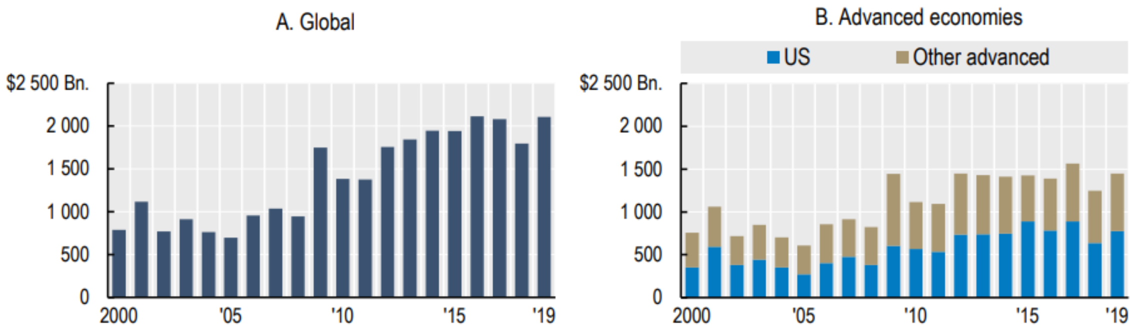

Figure 1 - Global corporate bond issuance and issuance in advanced economies (2019 USD, billion).

It is also worthy of notice that supported by a low interest rate environment, the mechanism of credit ratings has allowed companies to increase their leverage ratios and still maintain their ratings. This can be translated into the fact that

[7] Çelik S., Demirtaş G. & Isaksson M. (2020); "Corporate Bond Market Trends, Emerging Risks and Monetary Policy", OECD Capital Market Series; Paris.
[8] Source: European Commission.

today, the median firm in each investment-grade rating, is more levered than a decade ago.

Banking intermediation has decreased in recent years, on the other hand, activity on primary bond markets has increased. A report[9] from the European Commission Expert Group on Corporate Bonds, confirms the global trend of corporate bond for the European market. It points out that the outstanding stock of long-term debt securities has increased 3.6 times since 2002, with 70% of the increase happening after 2008. The same report explains that for the period 2009-2016, the European bond market has compensated the decrease of bank loans to non-financial corporations (NFCs) in Euro area countries. In fact, according to ECB data, the stock of loans extended to corporates decreased by 536 billion euro, whereas the stock of long-term debt securities increased by 567 billion euro over this period (*Figure 2*[10]).

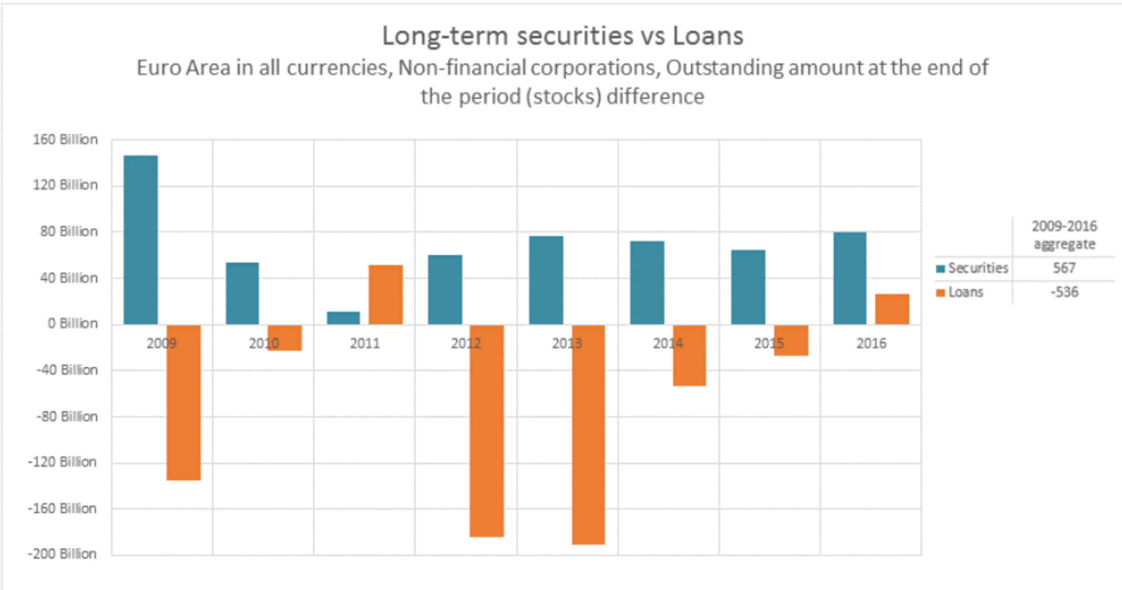

Figure 2 - Evolution of outstanding amounts of Long-term Securities vs loans for NFCs.

[9] Analytical report supporting the main report from the Commission Expert Group on Corporate Bonds; (November 2017); European Commission.
[10] Source: European Commission.

Despite the global cross-sector growth in bonds issuance following 2008, after the sovereign debt crisis financial corporations suffered a progressive decrease in financing operations sourced by bonds markets (*Figure 3*[11]). However, the need for replacement of maturing TLTRO-II funding will lead, in the near future, to a sizeable volume of debt that will need to be absorbed by the market. Financial corporation bonds markets shall so surely meet the structural needs of the industry.

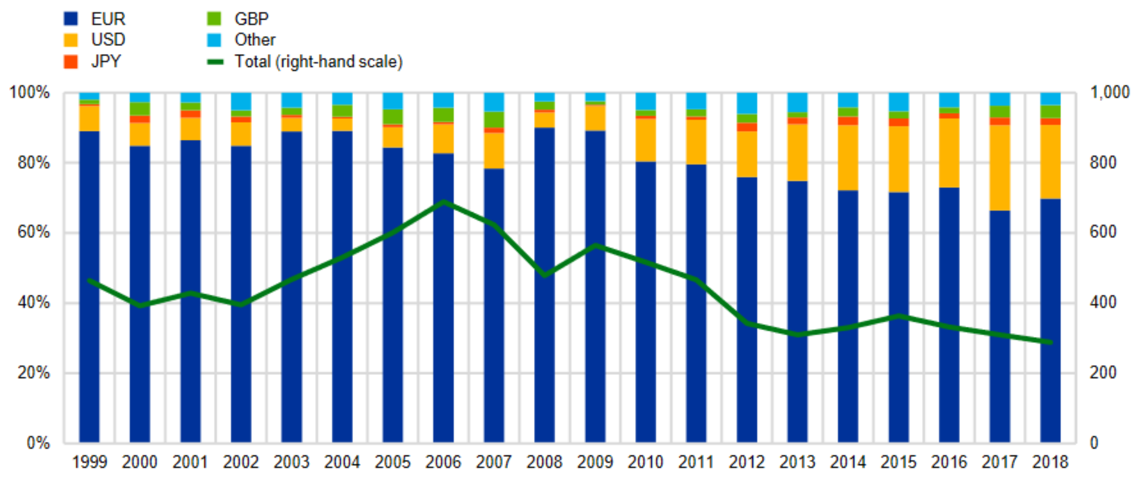

Figure 3 - Aggregate gross bond issuance by euro area banking groups (€ billions).

2.2 Government bonds, QE and chronicles

Current times are characterized by a monetary and a fiscal policy closely coordinated. But the complex way the European Union is structured can create obstacles to this coordination. Indeed, some investors fear that Germany's deep aversion to monetary financing will prevent the European Central Bank from keeping a lid on bond yields.

Linking the weighted-average bond yield to the inflation target is a powerful way for the ECB to justify its bond purchases and its willingness to hold down

[11] Financial Stability Review, November 2018 – Euro area financial institutions

peripheral bond yields. Ever since Mario Draghi promised to do "whatever it takes to preserve the euro" the ECB's willingness to underwrite the sovereignty of all euro-area countries has dominated the outlook for Europe's fixed-income markets. Despite signs of progress on a European Recovery Fund, it continues to do so today, and the ECB's commitment is as strong today as it was eight years ago. This dual mandate will only face strain when low yields conflict with the inflation target itself. At a time when central banks are anchoring yields close to the policy rate, thus suppressing the return potential from holding sovereign bonds, the ECB's willingness to stand behind peripheral bond markets, continues to make a positive case for European fixed-income markets.

With global bond yields close to record lows, the best period for government bond returns is probably behind the current time, but there are still opportunities for active investors, including the relatively high yields still available in the euro-area periphery.

More than twenty years have passed since 1998, the year in which the ECB was established, but the most famous and discussed manoeuvre was implemented much more recently: in 2015. The purchase of public and private bonds by the European Central Bank took place about six years after the US Federal Reserve initiated a similar program. The announcement of the European Quantitative Easing (QE) is regarded as one of the crucial moments of the "Draghi-era". For years, in fact, the Governing Council had proved reluctant to start a program of securities purchases which, according to a rooted line of thought, would have been extraneous to the mandate of the ECB itself (which is forbidden to monetize the debt of States). Between 2014 and 2015, however, a change took place at the macroeconomic level that was difficult for the central bank to ignore: Eurozone inflation points straight towards the minus sign, having dropped from 0.4% to 0.2%. A decline could have only been attributed, at least in part, to the austerity policies that characterized the Eurozone in the years following the crisis of 2011. The justification for Quantitative Easing was thus brought back to the key objective of the ECB, that of stability of prices at an inflation level below but

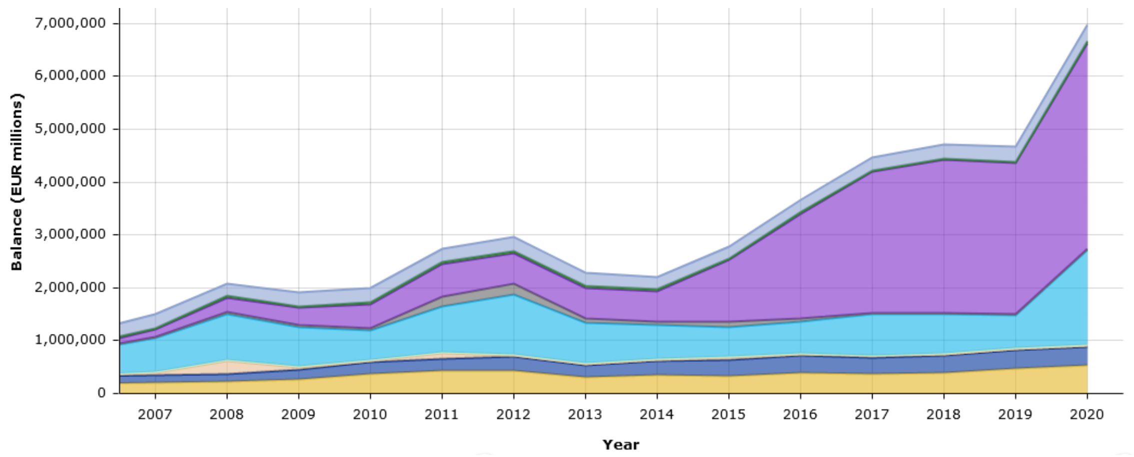

Figure 4 - Annual consolidated balance sheet of the Euro system; Purple shade corresponds to securities of euro area residents (the granular legend of each category constituting the graph is presented in the Appendix B).

close to 2%. Essentially, the program called for the ECB was to buy bonds from banks with the intent of raising the prices of these bonds and increasing the liquidity of the system. A direct aimed consequence was the decrease of a wide range of interest rates, making loans cheaper so that companies and individuals could have borrowed more, for less, in terms of borrowing costs. The ultimate meaning of this manoeuvre was therefore to push towards a trend of consumption and investment increase, supporting economic growth and the creation of jobs so that, with "price of prices", the ECB would have reached an inflation rate closer to 2%, in the medium term. The value of securities, in the ECB's portfolio, went from 590 billion in 2014 to almost 2,900 billion in 2018: an increase of 374%. Government bonds purchased by the ECB fall within this category of assets. from March 2015 to September 2018, the QE was extended several times and its volume of purchases was finally around 245 billion (spread over various tranches between 2015 and 2018). In order to understand the importance of QE from a technical point of view, it is sufficient to look at *Figure 4*[12]: the one that represents the evolution of the European Central Bank's balance sheet over the years. Starting from 2015 a clear change emerges: the size of the ECB balance sheet begins to rise at full speed. It was a sign that the bank was pumping ever greater amounts

[12] Source ECB.

of liquidity into the economic system. This happened to a much greater extent in the post-2015 period than in post-2008, when the crash of Lehman Brothers and the financial crisis hit.

However, the fortune of QE did not come to an end: in September 2019, in the last press conference that saw Draghi at the helm of the ECB board, it was confirmed that from the first day of November the ECB would have returned to buy bonds for 20 billion euros per month. It therefore appeared that Christine Lagarde had given the green light and that the future of European monetary policy would have continued to be "super accommodative", at least until the inflationary target is reached.

The effects of the recent history of ECB policy and government bonds markets have been massive. To have a clearer idea of their magnitude and duration, it is sufficient to look at *Figure 5*[13] where the evolution of average yields curves on the Eurozone is presented. It is clear how a flattening dynamic has been taken place constantly since 2010. The cash cost for top-ranked institutions has been on average negative for maturities up to 5 years for the last 4 years. Even the not

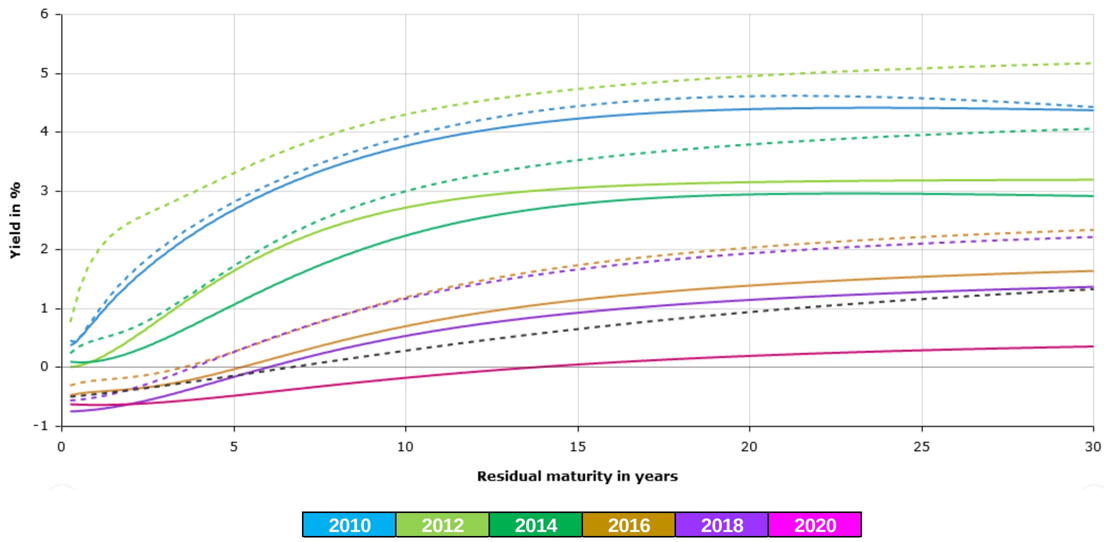

Figure 5 – Average Yields Curves on the Euro area, dashed line for all bonds, and normal lines for AAA ranked ones.

[13] Source ECB.

best-ranked entities, can on average borrow at negative cost for very short maturities lately.

2.3 Assets of interest

Historically there has always been a sort of skepticism in financing through financial markets for European corporations, at least for the ones of south Europe. This underestimation of markets functionality for financing purposes, as seen in the previous *Paragraph* (*2.1*), seems to has progressively ended, or at least that direction has been taken. The increase in demand together with growth in the issuance of European corporate bonds made this market very more liquid during the last years. Since liquidity of an asset is an essential feature to make it a useful channel of market information (due to the informative content of prices), the recent history of European corporate bonds, enhanced modelling application possibilities.

This last concept certainly drove the choice of corporate bond yields for the following analysis, however other important features have been considered during the sample selection. First of all, the role of financial institutions related to the subprime crisis makes the study of financial corporations' networks very interesting from a risk management and regulatory policy perspective. Furthermore, due to counterparty relations and proper balance sheets interdependencies (funds and asset portfolios composition), financial corporations are likely to be more interrelated than NFCs, leaving more space for the studying of interrelation on an unconditional and dynamic level. To summarize, all these features together with the recent history of the corporate bonds markets in Europe, led to the choice of financial corporate bond yields for the construction of a network system object of analysis.

The central role and bind between government bonds, and economic and monetary policies, since 2015, made them an interesting possible channel of connectedness spread, and market structure reflection. Furthermore, treasury yields on a short-term basis are strongly but indirectly related to consumption, since they drive borrowing costs for families and companies (or are at least closer to short-term standard benchmarks rates of lending operations). In addition to this, as said, the growing role in financial markets of European corporate bonds identify them as a quite new papabile information vehicle.
Since the current analysis aims to study interdependency in a dynamical and unconditional way, on the European markets, the choice of only a corporate bonds sample was not expected to reflect alone geographical together with idiosyncratic dynamics. That is why two main types of bonds, on the issuer side, have been chosen as objects of interest: corporate and government bonds.
A further sub-selection of bonds typologies has been made, not in relation to the issuer, but to the maturity. In fact, the final complete dataset analyzed comprehend two different samples of government bonds: a short-term one and a long-term one. Leaving specification on the selected issuers and maturities for C*hapter III*, some main differences between short and long-term treasury yields are here worth to be mentioned since they drove the just exposed dataset structure choice:

i. long-term treasury yields have a stronger rate risk component than short-term ones, and that is interesting to be counted since reflects market operators' expectations;
ii. closely to (i), long-term rates reflect also inflation expectations, and so market sentiment about the future;
iii. overnight rates are decided by central banks, and the relative closeness of short-term rates rather than long-term ones, make the formers to reflect more closely economic policy actions, while long-term yields may, as said, reflect expectations on those policies.

To sum up in what follows I built and analyzed the network structure of all these markets, and some interesting results will be shown. Simultaneously not only the quality of the estimated measures will be evaluated, but also differences and binds across the three samples network structures.

Chapter III. Data

3.1 Dataset description

As anticipated the current analysis has been carried on three datasets for European bonds' yields. The samples differ by the maturity of the securities and/or the nature of the issuers. Specifically, they are structured as follows:

i. 5-year corporate bonds;
ii. 2-year government bonds;
iii. 10-year government bonds.

All data has been downloaded by the data provider Bloomberg on a daily frequency basis, and then converted on a weekly basis by an ad hoc constructed algorithm, choosing just the observations that occurred on Fridays (Bloomberg method). All the analyzed securities are denominated in Euro.

Table 2 presents a summary of the thirteen corporations taken into account for the first dataset, with details about their complete denomination, country of origin, Bloomberg Ticker, and market capitalization. The firms have been chosen in order to express dependencies across Europe in the most homogeneous way. According to the dimension and economic structure of each country, the final dataset seems to represent well and proportionally all actors.

Table 3 contains a list of ten countries, whit their respective 2018 GDP, and credit rating. The second and the third dataset include yields for government bonds issued by these countries for the maturities of 2 and 10 years.

Country	*Ticker*	*Firm Name*	*Market Cap.*
Germany			
	DB	Deutsche Bank	17.68
	CMZB	Commerzbank	7.06
France			
	SOCGEN	Societè Generale	14.65
Italy			
	ISP	Intesa Sanpaolo	40.04
	UCG	UniCredit	19.34
Spain			
	SANTAN	Banco Santander	48.34
	BBVA	Banco Bilbao Vizcaya Argentaria	29.48
Netherlands			
	RABOBK	Rabobank	-
	ABNAMRO	ABN Amro	8.05
Austria			
	ERSTBK	Erste Group Bank	11.50
Denmark			
	NDASS	Nordea Bank	28.44
	DANBNK	Danske Bank	12.58
Portugal			
	BCP	Banco Comercial Portugues	1.86

Table 2 - Corporate bonds sample dataset (Market Cap. in € Billions).

Country	*GDP*	*Rating*
Austria	455	AA+
Belgium	542	AA-
Finland	276	AA+
France	2,778	AA
Germany	3,948	AAA
Ireland	382	A+
Italy	2,084	BBB-
Netherlands	913	AAA
Portugal	240	BBB
Spain	1,419	A-

Table 3 - Country issuing bonds of the Government datasets (GDP in € Billions, as of 2019, Rating from *Fitch Ratings).*

3.2 Modelled time series

The time series constructed for the current analysis range from 13 January 2006 to 25 September 2020. Bond yields of all three samples are visibly correlated sharing common paths through time. Also, non-stationarity in mean seems to be a common feature among the time series of the three samples.

Figures 6 through 8 below, show the time series used in estimation, plotted all together for each sample:

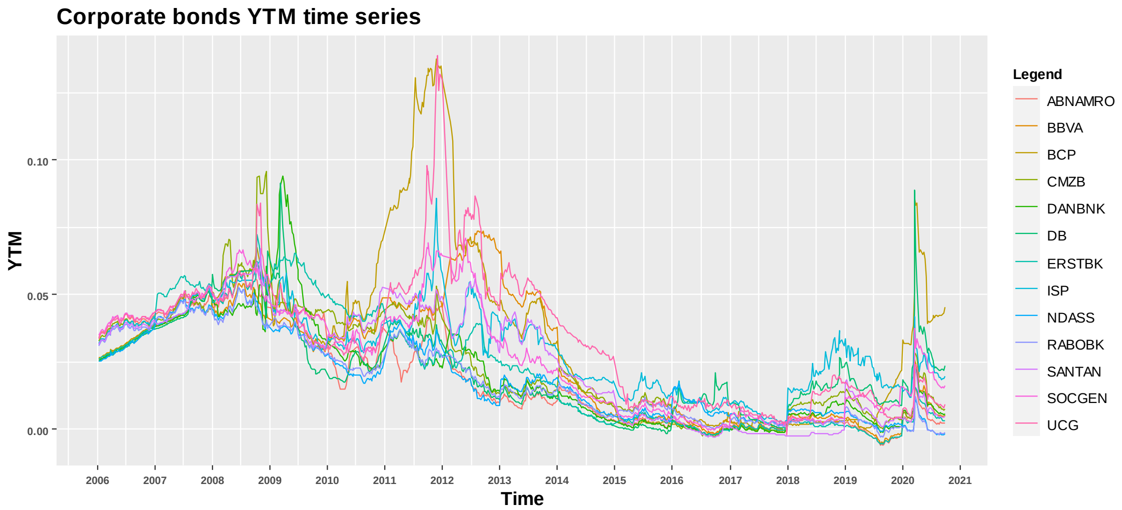

Figure 6 - Corporate bond yields time series.

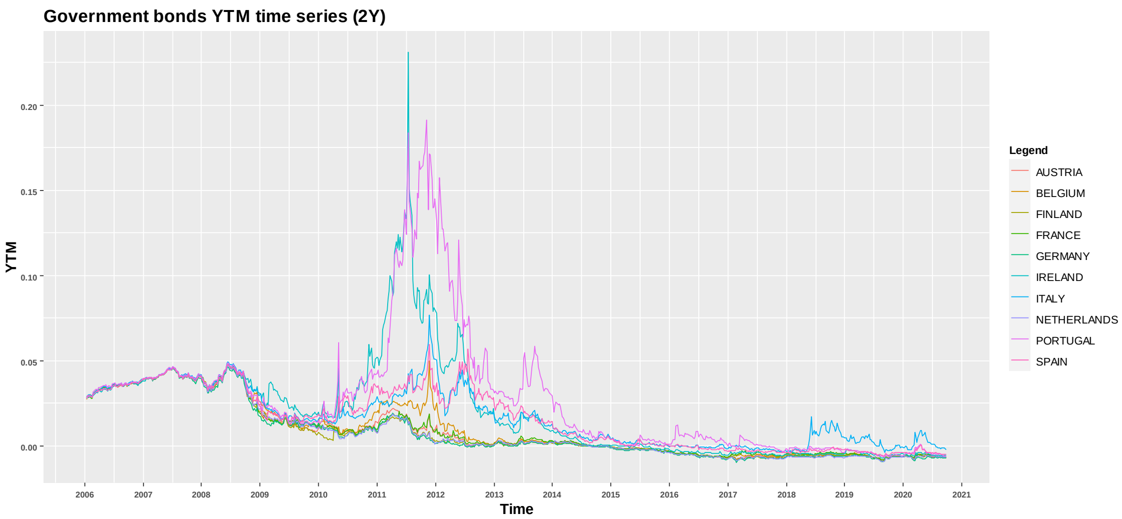

Figure 7 - Government bonds (2Y) yields time series.

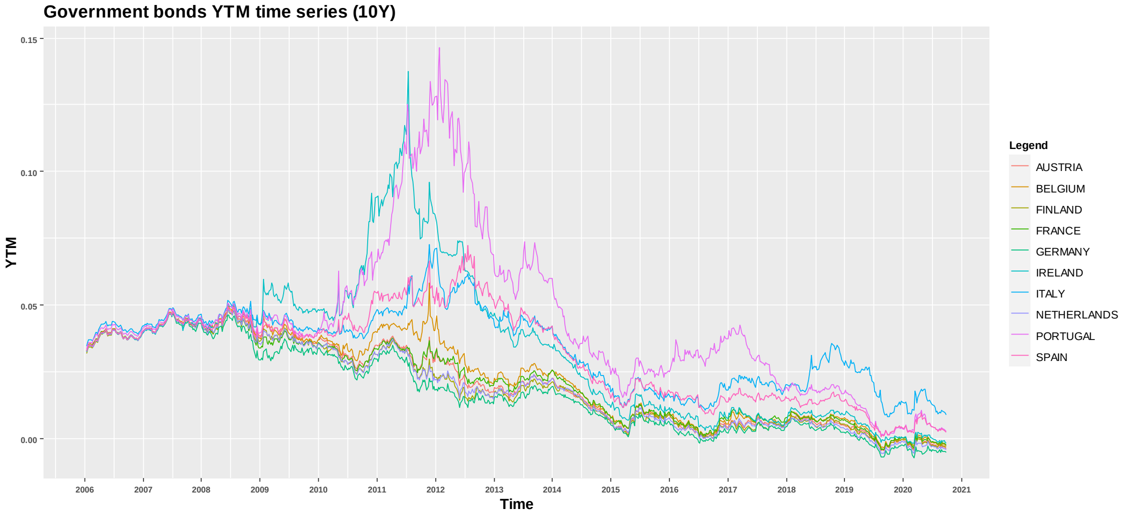

Figure 8 - Government bonds (10Y) yields time series.

As can be easily noticed, a first difference in the behavior of the three datasets is that the corporate bond yields time series show higher variance. This latter concept was quite predictable since corporations for their nature are far more risky investment than governments-related securities.

Another notable aspect is in the participation, on a sample level, to oscillation due to shocks during crisis periods. More precisely in the corporate bonds sample almost all-time series seem to have been heavily impacted during the 2008, 2010-2012, and 2020 (Covid-19 spread) crises, regardless of their dimension or their rating. That it is not true for the government bonds time series, where Portugal, Ireland, Italy and Spain seem to have been the principal victims of the shocks during the crises. This latter phenomenon can quite easily appoint the instability of those countries, at least from market operators' expectations perspective.

Regarding this last point, it can also be noticed that the latest three main financial crises, had an important impact on the series of the corporate sample, while the two governments datasets seem to have responded in a neat manner only in the 2010-2012 financial crisis.

The last fact worth mentioning is the closeness of the government bond yields time series, not only under a corporate *vs* treasury comparison view but also and mostly regarding the 2-year government bonds against the 10-year ones. For both samples, the closeness of the time series seems to break after 2008, but while the 2-year sample, after 2014, has strongly returned to the initial behavior, the 10-year one never recovered that feature. It substantially seems that at least on a European level, the uncertainty about the future has grown in magnitude and this has been reflected on market prices in volatility, since 2008.

Leaving specifications on the utilized model for the next chapter, follows the presentation of the actual fitted time series for each sample (*Figures 9* to *11*). Those are the *First Difference* of the original series, recognized as non-stationary in mean and *integrated of order 1.*

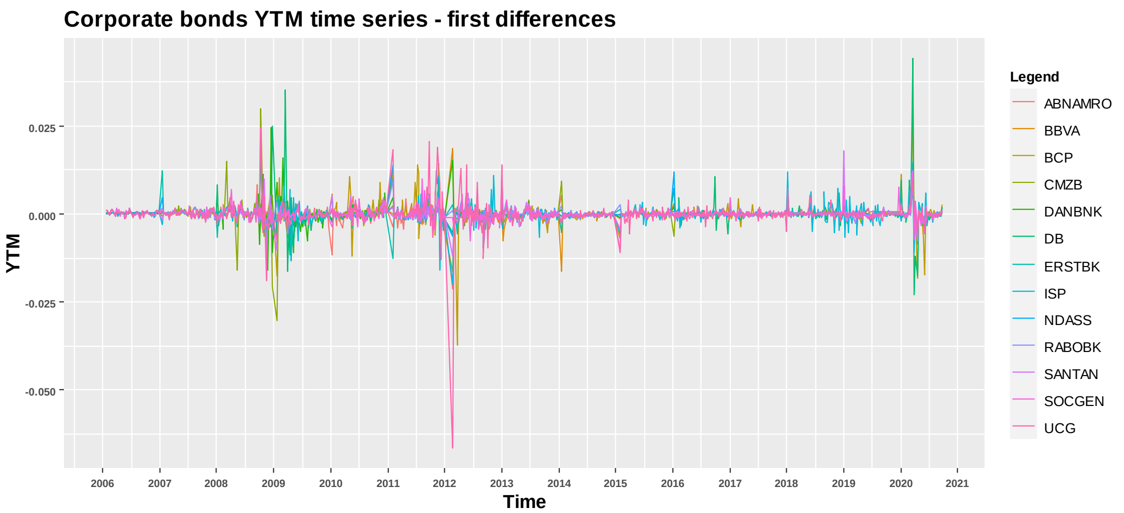

Figure 9 - Corporate Bond yields time series First Differences.

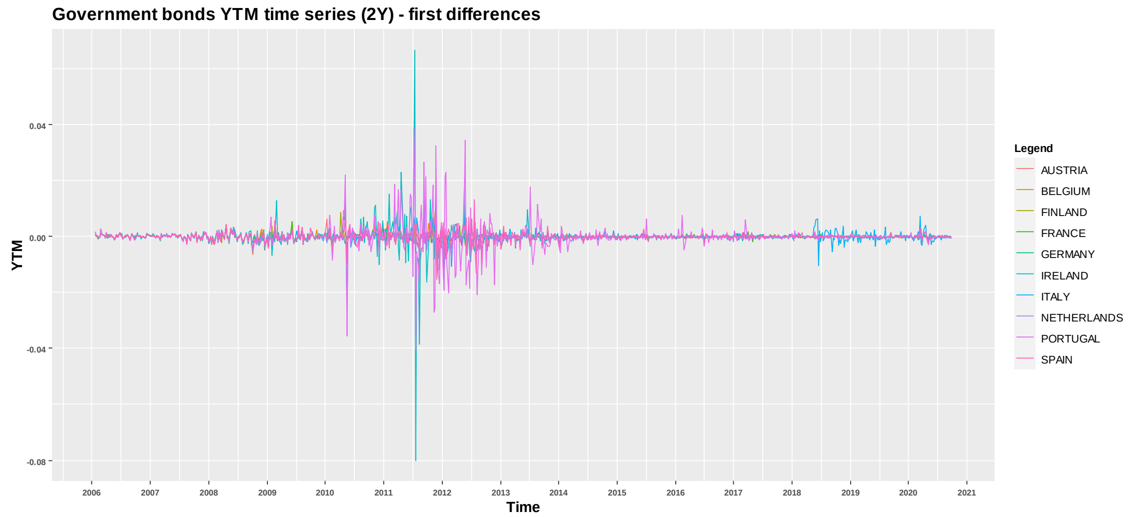

Figure 10 - Government bonds (2Y) yields time series First Differences.

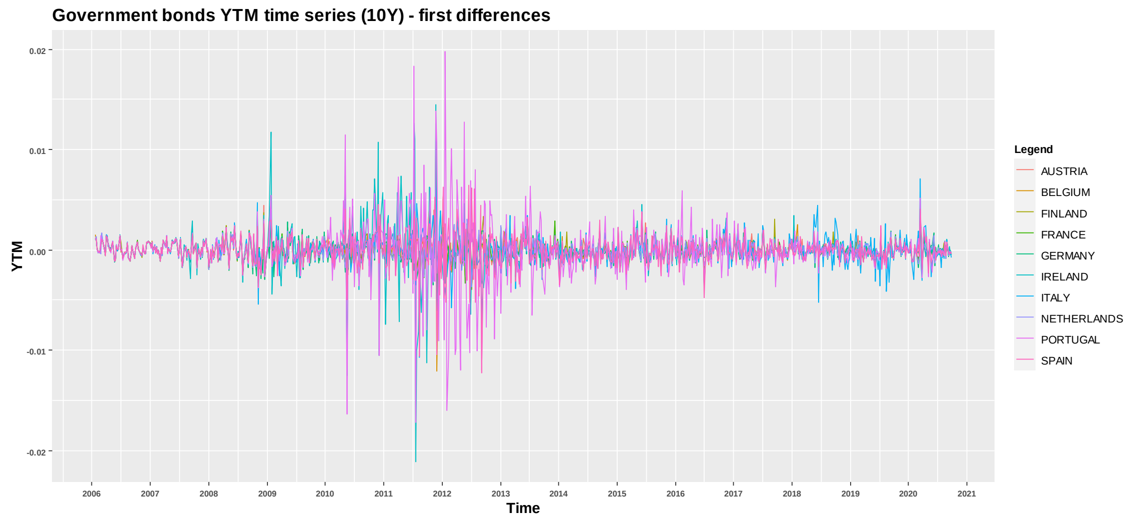

Figure 11 Government bonds (10Y) yield time series First Differences.

Chapter IV. Models

4.1 Specification & fitted data

As mentioned in *1.4.1* the current analysis is based on FEVD connectedness measures, applied in order to address, with a qualitative and quantitative approach, the interdependencies across European actors.

The first step in order to do so has been the choice of an approximating model for the data.

I fitted a Vector Autoregressive (VAR) model, of the following form:

$$r_t = \phi_0 + \sum_{i=1}^{p} \Phi_i r_{t-i} + \varepsilon_t \tag{4.1}$$

where given k as the number of time series for each sample, $\boldsymbol{r_t}$ is a k-dimensional multivariate time series, $\boldsymbol{\phi_0}$ is a k-dimensional vector, $\boldsymbol{\Phi}$ is a k x k matrix, and $\{\boldsymbol{\varepsilon_t}\}$ is a sequence of serially uncorrelated random vectors with zero mean and covariance matrix Σ .

Furthermore, the infinite Moving Average (MA) representation of the VAR model is of the form:

$$r_t = \sum_{i=0}^{\infty} \mathrm{A}_i \, \varepsilon_{t-i} \tag{4.2}$$

Where the k x k coefficients matrices $\mathbf{A}_{\boldsymbol{i}}$ obey the recursion:

$$\mathrm{A}_i = \sum_{j=1}^{p} \Phi_j \mathrm{A}_{i-j} \tag{4.3}$$

Whit $\mathbf{A_0}$ a $k \; x \; k$ identity matrix and $\mathbf{A}_{\boldsymbol{i}} = 0$ for $\boldsymbol{i} < 0$.

After a number of fitting attempts, the best structure has been identified in a VAR(1) model (Lag p=1).

A second main point was to differ the estimation of a *connectedness network* representing interdependencies given the sample dataset, from the observation of how this network changed over time. More specifically to allow for time-varying connectedness. This last concept is essential and central for the current analysis and for the utility of the computed measures, allowing them to be effective indicators during business cycles and financial crises. Substantially, allowance for time-varying connectedness is allowance for time-varying parameters. The approach used to perform such estimation is the widespread use of a *rolling window*, setting margins on the estimation sample. So, in order to track real-time connectedness, I set a uniform one-sided estimation window w, sweeping through each dataset sample, and using just the most recent w observations for the parameters estimation.

At the end I selected a one-sided estimation window w =100 weekly observations for each model fitting the data, although a robustness check has been made on more values of w *(Appendix B.2).*

Another parameter to be settled in modelling the dataset, and worth of considerations, is the connectedness horizon H, so the step of the forecast derived from the approximating model, and on which to perform the *Variance Decomposition.*

The considerations on this latter parameter, have to arise from the context, for example, in risk management applications one might choose a value of H related to risk measures. For instance, with daily data, a H=10 would be coherent with considerations for/alongside the 10-day Value-At-Risk (VaR) measure, required by the Basel agreement; likely to this, a portfolio management application would guide to a choice of H equal to the rebalancing period. For the current analysis an, H=2 (with weekly observations so equal to 14 days, so 10 trading days) has

been selected. This choice has been made according to the data obtained with a wide range of alternatives, but also according to the literature on similar analysis. There is anyway no robustness check to be done on this latter parameter, as for the just exposed meaning of it. However different results for multiple values of H are showed in *Appendix B.2*, together with a robustness check for the w width.
To summarize the choices made in term of model class, structure and parameters for the final best fitting, where a VAR(1) approximating model, with a rolling window w =100 for the dynamic estimation and a horizon for the FEVD H =2.

4.2 Estimation

A mixture of standard and non-standard estimation techniques has been used for the parameters computation of the current analysis. Specifications on the use in relation to each model and sample are let for the next paragraph.
Best Linear Unbiased Estimators (BLUE) have been obtained via Ordinary Least Square estimation (OLS), applied equation-by-equation. The OLS estimator is defined as follows:

$$\hat{\beta} = \arg\min_{\beta} \sum_{t=1}^{T} \left(y_t - \sum_{i} \beta_i \, x_{it} \right)^2 \tag{4.4}$$

For sake of notation transparency, the function to be minimized, so the residual sum of squares (RSS), will be from now on substituted with the "RSS" notation. So equivalently to *(4.4)* we have:

$$\hat{\beta} = \arg\min_{\beta} \; RSS \tag{4.5}$$

4.1.1 Elastic Net estimator

In the following applications, as said, connectedness assessment has been based on an estimated VAR(p) approximating model. For compelling applications, there is the need for the VAR(p) to be estimable in high dimensions, somehow recovering degrees of freedom. This can so be done by pure shrinkage (Ridge regression) or pure selection (as with traditional criteria like Akaike information criterion, or LASSO regression), but blending shrinkage and selection, using the so-called Elastic Net methodology, proved particularly appealing.

Recalling Ridge regression, the shrinkage procedure on parameters magnitude is achieved by the addition on the OLS equation, of a constraint on the square of the parameters vector. That is:

$$\hat{\beta} = \arg\min_{\beta} \; RSS + \lambda \textstyle\sum_i \beta_i^2 \tag{4.6}$$

Where $\boldsymbol{\lambda} > 0$ is a chosen parameter governing the shrinkage: greater the $\boldsymbol{\lambda}$, greater the penalty for having extra regressors in the model.

For later explanations purposes, the same equation can be expressed with a penalty function minimizing the square of the ℓ^2-*Norm* ($\|x\|_2$)[14] of the vector parameter $\boldsymbol{\beta}$:

$$\hat{\beta} = \arg\min_{\beta} \; RSS + \lambda \|\beta\|_2^2 \tag{4.7}$$

The Least Absolute Shrinkage and Selection Operator (LASSO) regression introduces a slight but important modification of the penalty function of the Ridge regressor. In fact, the penalty function of LASSO rather than being a quadratic

[14] $\|x\|_2 = \sqrt{\sum_{k=1}^{n} x_k^2}$

shows a kink at zero. This is achieved by the used of the ℓ^1-*Norm* ($\|x\|_1$)[15] in the penalty constraint:

$$\hat{\beta} = \arg\min_{\beta} RSS + \lambda\|\beta\|_1 \tag{4.8}$$

This modification implies that, unlike the Ridge setup, in LASSO some regression coefficients are set exactly at zero, and that, define the procedure of variable selection. This is a convenient feature, particularly when many potential regressors are considered, and that is the case of the data chosen as objects of interest for the presented analysis.

The difference between Ridge and LASSO regressions can be easily noted by looking at *Figure 12*[16], representing a simplified bi-dimensional space, with the $\boldsymbol{\beta}$ vector composed by just two parameters ($\boldsymbol{\beta_1}$ *and* $\boldsymbol{\beta_2}$). The colored area represents the *Norm* of the vector, and the red ellipses are the contours of the least square error function. It is clear how the error function is going to be minimized on a corner rather than on an edge of the coloured area related to the ℓ^1-*Norm*, while

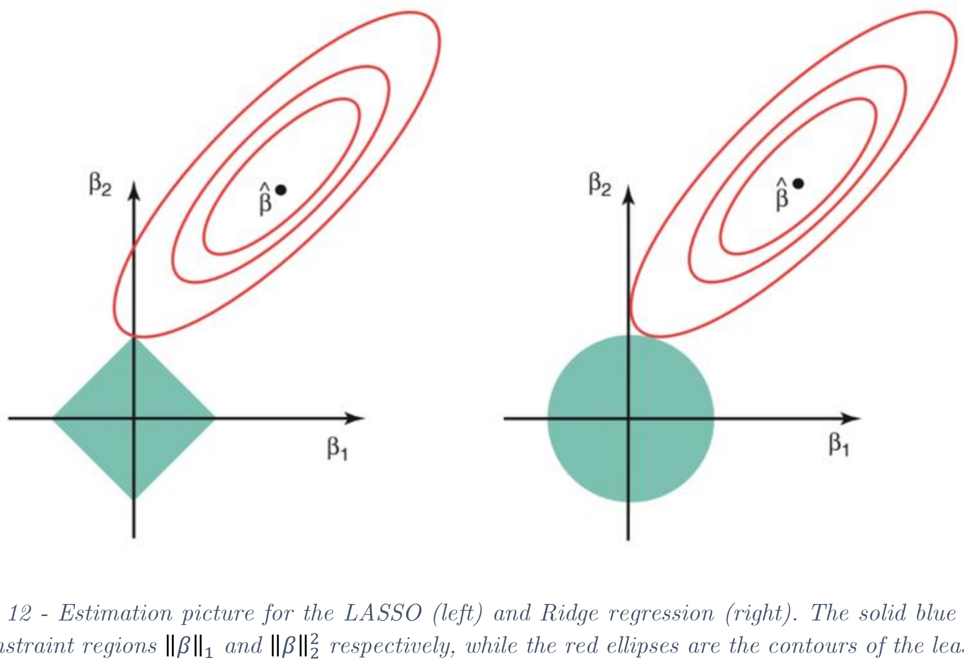

Figure 12 - Estimation picture for the LASSO (left) and Ridge regression (right). The solid blue areas are the constraint regions $\|\beta\|_1$ and $\|\beta\|_2^2$ respectively, while the red ellipses are the contours of the least squares error function.

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[15] $\|x\|_1 = \sum_{k=1}^{n} |x_k|$

[16] Source: Friedman J., Hastie T. & Tibshirani R. (2008); *The Elements of Statistical Learning.*

the circular area associated with the ℓ^2-*Norm*, would meet the error function just in relation to its relative position. As can be seen in the *Figure*, the corners of the coloured area on the left, correspond to intersections between the shade and the axes, and there, one of the two parameters takes the value *zero*.

The actual non-standard estimation technique used for current analysis is a refinement of both Ridge and LASSO regressions: the Elastic Net (NET) estimator. This latter substantially adds both types of constraints into the OLS equation:

$$\hat{\beta} = \arg\min_{\beta} RSS + \lambda_1 \|\beta\|_1 + \lambda_2 \|\beta\|_2^2 \tag{4.9}$$

Since in this latter expression $\boldsymbol{\lambda_1}$ and $\boldsymbol{\lambda_2}$ reflects not only the size of the penalty of extra regressors in the model but also the different kind of the penalty given (shrinkage and selection), a different representation of the equation could help parameters selection:

$$\hat{\beta} = \arg\min_{\beta} RSS + \lambda(\alpha \|\beta\|_1 + (1-\alpha) \|\beta\|_2^2) \tag{4.10}$$

Here $0 \leq \boldsymbol{\alpha} \leq 1$ is an additional penalty parameter to control the trade-off between the Ridge and LASSO penalty in the Elastic Net setting, while $\boldsymbol{\lambda}$ remains the only chosen parameter, governing the overall penalty weight.

4.1.2 Cross-validation

While the $\boldsymbol{\alpha}$ values for the following analysis have been chosen after iterations of model estimations, according to the best fit for the data, the $\boldsymbol{\lambda}$ level has been selected with the use of *machine learning* techniques. Specifically, *cross-validation* methods have been applied for the selection of the best value of $\boldsymbol{\lambda}$, for each model.

Cross-validation, or out-of-sample testing, is any of various similar model validation techniques for assessing how the results of a statistical analysis will generalize to an independent data set. One round of cross-validation involves partitioning a sample of data into complementary subsets, performing the analysis on one subset (called the training set), and validating the analysis on the other subset (called the validation set or testing set). To reduce variability, in most methods multiple rounds of cross-validation are performed using different partitions, and the validation results are averaged over the rounds to give an estimate of the model's predictive performance.

In summary, cross-validation combines averages measures of fitness in prediction to derive a more accurate estimate of model prediction performance.

For the following analysis, in order to account for time-dependence, cross-validation has been conducted in a rolling manner. Defining time indices as:

$$T_1 = \left\lfloor \frac{T}{3} \right\rfloor \text{ and } T_2 = \left\lfloor \frac{2T}{3} \right\rfloor$$

The training period $T_1 + 1$ through T_2 has been used to select $\boldsymbol{\lambda}$, $T_2 + 1$ through T has been used for the evaluation of forecast accuracy in a rolling manner. The process can be better visualized in the following *Figure 13*[17].

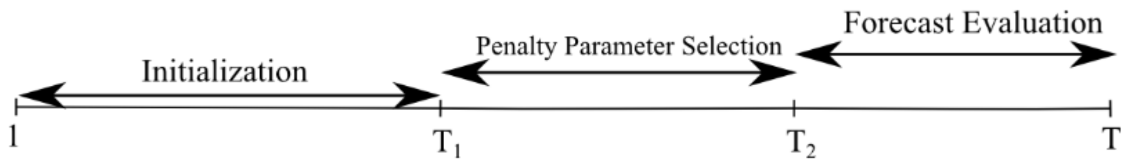


Figure 13 – Cross-validation data set slicing structure.

The optimal $\boldsymbol{\lambda}$ has been chosen minimizing one-step ahead *mean squared forecast error* (MSFE) over the training period.

[17] Bien J., Nicholson W.B. & Matteson D.S. (2017); "VARX-L: Structured Regularization for Large Vector Autoregressions with Exogenous Variables"; International Journal of Forecasting.

4.3 Details on the applications

As mentioned before the description of the connectedness frameworks has been carried on in a general way and in a historical one (time-varying parameters). Practically the measures computed for the analysis have been constructed on *static* basis (i.e. all data have been used for estimation), and in a *dynamic* way (utilization of the estimation window w).

Furthermore, a mixture of the two approaches has been applied nearby the latest economic crises, in order to capture the most important movements at a pairwise level due to market shortfalls. Substantially for some frames in time, pre and during the actual crisis, a net pairwise connectedness table has been computed and compared, with singular link granularity, to the distributions of the same parameters computed on the latest 50 and 15 weeks. Each link has been then selected only if greater than the latest percentiles of the over mentioned distributions. Those links have been so categorized into three classes:

i. greater than the 90^{th} percentile;
ii. greater than the 95^{th} percentile;
iii. greater than the 99^{th} percentile.

Each link class has been assigned with a weight and then the frames of connectedness frameworks have been shown in plots, as pre and during crises, in order to catch the dynamics of net pairwise connectedness.

The choice of the estimations techniques has been driven by the quality of the results, and the coherency of the data. Elastic Net regression methods have been applied for the parameters estimations of the *static* models, while a standard OLS approach has been chosen for the *dynamic* estimations of the models.

More technical details on the *R* programming techniques, applied in order to make the computations, and on the methods and library used for the graphic productions, are reported in the *Appendix C.*

Chapter V. Estimation results

5.1 Static modelling

This section presents the results obtained with a static estimation approach. The graphical and matrix representation of the FEVD-based connectedness measures are preceded by the sparsity plot of the estimated parameters for each model. This latter is a graphical matrix representation of the coefficients selection procedure made by the use of the Elastic Net techniques. The grid represents the coefficients matrix of the VAR(1). A blank (white) square indicates the absence of the corresponding coefficient, while a coloured square indicates its presence and the magnitude according to the colour scale (i.e. darker the square, greater in magnitude is the parameter).

5.1.1 Corporate bonds

Figure 14 shows that the estimation techniques reached a good degree of parsimony in the parameters' selection and estimation procedure, maintaining a final model able to explicate a quite interesting network structure (as follows). A sort of magnitude cluster determines anyway the principal importance of some variables for themselves, on an auto-regression level.

In *Table 4* it can be seen the *Connectedness Table* obtained for the corporate bonds sample by the use of the entire available dataset (in terms of times series length). The actual situation shows that the diagonal elements (representing the own connectedness) tend to be the largest individual elements on the table. However, at a pairwise level, there is still high connectedness.

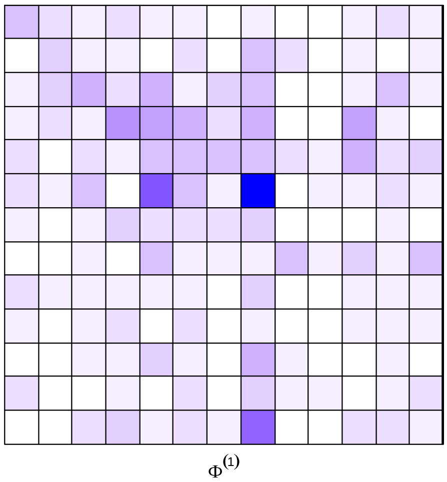


Figure 14 – Sparisity pattern of the Elastic Net VAR estimation, alpha=0.1, Corporate sample.

UniCredit Bank (UCG) results as the major influencer among the others. It is in fact the corporation having the highest score on the total *to* others connectedness section (red), that corresponds to the sum of the all off-diagonal elements in the UCG column. This influence is concentrated on some specific actors: ABN Amro bank (ABNAMRO), Intesa Sanpaolo (ISP), Nordea Bank (NDASS) and Santander (SANTAN). The above mentioned relations are actually the strongest connections at a pairwise level. Pairwise links are identifiable in the upper-left 13x13 submatrix. Regarding UniCredit Bank's influence towards Intesa Sanpaolo, the country effect seems to be the most reasonable source, but also the fact that these two banks have lately been the biggest rivals in the nearby markets. The connectedness *to* others, confirms the role of UCG as a major European player, influencing even the largest financial institution on the Euro-area market (i.e. Santander). Even the influences towards the other northern Europe based corporations can be explained knowing the spread presence of UniCredit Bank's operations and branches on the German soil, identifying it as a competitor of north Europe based financial firms as well.

The second main influencer on the table is Banco Comercial Portugues (BCP), which concentrates its connectedness towards major financial institutions as Intesa Sanpaolo, Santander and Deutsche Bank, despite its size compared to these other companies. An explanation of this result can be given by the cross-Europe framework character of the bank (high dimension and spread on the Poland and Greek market, beyond Portugal and Spain). This, summed to the activity growth after the creation of Millennium group, may have led to a linkages' proliferation with major players, despite the small dimension of BCP. A further source of connectedness could probably be the history of high instability of its own host country (Portugal), pointing out Banco Comercial Portugues as a possible weak ring of the European financial framework (worst credit rating of the sample), giving signals for general financial shortfalls. Another possible explanation is a spread of its own securities among the above mentioned major players investments funds (probably for the related high promised yields).

On the same side of the table, can be seen that Deutsche Bank (DB) is the third major connectedness transmitter, not surprisingly given its dimension and the global scale of its operations. A possible source of connectedness transmission could be also related to the diffusion of scandals linked to derivatives speculation activities in the latest years. Such a generalized bucket of connectedness sources is actually translated in a quite homogeneous spread of links *to* other corporations

	ABNAMRO	BBVA	BCP	CMZB	DANBNK	DB	ERSTBK	ISP	NDASS	RABOBK	SANTAN	SOCGEN	UCG	From
ABNAMRO	34.6	0.2	8.6	4.5	0.1	6.5	1.5	5.4	4.5	3.1	4.0	5.1	21.9	65.4
BBVA	0.1	41.1	9.7	2.0	7.7	9.0	7.0	3.0	3.5	5.2	4.9	5.7	1.1	58.9
BCP	2.9	3.3	47.5	5.2	0.4	11.2	1.4	6.9	2.6	1.6	5.7	3.7	7.7	52.5
CMZB	2.6	1.0	8.1	49.2	0.8	3.8	4.5	6.2	2.8	2.6	5.0	3.4	9.9	50.8
DANBNK	0.4	7.2	1.3	1.6	60.3	6.6	1.8	2.6	2.7	5.5	1.8	2.8	5.5	39.7
DB	2.2	2.9	11.7	2.6	2.2	54.5	0.6	6.2	3.7	2.9	3.5	3.7	3.3	45.5
ERSTBK	2.2	9.6	5.4	11.7	2.4	3.4	45.3	1.9	2.0	3.9	3.0	6.3	3.0	54.7
ISP	2.4	0.9	8.9	4.5	0.0	6.2	0.4	44.7	2.1	0.6	7.1	3.6	18.6	55.3
NDASS	4.5	3.3	7.5	5.2	2.4	10.3	1.4	5.2	24.6	11.2	5.2	6.3	12.8	75.4
RABOBK	3.9	6.1	5.8	5.9	7.0	11.0	3.3	2.1	14.3	22.0	5.2	10.3	3.1	78.0
SANTAN	2.6	2.9	10.9	5.5	0.2	6.4	1.3	10.8	3.3	2.7	31.5	5.6	16.2	68.5
SOCGEN	4.1	4.3	8.1	4.9	2.1	8.0	3.5	6.8	5.1	6.6	6.9	31.5	8.0	68.5
UCG	5.7	0.2	6.0	4.4	0.5	2.3	0.5	11.0	3.2	0.6	6.3	2.3	56.9	43.1
To	33.4	41.9	92.2	58.1	25.8	84.8	27.3	68.1	49.8	46.5	58.4	58.9	111.1	58.2
Net	-32.0	-17.0	39.6	7.3	-13.9	39.3	-27.4	12.8	-25.6	-31.6	-10.0	-9.6	68.1	

Table 4 - Connectedness table, Corporate bonds sample.

(at a magnitude level), in contrast to the more specific influence direction of UniCredit Bank (less spread and more concentrated on single network nodes).

Generally, the total *to* connectedness part of the table seems to be the more spread compared to the total *from* part, anyway considerations on its magnitudes must recall that the columns sum is not constrained to the addition to 100%.

Looking at the receiving part of the table is worth mentioning that the average impact of external companies shocks on idiosyncratic forecast error variance contributes is on mean far more than 50%. A firm-by-firm valuation on the connectedness received *from* others can be done in a total directional perspective, looking at the blue part of the table, containing the sum of all the off-diagonal elements of each row.

The bottom of the sample is touched by the Danish Danske Bank (DANBNK), with less than 40% of connectedness received *from* others. This dependency is quite homogeneously spread from the network actors, as well as its moderate *to* directional influence. Given the situation, Danske Bank can be identified as the most independent corporation in the analyzed network. This is not surprising, considering that it is the largest financial firm of a north European country, with a solid financial history and almost 55% of its total revenues coming from Denmark, and the remaining mostly from the rich and stable Sweden and Norway countries. Also, the composition of its operations is as much as 65% sourced by standard financial services like cash management, personal, business, corporate, and institutional banking services[18]. All these features identify Danske Bank as a solid and safe institution, partially explaining its relative independence.

Two actors rise among all, on the receiving side of the table, although their *from* connectedness is widespread: Nordea Bank (NDASS) and RaboBank (RABOBK). These two actors are the most influenced by the others of the network, with a forecast error variance explained for more than 75% by other corporations' shocks. The network links degree portions of these two banks are quite interesting to be

[18] Source Bloomberg data provider on security description

considered together. In fact, the *to* others connectedness sides are quite similar in spread among actors, and total value. Also, the biggest pairwise directional part (i.e. the *from* others connectedness side) is quite similar, having as main source of connectedness, the already mentioned major influencers (Deutsche Bank and UniCredit Bank), together with each other. Being one for the other between the main sources of received connectedness sets these two corporations as twins in the networks, more than a sub-network. This because at a pairwise level, the final *net* connectedness set off itself. A first step in the results explanation process is obviously the mention of structural and geographical similarity of these two firms. Both are among the biggest in the sample (in market capitalization terms), with a very similar level of operations and revenues, and are established in rich northern European countries. A more specific argument for the explication of this situation can be found in the recent common financial history of these banks. Nordea Bank has seen a progressive decline in its net revenues and total loans since the middle of 2016, triggering a downsizing process. It is now well-capitalized (CET1 ratio of 17.1%) and on a path of recovery, and it suffered Covid-19 crisis less than other European actors, but in a crucial moment of its recovery process[19]. Rabobank reacted as well better than other European actors to the Covid-19 crisis, also if its fundamentals may have been weakened by the crisis, due to its low diversification rate. The CET1 ratio of 16.6% is close to the Nordea Bank one and also this Oland institution comes from a 4-year decreasing path in net profits[20].

The green row in *Table 4* shows the total *net* directional connectedness, obtained by the difference between the total directional connectedness *from* and *to* others. A first look at that row confirms the role of leading influencers for Deutsche Bank, UniCredit Bank and Banco Comercial Portugues, while the most influenced firms

[19] Phillip Richards, Mar'Yana Vartsaba (04/02/2021); Bloomberg Intelligence Data-driven research.

[20] Jeroen Julius (16/10/2020); Bloomberg Intelligence Data-driven research.

at a total *net* level, are again Nordea Bank, RaboBank, but even the Austrian Erste Bank (ERSTBK).

Moving now to a pairwise level of the just mentioned *net* measures, it can be said that the *net* pairwise interconnections show a firm-by-firm idiosyncratic situation. *Figure 15* represents the structure of these relations, for a better understanding of the network framework on a static estimation level. The direction of the arrows shows the *net* directional connectedness firm-by-firm; also the size of each arrow is directly proportional to the connectedness magnitude. Finally, the dimension of each node reflects the dimension of each corporation in terms of its market capitalization.

The role of major influencers is confirmed again, and also on a *net* pairwise level, for UniCredit Bank, Banco Comercial Portugues, and Deutsche Bank.

Among the main *net* receivers there are still Nordea Bank and RaboBank, together with Erste Bank and ABN Amro (ABNAMRO). The fact that all these *net* receivers are frugal[21] countries-based firms, state that solid and rich economy-

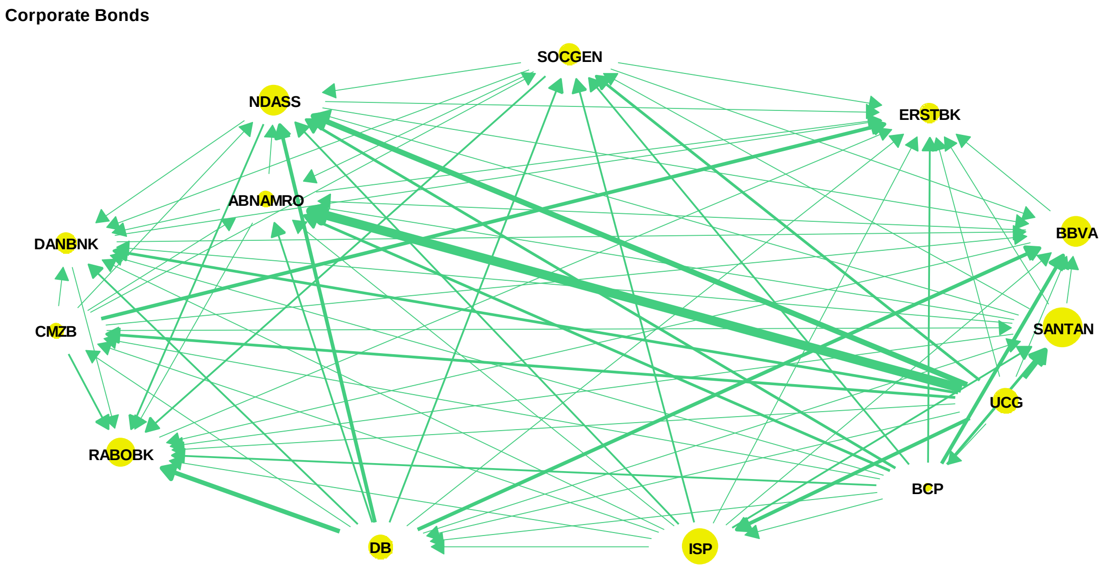


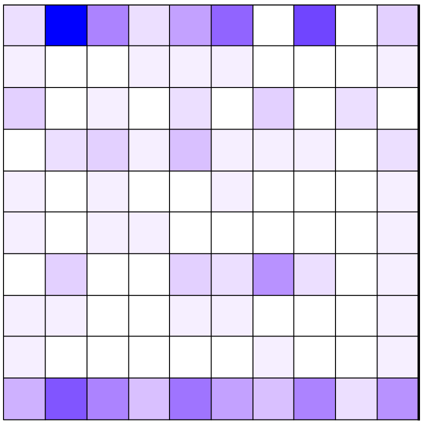
Figure 15 - Corporate bond Network NET pairwise connectedness.

[21] The Frugal Four is the nickname of an informal cooperation among like-minded fiscally conservative European countries, including Austria, Denmark, the Netherlands and Sweden. It partly evolved as a successor of the New Hanseatic League that was set up to make up for the loss of the like-minded United Kingdom in the European political arena after Brexit.

based corporations may do not impact competitors results in nearby countries, but they certainly suffer the influence of southern European-based financial firms. A last due comment on the connectedness table presented in *Table 4*, is related to the bottom-right pivot, coloured in orange: the *total connectedness* of the network. This shows a level of 58%, a large magnitude indeed, but not actually very high in a historical perspective. Further comments on the actual total connectedness level will be more appropriate after looking at the later presented historical path of that measure (i.e. dynamic modelling). However, as it will be shown, a total connectedness value of 58% is not coherent with a pre/during crisis level, i.e. it is – historically - usually higher, and the dynamic estimation carried on with a rolling window, shows an up to date level greater than 85%. This comparison indicates that, on an unconditional level of parameters estimation (*as-of* the end of September 2020), interdependencies between financial firms that arose during the last crisis, have been for the most absorbed.
This latter statement obviously does not take into consideration the very big movements and volatility on the markets, observed after the declaration of the discovery of a Covid-19 disease vaccine, by the Pfizer corporation, in December 2020 (data not included in our sample).

5.1.2 Two-year government bonds

In *Figure 16* the sparsity plot of the variable' s selection procedure for the approximating model fitting the 2-year government bond is presented. It can be seen that the parameters selection gave back a quite sparse model, with the most detained coefficients in the first and last rows of the parameters matrix VAR(1).



$\Phi^{(1)}$

Figure 16 - Sparisity pattern of the Elastic Net VAR estimation, alpha=0.1, 2Y Government sample.

Table 5 below reports the connectedness table obtained with the use of the entire available dataset for the estimation process.

As for the corporate sample the diagonal elements tend to be the larger on the table, with Portugal and Ireland as countries with the greater portion of forecast error variance explained just by their own dynamics (i.e. about 70% for both). Except for these two outliers, the 2-year government sample is less self-explained on a variable-by-variable level, than the corporate one: the average value of diagonal elements is 35.59%, against the 41.81% of the first sample. On the *from*

	PORTUGAL	NETHERLANDS	BELGIUM	ITALY	FRANCE	GERMANY	SPAIN	FINLAND	AUSTRIA	IRELAND	From
PORTUGAL	71.16	0.13	0.49	3.55	0.11	0.18	2.27	0.15	0.08	21.87	28.84
NETHERLANDS	0.04	20.75	10.54	2.11	16.76	16.72	3.25	14.53	14.77	0.52	79.25
BELGIUM	6.32	5.77	26.26	12.90	9.12	4.15	12.82	4.94	9.76	7.97	73.74
ITALY	13.77	0.78	7.75	37.31	1.72	0.28	18.29	0.58	2.02	17.50	62.69
FRANCE	0.29	13.88	13.79	4.10	21.85	12.86	6.02	11.89	15.04	0.28	78.15
GERMANY	0.61	17.84	8.06	0.63	16.57	22.38	1.72	16.55	14.19	1.44	77.62
SPAIN	9.68	1.11	8.02	19.65	2.45	0.56	40.17	0.97	2.75	14.64	59.83
FINLAND	0.28	15.44	9.57	1.62	15.27	16.49	3.05	24.00	13.54	0.75	76.00
AUSTRIA	0.09	12.23	14.77	4.95	15.05	11.02	6.75	10.55	23.78	0.81	76.22
IRELAND	22.03	0.11	1.16	4.52	0.10	0.15	3.43	0.11	0.13	68.27	31.73
To	53.12	67.29	74.17	54.03	77.13	62.40	57.59	60.28	72.26	65.79	64.41
Net	24.28	-11.96	0.43	-8.66	-1.02	-15.22	-2.24	-15.72	-3.96	34.06	

Table 5 - Connectedness table, 2Y Government bonds sample.

others directional connectedness side of the table, the magnitude of pairwise measures confirms a network structure's feature noted before (corporate sample): the fact that northern Europe countries, or the ones with strong structured economies, tend to be more influenced in the network than the other governments. The mentioned ensemble includes here also France that, even if is not a country with a strictly north Europe economy formulation, is a major European player (second for GDP in the actual Euro area), with a solid credit rating.

The structure of rich countries' received connectedness, is not, as for the corporate sample, widely spread among the network's actors, or mainly sourced by the south European countries, but is actually strongly "feed" by northern Europe countries themselves. It seems so, that on a short-term government level, frugal and leading economies tend to be the major influencers between themselves, and this phenomenon brings the dependencies to be settled off, being so for the most compensated in a *net* perspective. Anyway, the diagonal elements of their own connectedness are still low, so these economies are actually guided all together within the network movements, but the influences tend to do not be directed in a particular way. Between this set of countries, the only one partially excluded by the dynamic just presented is Belgium. In fact, this country is influenced mostly by Italy and Spain having the sum of directional connectedness *from* these countries almost as big as the portion of own connectedness. Belgium is the only north European country, together with Ireland, leaving a significant amount of directional connectedness *to* the states of the group described above, not settled off in a *net* perspective. While Belgium has the most spread significative pairwise connections, Portugal and Ireland detain the biggest links in magnitude in the upper left *10* x *10* submatrix, two of which between each other.

On a pairwise level, Italy and Spain are the actors with the least spread connectedness *from* others. Specifically, Italy has been influenced mostly by Portugal, Spain and Ireland. Italy undergoes so by the influence of countries with the smallest and troubled economies among the actors chosen for the government sample. For Spain, the situation is the same, with Italy as its own counterparty in a symmetrical way. The prospect obtained from the analysis is so that the smallest and more troubled economies in the network behave as triggers for the two more similar economies in terms of structure, dimension and financial health, among the southern Europe countries. Substantially the connectedness chain starts from the riskier governments, as an alert for the immediately less risky but unstable ones.

On the *to* others connectedness side of the table total directional measures are quite homogeneously spread among the networks' nodes. An exception is constituted by Belgium, France and Austria: the leading influencers with a little more connectedness directed *to* the others, than the average one in the network. As said before, the interdependencies among these actors are mostly concentrated within north Europe economies. A major link worth to be mentioned among the ones sourced by these three main influencers, is the one from France to Germany, with a magnitude as big as 16.57%.

On the total *net* connectedness side of *Table 5* it can be seen how the role of *net* influencers is confirmed for Ireland and Portugal, while all the other countries remain net receivers. Particularly sensitive to the Belgian influence, are the frugal economies. In the end, Belgium and France, remain almost neutral, having all their pairwise relations settled off on a system-wide level.

Figure 17 shows the network structure of effective relations once accounted for *from* and *to* other influences, on a node-by-node approach: *net* pairwise interconnections. Glossing over the meaning of arrows size and direction already explained, the main difference from the previous graph worth of a description is that here nodes dimensions have been settled in proportion to the GDP of each country (instead of market capitalization, for obvious reasons).

Looking at the *Graph* is straight forward to notice that the number of connections left on a pairwise level is still big as for the corporate bonds sample, however, the

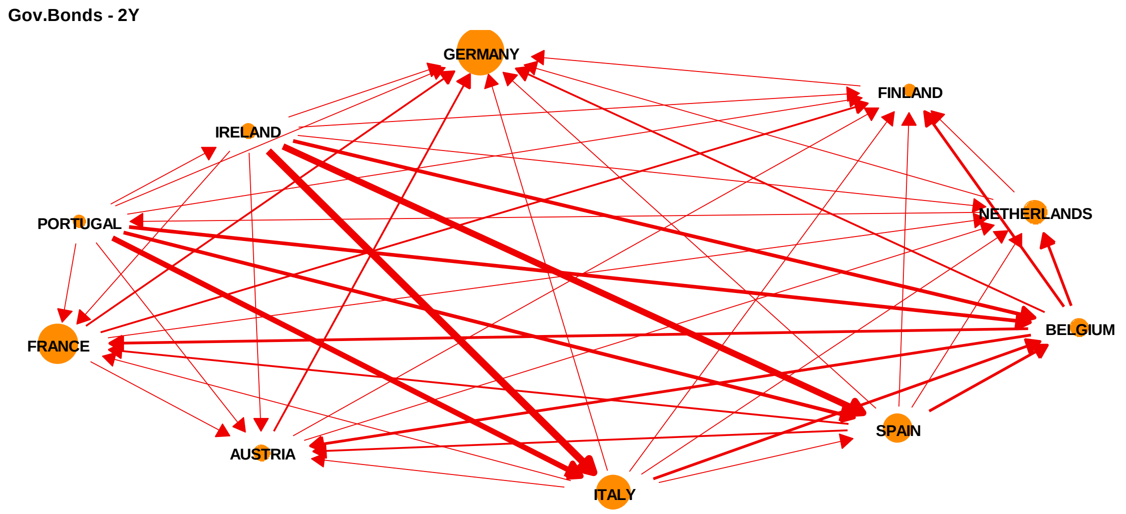


Figure 17 – 2Y Government bond Network NET pairwise connectedness.

current dataset shows a neater difference between the magnitude of connections. Pairwise influences are quite less spread, with a marked difference between a couple of strong ones, and the rest of the network's edges. Substantially magnitude and directionality seem to be related to rating[22] and economy dimension.

All countries with a high credit score (more or equal AA-) compared to the others, are *net* connectedness receivers, regardless of the economy size (i.e. GDP amount). For what concerns countries with the worst rating among the others in the network, GDP size and credit score drive in synergy direction, and size of the pairwise *net* connections. In fact, between the four worst performers on a rating level, the two of them with a smaller economy (Portugal and Ireland) are *net* influencers for almost everyone, also detaining the biggest connections on the *Graph* (in magnitude terms). The other two badly ranked countries (Italy and Spain), with a low credit score but large economies, are *net* general influencers as well, but also co-protagonist of the biggest pairwise connections in the graph: the ones from Portugal and Ireland. The above presented relations comprehend also Belgium, with values really close to the sample *median* of both GDP and rating. This country is then configured as a *net* receiver, with mediumly strong pairwise

[22] Country Ratings sourced from Fitch Ratings Incorporated

connections *from* others, and a couple of connections *to* others left after netting computations.

So far, geographical components seem to do not be the major drivers for network interrelations, leaving the membership of the north Europe zone a marginal factor compared to rating and GDP (see Ireland associated with south economies and France to frugal ones).

The last consideration has to be made on the total system-wide connectedness (bottom right orange element in *Table 5*), measuring 64.41%. This value tends to be in line with the average total connectedness through time, estimated with the rolling window approach. The magnitude is quite large compared to the one estimated for the corporate sample, identifying the short-term government network as more interconnected.

5.1.3 Ten-year government bonds

Figure 18 below shows as before the sparsity plot of the variables selection procedure for the approximating model, fitting the 10-year government bond yields. Among all the equations in the VAR(1) model, the first, third, seventh

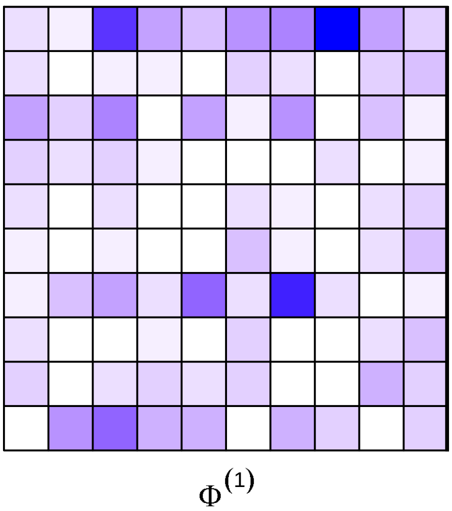


Figure 18 - Sparisity pattern of the Elastic Net VAR estimation, alpha=0.1, 10Y Government sample.

and tenth are the ones with more selected parameters. Those not only have the highest number of coefficients, but also the ones with the biggest magnitude. Anyway, presence and value of parameters are quite homogenously spread (more than in the model estimated on the 2-year sample).

In *Table 6* I reported the connectedness of the measures obtained using the entire available dataset of 10-year treasury rates.

	PORTUGAL	NETHERLANDS	BELGIUM	ITALY	FRANCE	GERMANY	SPAIN	FINLAND	AUSTRIA	IRELAND	From
PORTUGAL	71.48	0.28	1.87	5.46	0.82	0.20	5.74	0.35	0.67	13.13	28.52
NETHERLANDS	0.38	17.79	11.54	3.16	14.46	15.55	3.37	16.09	14.63	3.03	82.21
BELGIUM	4.47	8.79	20.41	8.73	11.45	7.17	8.78	9.28	12.25	8.66	79.59
ITALY	10.55	2.53	9.19	33.94	5.34	1.14	19.59	2.37	4.28	11.06	66.06
FRANCE	1.61	13.18	13.72	6.08	16.65	11.85	5.59	12.88	14.21	4.22	83.35
GERMANY	0.13	17.15	10.40	1.59	14.33	20.17	2.08	17.57	14.52	2.07	79.83
SPAIN	10.46	2.53	8.81	18.81	4.61	1.40	35.63	2.45	4.58	10.72	64.37
FINLAND	0.46	15.93	12.08	2.93	13.99	15.78	3.23	17.95	14.43	3.22	82.05
AUSTRIA	1.29	13.18	14.47	4.80	14.03	11.88	5.46	13.13	17.45	4.30	82.55
IRELAND	17.28	1.68	6.28	7.72	2.61	0.94	7.77	1.80	2.69	51.24	48.76
To	46.63	75.25	88.37	59.27	81.64	65.91	61.60	75.92	82.26	60.43	69.73
Net	18.11	-6.96	8.78	-6.78	-1.70	-13.92	-2.77	-6.13	-0.29	11.67	

Table 6 - Connectedness table, 10Y Government bonds sample.

On this last sample, considerations about the diagonal differ from the previous system: its elements are no longer the biggest on the table, or at least that is not true for every element of this matrix. Although for every row the biggest element still being on the diagonal pivot, fractions of own connectedness are as little as about 17% somewhere. The values on the diagonal are quite spread in magnitude, ranging from 17% to 72%, but the average element is quite small in level (i.e. 27.94% against the 35% and 41% of the previous samples). Given this outcome, the long-term sample can be defined as the more interrelated out of the three analyzed.

Looking at *Table 6* from a perspective of connectedness received *from* others helps to notice that network' s conformation here is very similar to the one of the short-term system. In fact, the major connections are between northern European countries and major economies such as France and Germany. Quite strong links are notable also for Italy and Spain, in both directions. This latter conformation of connections, as explained before, tend to balance each link from *net* perspective, canceling directional relations between economies of northern Europe (but leaving a gathering of sensibility on system's changes for these ensembles). Belgium here confirms its role of cross-geographical influencer, having a widely spread bucket of significant connections *to* others. It is receiving quite an amount of connectedness as well, but primarily from rich and solid countries.

An analysis of the directional connectedness *to* others brings at the same conclusions, as for the *from* perspective: close similarity with the short-term bonds network. So again, there is a gathering of connections between north Europe-based economies, furthermore, Portugal and Ireland are the effective leaders in pairwise connectedness, with a concrete *net* effect. These latter two countries differ a little from the previous sample, in forecast error variance explained. The spread of connectedness *to* others is wider for both countries. On a links' magnitude level Portugal is less influencing, remaining with almost the same diagonal element, while Ireland has less own connectedness and larger directional links.

A node worth mentioning, in terms of total *to* pairwise connectedness, is Finland, which, compared to the short-term network, has a role of influencer more important. This, for the most, thanks to the growth in the relevance of connectedness transmitted to Belgium.

Substantially the major differences between the connectedness table of long-term and short-term bond yields, are at a total *net* connectedness level. Although none of the actors in the system shows differences in the signs of the total *net* connectedness, the magnitude of these relations differs quite a lot for almost half of the network nodes. Finland is a *net* receiver on the long-term sample as in the previous network, but the value of its total *net* connections differs by almost 65% compared to its short-term value. The main differences for Finland are in the already mentioned influence towards Belgium, and in a positive delta in the portion of own variance explained by itself. Ireland as well, in the long-term network seems to have a different role: its total *net* connectedness is almost 70% smaller than in the short-term sample. This is due mostly to the big negative difference in the influence versus Portugal, Italy and Spain (its major-related nodes on the short-term network), and by an increase in its own connectedness. Major differences between the two samples can be found again for Belgium together with Austria. The former in the short term is a *total net* neutral node, the latter instead is neutral in the long-term network. For both countries, major deltas can be found in their own connectedness (decreased of about 25% in the long-term sample compared to the short term one), and, for Belgium, in a substantial increase in the connectedness transmitted to Ireland. However, the role of Austria is still marginal in both samples.

Moving again to a more granular analysis on a pairwise *net* directional connectedness level, *Figure 19* below, shows the relations between countries with

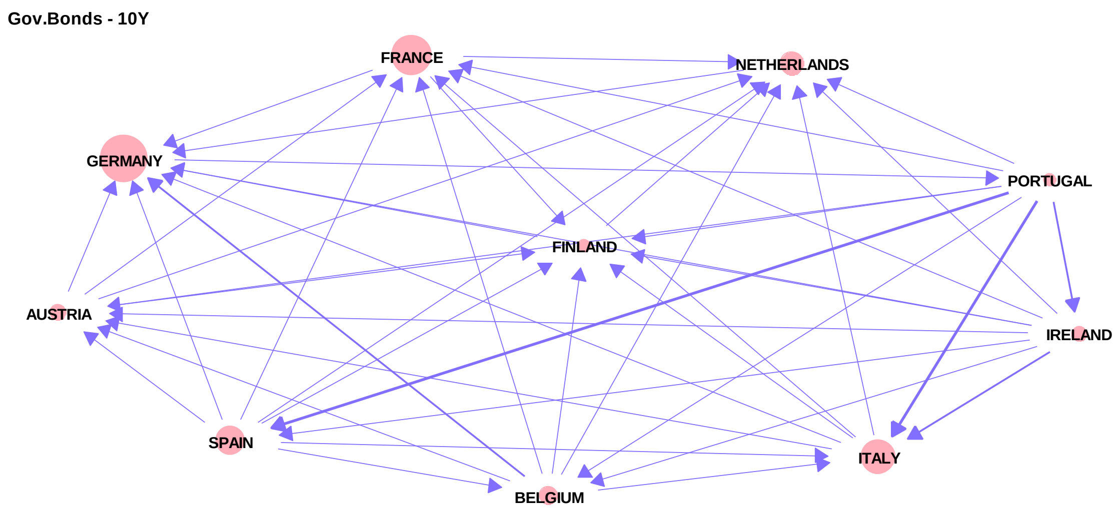


Figure 19 - 10Y Government bond Network NET pairwise connectedness.

the same graphic representative logic of before. *Net* pairwise relations are quite lighter than in the short-term network. The relation noted between credit rating and economy dimension, with direction and magnitude of *net* pairwise linkages seems to be valid on the current network as well. This association seems to be more elastic in the 10-year yields system. In fact, Portugal, the smallest economy and almost the worst ranked country, remains an influencer (the only one in a neat way), while Ireland, which is a little bigger in GDP terms and better ranked, is still as well a general influencer but without important *net* pairwise connections. On the same side, Italy, bigger than Spain in GDP terms, is here as well quite strongly influenced by Portugal and now also by Spain (on the short-term sample was the opposite), standing as a general receiver and sender of connectedness at the same time (with obviously pairwise differences). Spain, that in the short-term network was in the situation of Italy, here is quite strongly influenced by Portugal (and slightly by Ireland) but remains a general *net* influencer among the network actors.

On a non-granular level, a comment on the total connectedness of the system is due. This latter dataset shows the greatest level of total connectedness out of the three samples: it is almost 70%. In a comparative perspective this connectedness measure is in line with the results obtained via dynamic estimation, but in magnitude, is slightly less than the average value computed through time.

5.1.4 Comparative analysis

Given the large number of bonds and countries included in the samples, there is always a high degree of connectedness for the full networks. As will be shown below, there is always a high degree of connectedness (i.e. at least 50%), even during low volatility periods. For the corporate sample, as the institutions included in the current analysis are all operating in the finance industry, both industrywide and macroeconomic shocks, affect each one of their bonds. On the other side, for the government sample, mainly macroeconomic shocks, should lead network structural changes.

Since some of the considered firms and their bonds are more vulnerable to external and/or industry-wide shocks than others, they are likely to be transmitting these shocks to other financial firms, generating as shown a higher degree of connectedness at a pairwise net level. Other markets are not subject to common shocks as frequently as the finance industry ones, so idiosyncratic disturbances are more likely to be transmitted to other firms in those latter markets. For that reason, compared to a similar number of bonds from different industries, the connectedness of a group of bond yields in the finance industry is likely to be higher.

A noticeable general relation that arose after the analysis of all three samples, is that, so far, the greater is the total connectedness of the sample, the smaller is the magnitude of single net pairwise relations. This result could be caused by the fact that some external factors, generated from entities not included in the network, tend to heavily affect all the actors. In fact, despite, for example, the poor strength of pairwise net links in the last sample analyzed, gross single pairwise measures on the table are quite strong and directed, but simply reciprocally settled off in a net perspective. External macroeconomics shocks actually generate shortfall impacts on the European countries despite their specific economic health, a pretty obvious argument since they are in a monetary union, sharing policies and big portions of budget expenses. On the other side, for example, corporations are more affected by idiosyncratic dependencies, remaining heavily connected on a system-wide level, but with interdependencies structures defined more peculiarly, on a firm-by-firm level. This last concept can explain how the corporate sample, having the least total connectedness value, is the one with more marked net pairwise connections.

A relation common to all three samples is the fact that instability and or a weak structure, label an actor as a net influencer in the network. Recalling for example the role of Portugal and Ireland in the government sample, credit rating components, rather than the geographical ones, seem to play as major drivers for connectedness channels, letting the shocks in the more unstable and fragile countries (i.e. bad credit raking and small economies) to be heavily transmitted versus the immediately less fragile states in the networks (e.g. Spain and Italy).

For the corporate bonds network, this dynamic is a little different. At a net pairwise level, institutions with a bad credit score indeed have the role of influencers, but there is not the "middle step" in connectedness, which can be seen in the government samples. So, if in the last two samples, small and troubled economies directly and heavily influence the slightly healthier ones, and then both categories influence the rest of the network, in the corporate system major pairwise net connections are directly from the "worst" to the "best" node. An example of this dynamic is UniCredit Bank being an important net transmitter towards AbnAmro Bank, Nordea Bank, and Santander, as well as Deutsche Bank, influencing Rabobank, Danske Bank and Nordea Bank again.

In a market shortfall, small and troubled institutions are of course the first likely to finish in the need of a bailout, and the second repercussions are likely to be on the safer entities, not that much safer and/or profitable to stay out of the cyclone of the crisis.

Behind this behavior of network links, there are dynamics that reflect fear spread, and conjunctural patterns proper of crises. There is so some kind of progressivity in the spread of connectedness associated whit the government sample. A domino falls on each country at a European level is less likely to happen, or at least is going to happen more progressively than for the corporate financial industry. In fact, the "best" countries in the government sample (the more solid ones and with a good credit score) remain even heavily correlated, but with a weak pairwise *net* component. This reflects codependency of financial markets and European Union countries, and a framework outlining a "trigger mechanism" for the shortfall effects, like if connectedness has some stages: passing through directly connected firms (bad or medium ranked ones), arriving then even to the more isolated (well ranked). The obvious instability of corporations, compared to governs, makes this trigger mechanism work in a more "tragical" way for the first sample, letting bad ranked institutions, even if with a small/medium size, to directly influence the healthier corporations (e.g. Banco Comercial Portugues on Nordea Bank).

A last comparison between the two government bonds samples will now omit the single specific differences outlined in the previous paragraph. Generally, the long-term network is more interconnected than the short-term one, with significative negative deltas on the diagonal elements. As said before there are not noticeable swaps of roles between nodes of the two networks, that have so mainly the same structure.

In line with what noticed at the beginning of this paragraph, the greater total connectedness of the long-term sample is translated into poorer pairwise net relations. Due to the uncertainty about the future, the long-term bonds network is so more connected, and this concept could be interpreted in a similar way as for the reason why, in common times, treasury yield curves have a positive slope. Anyway, probably for the same reasons, idiosyncratic relations are less strong in the long-term, than in the short one, leaving the former being less useful as a risk management or regulatory policy tool.

5.2 Dynamic modelling

This section contains the results obtained using a dynamic estimation approach, based on a *rolling window*. The results will be presented on a total network level, together with a firm-by-firm (and country-by-country) representation of each measure. Details on models and estimation procedures not already mentioned in *Chapter 4*, are let for the quantitative and instrumental *Appendix* (*A* and *C*), while further graphical representations are reported in *Appendix B*.

5.2.1 Corporate bonds

Figure 20 below shows the dynamic estimation of the network's total connectedness through time, for the corporate bond sample. Given the use of a rolling window of 100 weekly observations, there is a cut in the data available, so the older historical measure of connectedness has been computed only as-of the beginning of 2008.

Given the partial lack of measures, the analysis of the subprime crisis must be limited in considerations. The first value of total connectedness computed refers to a date when some of the first milestones of the crisis have already occurred. First losses by US banks, related alarms (New Century bank reports), and the beginning of broad shortfalls across US markets have already been occurred, at the beginning of 2008. Anyway, a major event can be read: the Lehman Brothers crack. This event had an impact on European connectedness, not in a major way, but bringing the total connectedness of the system to rise by 7% in a couple of weeks between September and October 2008. Reading the 2007-2009 crisis from a more macro perspective, it is worth mentioning that the average level of

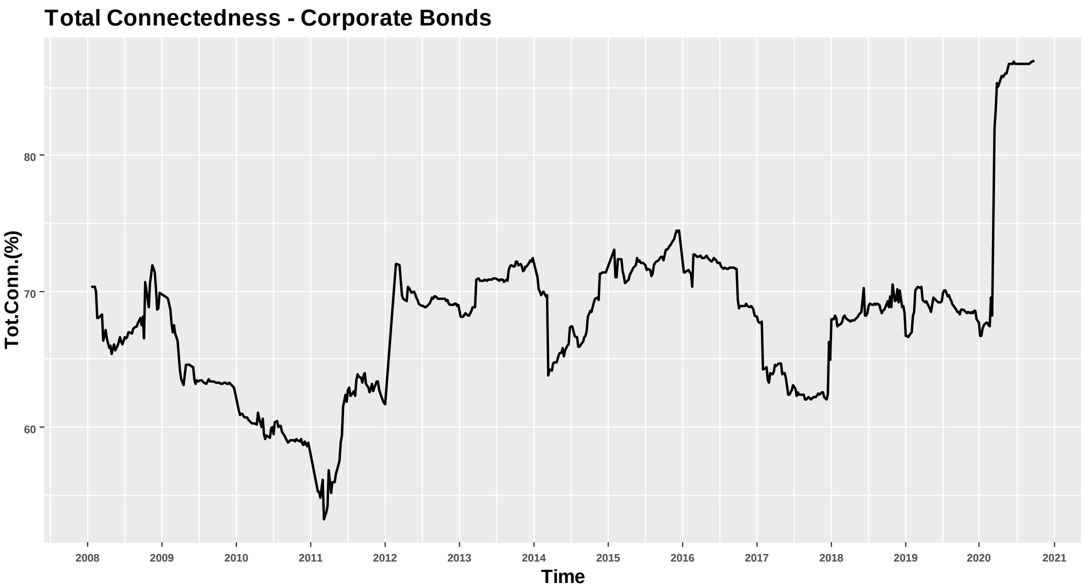


Figure 20 – Total Connectedness through time via dynamic estimation, w=100, h=2, Corporate Bonds sample.

connectedness in the corporate bonds network was quite high (i.e. 69%), but with a large variance as well (ranging from 65% to 73%). Indeed, the level of connectedness observed is on average not very distant from what has been computed for later times, and the lack of data for 2006 and 2007, leaves very little space for the interpretations on the connectedness variation related to the subprime crisis. The current analysis will so skip further considerations until the final and comparative section.

After the stocks market rebound of February 2009, occurred on European and global markets, the total connectedness has progressively declined without major stops until the beginning of 2011.

The European sovereign debt crisis, which began in 2010, and is actually not yet completely solved, brought the total connectedness of the corporate system to variate the most compared to all the periods analyzed, except only for the Coronavirus crisis. In October 2009 Greece's Prime Minister declared that the balance sheets sent by the previous Greek governments to the European Union had been falsified with the aim of guaranteeing Greece's entry into the Eurozone, the *deficit / GDP* ratio raised from 3.7% to 12.7% giving start to the events chain triggering the European sovereign debt crisis. Between this month and the first weeks of 2012, the total connectedness ranged from a minimum of 52% to a maximum of 73%. The path followed by the measure takes the shape of a *"J"*, with an initial fall of the total connectedness and then a rapid steep increase until the maximum point where it fluctuated for some years. Following the measure during the milestones of the crisis, can be noted how the declaration of the Greek government, did not cause a change in the trend of total connectedness, and neither a neat increase nor a decrease of its evolution rate. The total connectedness of the network has been still declining touching its all-time bottom, until the end of March 2011. Then the system interrelation measure started a steep path of growth after the events of April 2011. In this latter period Portugal joined Ireland in the request of financial aids from the European Union and the International Monetary Fund. Furthermore, in the meantime, Standard & Poor's changed its outlook about Italy from "stable" to "negative". Since then, the total connectedness of the corporate network has been increasing at a high rate for almost three months, going from 52% to 64%, and stabilizing then at the latter level until the end of the year. What seems to have been a second triggering event then is the "*rating cut season*" of October 2011. Credit score downgrades of even two notches, which have already happened for Ireland and Portugal, hit Spain and Italy as well. All major rating agencies took these decisions, beginning also to publicly consider downgrades and outlook changes for the best ranked European countries (e.g. France warning by Moody's on its AAA rating outlook from "stable" to "negative"). These events started another period of steep growth in the total connectedness measure that at the end of January 2012 reached a level of 73%.

Moving to a more granular level, *Figure 21* below, shows the evolution of net pairwise connectedness through time, before and after decisive moments of the sovereign debt crisis. Only links greater in magnitude than the final percentiles of the connections computed over the last 50 periods have been selected. The big blue arrows represent connections greater than the 99th percentile, the medium size black ones are greater than the 95th, and the thin red arrows are the ones greater than the 90th percentile. The same representation has been made also referring to a window more up to date (dynamically speaking), selecting links over the distribution of the ones computed over the last 15 periods (*Figure 22*). Both graphs show the same connectedness directionality and concentration on milestone events. In September 2009 before the Greek' Prime Minister declaration, just a few links passed the selection procedure. In May 2011, after the first brutal change of path and evolution rate in total connectedness, probably due to Portugal and Ireland crisis consolidation, and the first round of important rating downgrades, the linkages were more and greater in magnitude. At the begin of May 2012, after the Fiscal Compact treaty constitution, the system reached a high level of total connectedness, and high pairwise relations proliferated giving

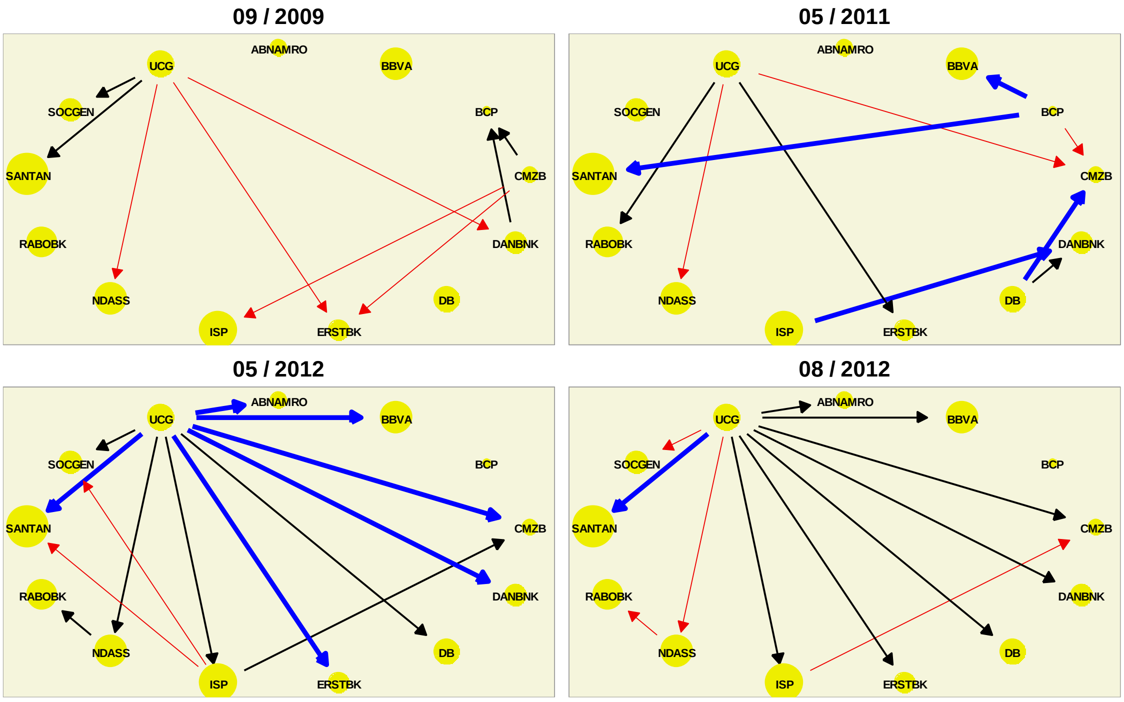


Figure 21 – Corporate Network pairwise links greater than the 99th (blue) 95th (black) and 90th (red) percentile over the ones computed on the last 50 periods.

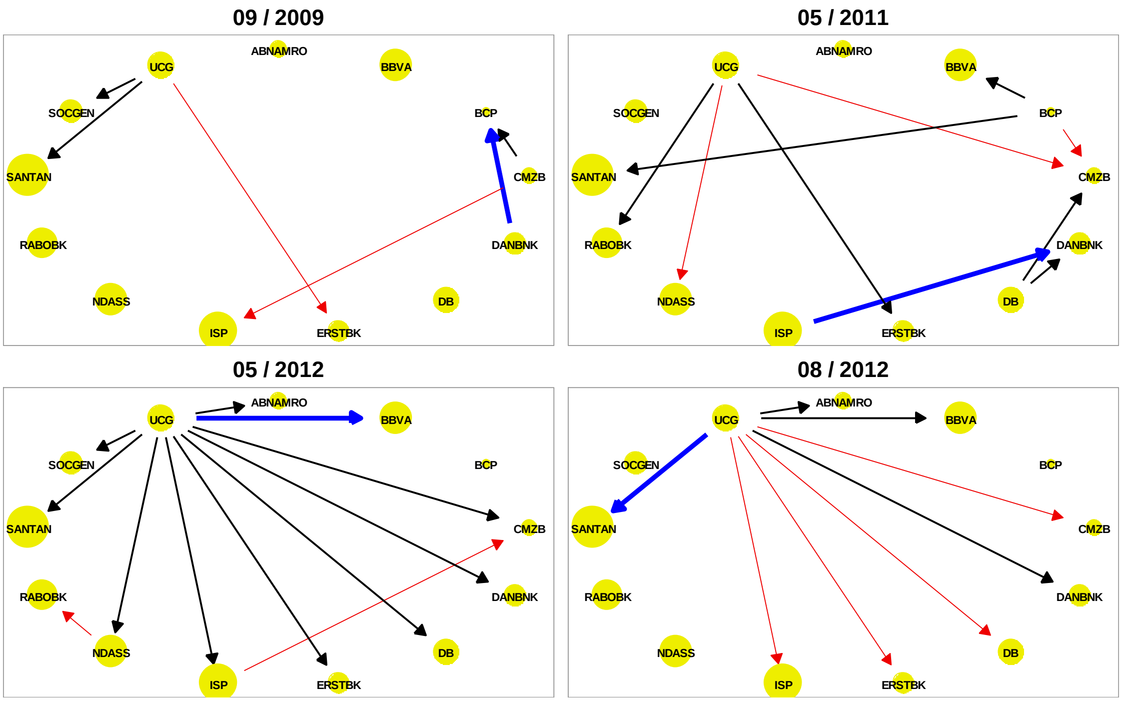


Figure 22 – Corporate Network pairwise links greater than the 99th (blue) 95th (black) and 90th (red) percentile over the ones computed on the last 15 periods.

UniCredit Bank a central role as European influencer among the others. The last network graph shows the situation immediately after Mario Draghi (European Central Bank governor) "*Whatever it takes*" famous speech, on ECB intentions of defending Euro currency at all costs. There, major linkages across the network have been decreased in magnitude, with UniCredit Bank remaining as a major leader in connectedness transmitted to other actors. This behavior suggests that the financial European framework reacts on a polarized basis under uncertainty and crises-related shock dissipations, condensing the majority of connectedness spread into few powerful channels (firms).

Following the escalation of 2011, the total connectedness of the system remained then oscillating around 70% for almost 2 years, until the beginning of 2014. After reaching a sort of "stability in connectedness", in 2012, corporate bonds network's total connectedness remained still for quite a long, with a high degree of interdependency. Historically speaking, the second semester of 2012, signed the start of a sort of cyclical path for total connectedness. The interdependency measure in fact, from the half of 2012 and the end of 2019 shows three longer periods of high connectedness, with oscillation around mean values as high as 70%, and two shorter periods of lower connectedness, with oscillation around mean values of 63%.

The spread of Coronavirus around the globe from China hit Europe as the first continent in term of disease spread and number of deaths. This brought each country to progressively apply national lockdowns in the wake of Italy: the first country to directly suffer consequences in terms of intensive care saturation and number of deaths associated with the disease. An immediate crisis hit all markets in a very short term, concretizing expectations of the biggest real crisis after the depression followed by the second World War.

Coming from two years of quite high total connectedness (oscillation around a mean value of 68%), the beginning of 2020 saw the above mentioned measure rising from 67% to 82% in a couple of weeks, in line with the broad and spread markets shortfalls on a global scale. This rise hit an all-time record (in reference to the period here considered) on absolute level (magnitude), but even at an evolution rate level (15% more in three weeks). The system's total connectedness remained around 80% since the beginning of the crisis. The last date on the sample analyzed was not comprehensive of the day of declaration about the discovery of a vaccine for the Covid-19 disease. The sparsity of clues about the time left for the development of a cure, and the proliferation of new disease variants left markets in a situation of high uncertainty. So a high level of total connectedness in financial firms seems coherent, given the dimension of the actors in the sample and the fundamental role of financial institutions in the economy. This last global crisis, as opposed to the subprime one and to the sovereign debt one, is a real crisis and not a financial one. Despite the source of the crisis, contamination and cross-implications are always spread among sectors and operators, but it is evident how the network reacted in a different way to the Covid-19 crisis, compared to 2010. The "response" of the measure has been quicker and steeper in rising without intermediate progressive steps. As will be shown, also the polarization of connectedness channels has been quicker for this last crisis.

Beyond considerations on the total grade of interrelation, a *net* pairwise evolution analysis has been carried on and presented in *Figure 23*. Here the network frames have been taken on moments closer to each other: the first week of February and the third of March 2020. These two kinds of connections selection procedures did not really differ in results. Global shortfalls on a stock markets level have been occurred from the second week of February, bringing major stock indexes like STOXX 50, STOXX 600 and S&P500 to lose capitalization by more than 30% in just two weeks. In the *Graph* can be noted how connections on a corporate level were quite poor in magnitude, while immediately after the crisis started, they have been increased. It is clear how Detusche Bank had the role of European influencer among the others, with very similar dynamics occurred for UniCredit Bank in the sovereign debt crisis. Despite the fact that the first country to be in

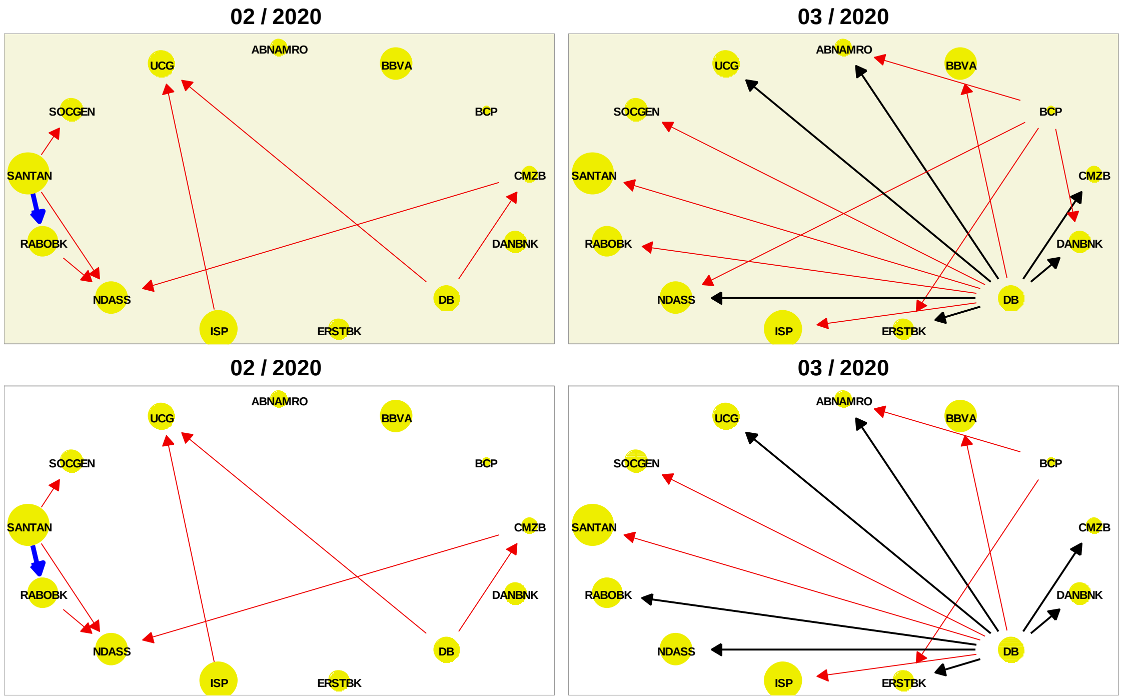


Figure 23 - Corporate Network pairwise links greater than the 99th (blue) 95th (black) and 90th (red) percentile over the ones computed on the last 50 (beige background) and 15 periods (white background).

need of a national lockdown was Italy, the graph shows how the interrelations have evolved from a European perspective, with a poor geographical component. The German bank was in fact leader in influencing even before the crisis, so likely to be the main channel of transmission after the market shortfall as well.

While detailed graphs on the dynamic evolution of total pairwise connectedness (firm-by-firm) are left for *Appendix B*, differences in these relations can be seen in *Figures 24-25*. There, the evolutions of *from* and *to* degree distributions are plotted. While by construction the mean value of both lines is the same, and equal to the total connectedness measure, big differences can be noted on a distribution level. First of all, variation in the *to* connectedness is much greater than in the other one. It can also be noted that while the *from* connectedness distribution tend to be right-skewed, the *to* measure is strongly left-skewed. Temporal changes in the dispersion and skewness of the *to* and *from* connectedness also contain useful information. For example, it appears that *to* connectedness gets not only more dispersed but also right-skewed with a very long right tail during crises, while simultaneously *from* connectedness lose skewness. That is, during crisis

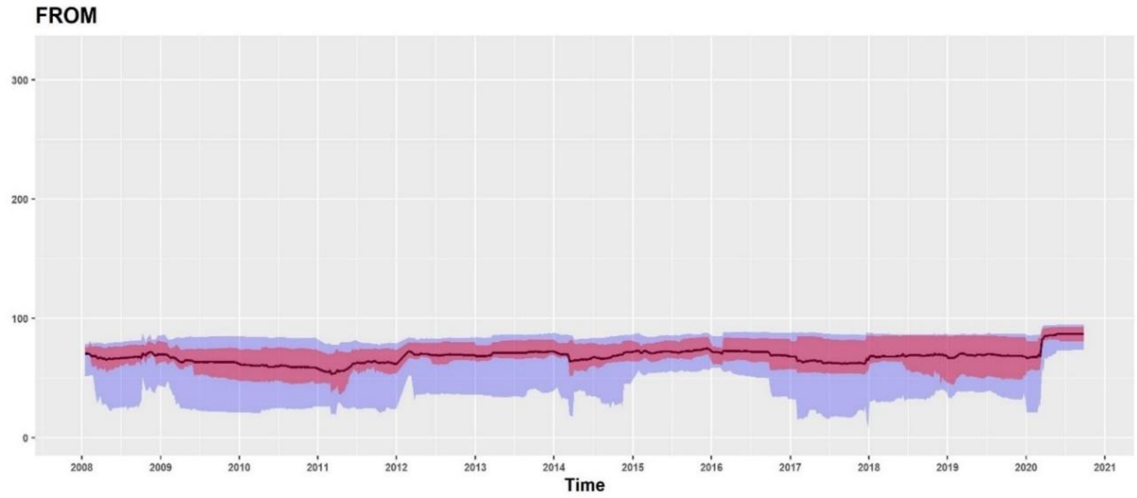


Figure 24 - Rolling Distribution of Total Directional Connectedness from others, together with the min-max range (blue band), interquartile range (red band) and mean (black line).

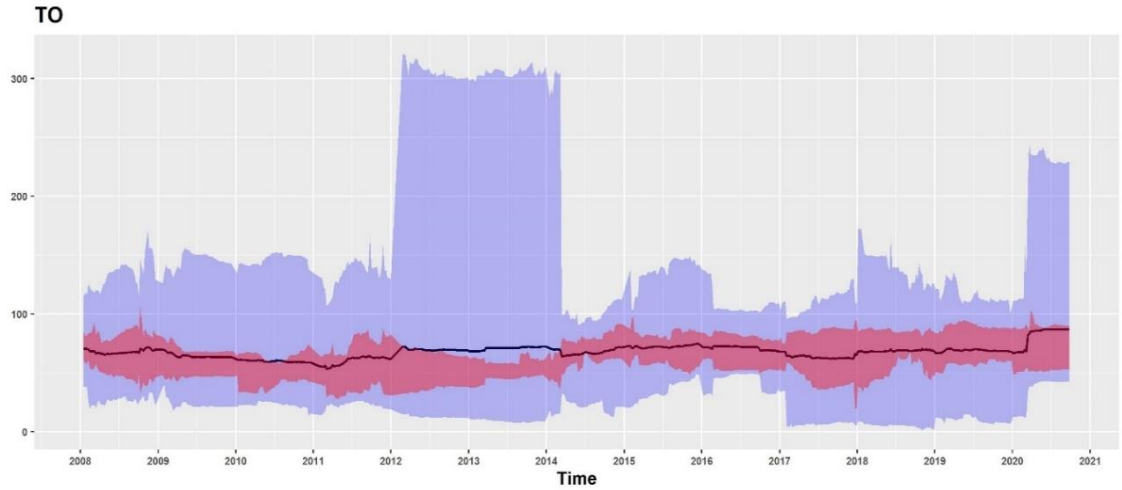


Figure 25 - Rolling Distribution of Total Directional Connectedness to others, together with the min-max range (blue band), interquartile range (red band) and mean (black line).

times relatively more than non-crisis times, there are few firms transmitting very much, while on the receiving side all actors tend to be nearer to the mean value. This situation can be further translated in a really interconnected network, driven by crucial firms at crucial times; those are the distressed firms potentially poised to wreak havoc on the system. This is a confirmation of what noticed from the net pairwise network frames shown before (*Figure 21-23*), e.g. UniCredit Bank during the sovereign debt crisis, and Deutsche Bank during the Covid-19 one.

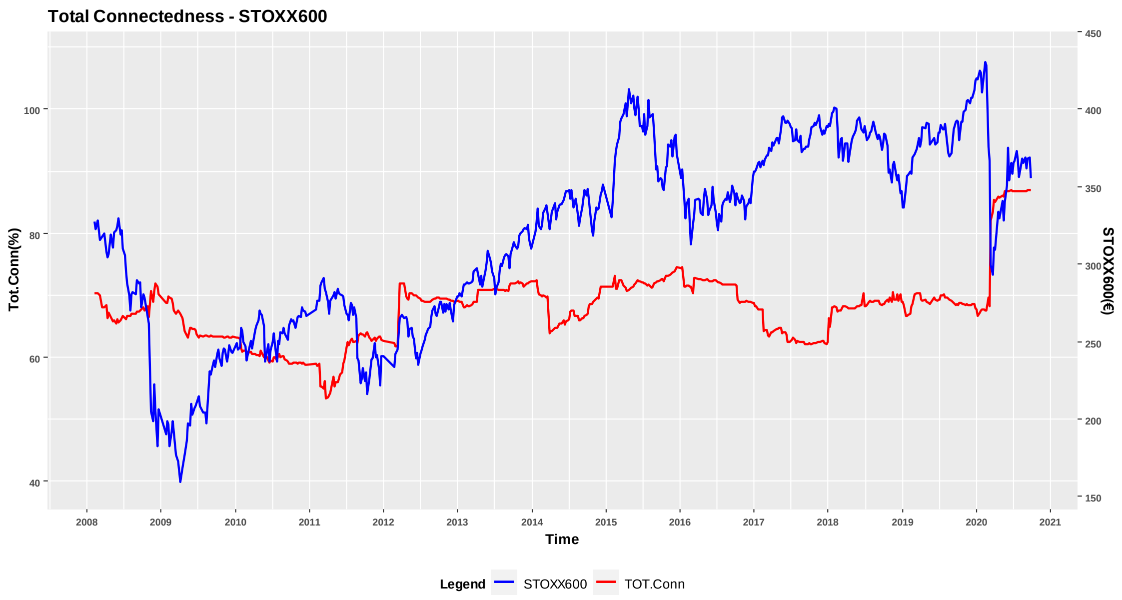


Figure 26 – Dynamic Total Connectedness of the Corporate sample together with historical prices of the STOXX 600 index (right scale).

Financial crises bring stock markets to have shortfalls in capitalization and, historically, economic shocks tend to be more often negative than positive. In fact, innovation disruptions occur in a maybe rapid, but more progressively way than crises and even effective economics policy take time to show positive results on a stock market level. So positive influence on markets like these, even if large in magnitude of the effects, cannot be labeled as shocks. Since connectedness variation, modify the amount and the rate at which shocks spread, a lookout on the relation between the measure presented and the historical behavior of markets is due. The analysis carried on so far, suggest that this relation is inverse, i.e. when connectedness rise we are facing crisis times and so shortfall in markets capitalization. *Figure 26*, plotting rolling estimations of total connectedness, together with historical prices of a main European stock index (STOXX 600), confirms this dynamic, that even if is not neat and perfectly correlated, exist. Unfortunately, proportions of respective changes are not constant, so even if it seems to be an inverse relation, the explanatory power of the connectedness measure is limited for modelling purposes.

Final considerations on the corporate network arise so from the evidence of the fact that connectedness between financial institutions rises during crisis periods, and its polarization increase as well. Every actor in the system tend so to absorb shocks of a bunch of main influencers transmitting the financial effects of crises to everyone in the system.

5.2.2 Two-year government bonds

Figure 27 below, shows the dynamic estimation of the network's total connectedness through time, for the short-term rates of the government bonds sample. A first look at the historical evolution of this measure, immediately recalls the path of the corporate sample. In fact, almost all big changes in connectedness have the same direction for both networks. This confirms that bond yields networks grow in connectedness during crisis times.

Despite similarities in the dynamic of the rolling total connectedness of the two samples, some differences are worth to be mentioned. The first one can be seen in the magnitude of changes, that for short-term treasury yields measures seem to be smaller. In fact, even if connectedness changes during crises arise in a non

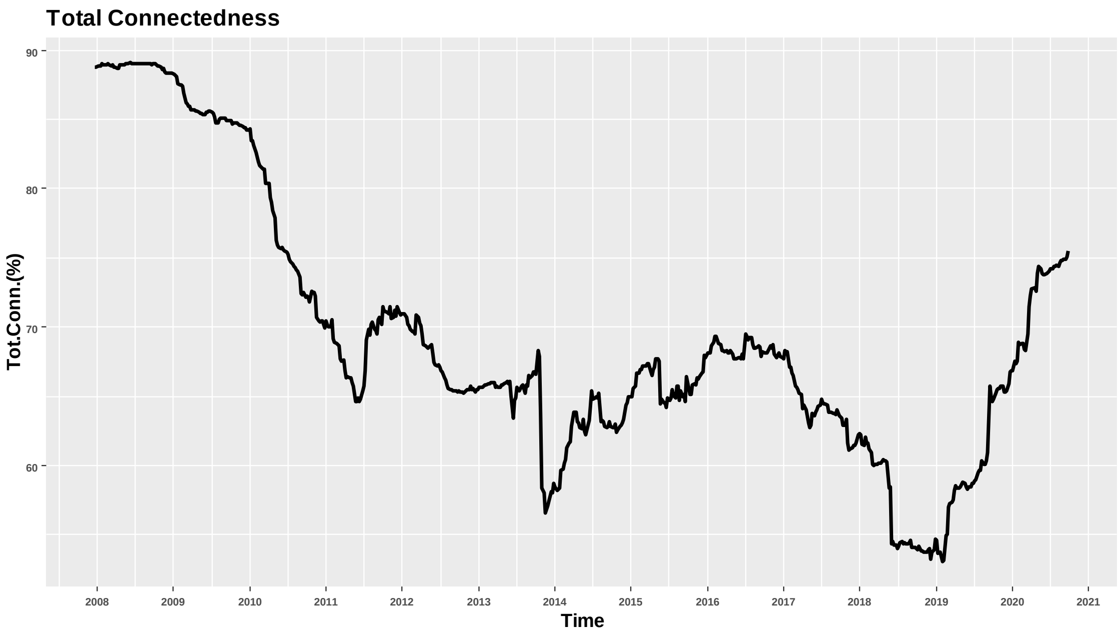


Figure 27 - Total Connectedness through time via dynamic estimation, w=100, h=2, Government Bonds sample (2-year rates).

smoother way whit respect to the corporate network, their percentage values are quite smaller than the ones of the first sample analyzed.

Another big difference whit respect to the corporate sample is in the value of connectedness during and after the subprime crisis. The short-term network comes from the already began 2007-2009 crisis, with an all-time high level of interrelation: 88%. Even if then the pattern followed the evolution already exposed of the corporate network, the first sample analyzed did not have a so high value of connectedness during the subprime crisis. Connectedness variation and increments steepness should be taken into consideration in order to evaluate the proper dynamic of the crisis effects related to the European treasury bonds, and the presented time range has not enough data to analyze them. Anyway, the fact that the two samples shared a common path and oscillation around the more or less same levels, after 2010, points out that the subprime crisis had for sure hit in different manners the two samples. To summarize deep considerations on the 2007-2009 crisis, have again to be limited because of the lack of data, but it is anyway clear how the impact of the subprime crisis has been really strong on a short-term government level, compared to a corporate one.

A third main difference in the path of total connectedness so far exposed, with the corporate sample interrelation, is in the behavior of the measure during the 2018-2019 period. The main events of economic relevance happened during those years, regard U.S. commercial tariffs. In January 2018, the presidency of Donald Trump imposed tariffs on solar panels and washing machines of 30% to 50%, as part of his "*America First*" economic policy. In March 2018 he imposed tariffs on steel (25%) and aluminum (10%) from most countries which, according to Morgan Stanley, covered an estimated 4.1% of U.S. imports. In June 2018 this was extended to the European Union, together with Canada, and Mexico. The tariffs angered trading partners, who implemented retaliatory tariffs on U.S. goods, giving start to a global scale *trade war* with United States and China as protagonists. In order to understand the magnitude of these happenings, it would be useful to consider an analysis of May 2019, conducted by CNBC[23] , that found that Trump's tariffs were equivalent to one of the largest tax increases in the U.S. in decades.

Jean-Claude Juncker, the president of the European Commission, condemned U.S. steel and aluminum tariffs. The European Union filed the WTO challenge against the United States in June, once the tariffs took effect. European Union retaliatory tariffs took effect in June 2018, imposing tariffs on 180 types of products, over $3 billion of U.S. goods. Affected products included steel and aluminum, agricultural goods, clothing, washing machines, cosmetics, airplanes and boats. Additional tariffs were imposed in October 2019. The European Union's deepest concerns about Global trade trend were for the high tariffs on imports of cars and car's parts where the EU's exports to the United States were €50 billion, versus €6.4 billion of steel and aluminum trade[24] (in 2018), where there is no global overcapacity, and where EU companies had invested heavily in the United States. The stress scenario derived from the trade war has been reflected on total connectedness in different manners across the networks. In the corporate sample, in fact, the 2018-2019 period was characterized by a high level of connectedness, coming from a decreasing period started at the end of 2016. The short-term government sample instead, started the same path of connectedness decreasing in 2016, but suffered the trade war only when its effects concretized, so at the begin of 2019, with a lagged upturn in connectedness.

A last notable feature of the rolling total connectedness for short-term treasury yields is the steep fall that happened at the end of 2013. The same change happened for the corporate sample, but with a six-month lag, and with a relative magnitude not so large, compared to the one of this second network.

[23] Liesman, Steve (May 16, 2019). "Trump's tariffs are equivalent to one of the largest tax increases in decades"; *CNBC*.

[24] Chase P., Mukai Y. & Sparding P. (2018); "Consequences of US trade policy on EU-US trade relations and the global trading system"; Paper requested by the European Parliament's Committee on International Trade.

Figures 28-29 below, show as before, net pairwise connectedness evolution through time. As before, the connections selection has been made related to the distributions over two periods, a longer one, and a shorter one (last 50 and 15 computations). Again, the results obtained with the two different windows confirm the same dynamic, with differences in magnitude and number of relations, due to the sparsity induced by the different buckets for the selection procedure. As just said, the total connectedness of the short-term treasury yields sample, was higher than the corporate one, after and during the subprime crisis. At the end of 2009, it has just started its decreasing path "following" the corporate connectedness, remaining anyway at a level as high as 84%. This is reflected by the first frame of pairwise connections, dense of strong directed relations. Most of those were directed toward Ireland, and from both, middle and big size countries (in GDP terms), and AAA and AA ranked states. The over mentioned situations

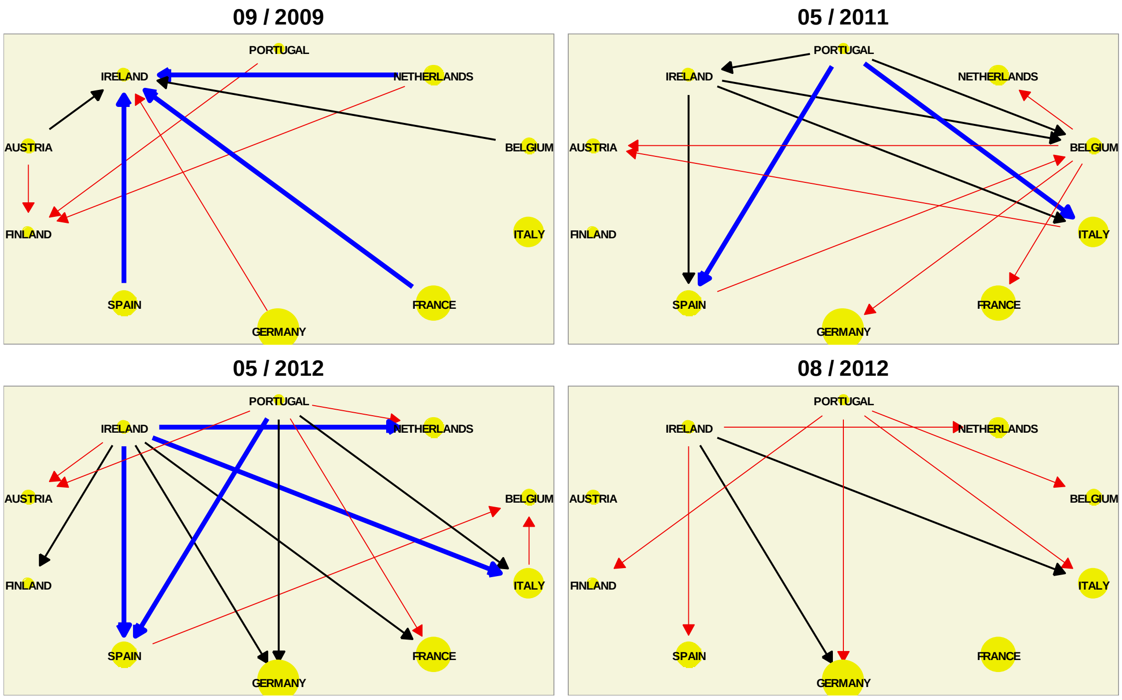


Figure 28 – Government Bond (2Y) Network pairwise links greater than the 99th (blue) 95th (black) and 90th (red) percentile over the ones computed on the last 50 periods.

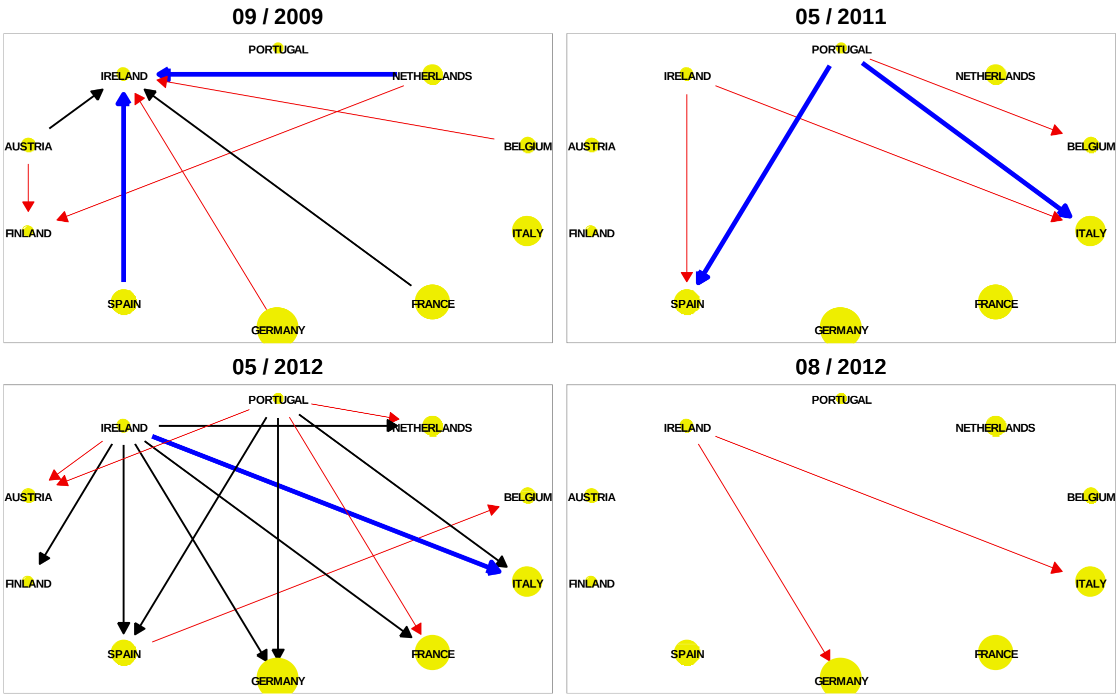


Figure 29 – Government Bond (2Y) pairwise links greater than the 99^{th} (blue) 95^{th} (black) and 90^{th} (red) percentile over the ones computed on the last 15 periods.

reflects an interesting behavior of connectedness. The period between the begin of 2009, and the first month of 2011 was characterized by high but also, rapidly decreasing total connectedness. The analysis carried on so far has established that connectedness among bond yields tend to increase during crisis periods, polarizing as well at a source level, giving troubled institutions the role of influencers towards all the other actors. It seems now that on periods of decreasing connectedness and recovery of markets capitalization, the polarizing phenomena takes a reverse structure, with small and more fragile entities influenced by the ones with opposite features.

After the rating cut season beginning, anyway, the total connectedness started to increase again, showing the "standard" dynamic of connections proliferation and directionality consolidation from troubled countries to stronger ones. In May 2011 Ireland and Portugal took the role of main network influencers, with Belgium Italy and Spain as main connectedness receivers. One year later while the total connectedness of the system was at its relative maximum, of the sovereign debt crisis period, directionality has been consolidated and the relation passing the selection procedure were dense and big in magnitude. Ireland and Portugal were confirmed as leaders in influencing other countries, while the *net* receivers were the biggest economies among the actors of the network i.e. Germany, France, Italy, Spain and Netherlands. Among those, Italy, the first big country to be questioned by rating agencies in time, during the 2010-2012 crisis, were the one detaining the stronger directional *net* connection: from Ireland. As for the corporate sample, the period immediately after Mario Draghi's speech was characterized by a decrease in connectedness and the disappearance of relations in the extreme right tail of their distribution.

The Covid-19 spread and the related markets shortfall already discussed did not disrupt in a neat manner the path of total connectedness of the system. The jump in connectedness was indeed notable, i.e. from 67% to almost 75% in a couple of weeks, but was neither an absolute nor a relative maximum for the period analyzed. The level reached was actually the highest since the first months of 2010, and the steepness of the path followed from before, and after the crisis explosion was really high. Anyway, the connectedness of the network came from an entire year of high evolution rate due probably to the trade war spread on a global scale. The increase in connectedness from its all-time bottom (53%), touched at the beginning of 2019, makes considerations on the jump due to the Covid-19 a little unreadable: connectedness was already rising at a high rate before the crisis. It can be surely said that a big jump occurred, breaking the maximum level of connectedness of the last ten years, but compared to the reaction of the corporate bond sample, the short-term government one has not suffered a framework total recalibration.

The smoother impact of the Coronavirus crisis is confirmed by looking at the dynamic estimation and selection of net pairwise connections (*Figure 30*). The situation before the pandemic explosion was characterized by sparsity of strong directional connections. The only ones selected were between frugal economies and a stronger one from Italy to Spain. After the crisis explosion stronger

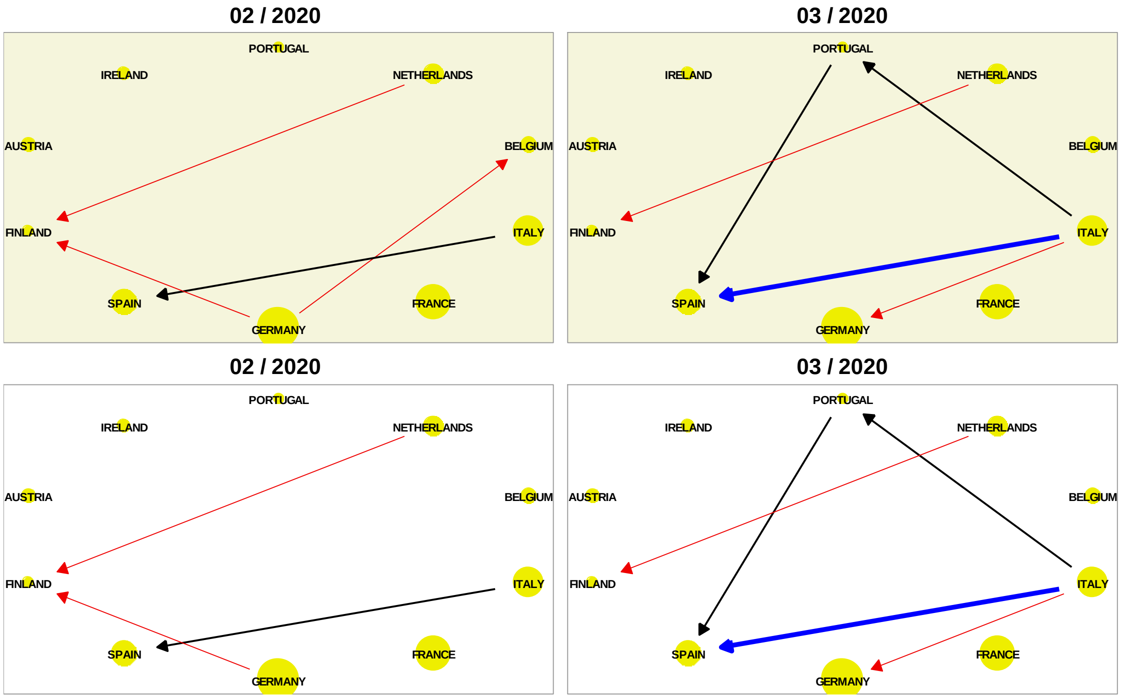


Figure 30 - Corporate Network pairwise links greater than the 99th (blue) 95th (black) and 90th (red) percentile over the ones computed on the last 50 (beige background) and 15 periods (white background).

connections arose, Portugal became a *net* influencer towards Spain, and Italy took the role of main influencer with the strongest relations to Spain and Portugal. The role of Italy during the latest global financial crisis makes sense since it was the first country suffering health, social and economic damages from the pandemic spread. It is worth also mentioning that at first, the situation in Italy was globally seen as idiosyncratic, with governments and public opinion frequently oriented to a bad management of controls and weakness of infrastructures as main features guilty of letting Italy being an isolated case (in gravity terms). The interrelation established between Italy, Spain and Portugal is also in line with the progressive contagion mechanism noticed and analyzed in the static modelling *Section (5.1.4)*. Anyway, as said before, the proliferation of connections was slightly poorer than for the corporate sample, confirming the lighter impact of the Covid-19 crisis on a short-term government level.

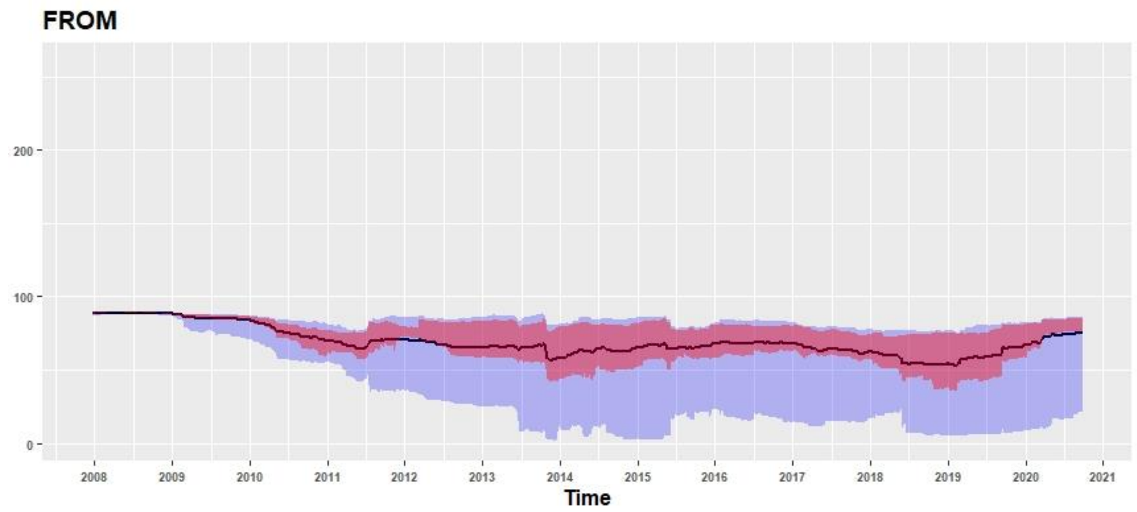


Figure 31 - Rolling Distribution of Total Directional Connectedness from others, together with the min-max range (blue band), interquartile range (red band) and mean (black line).

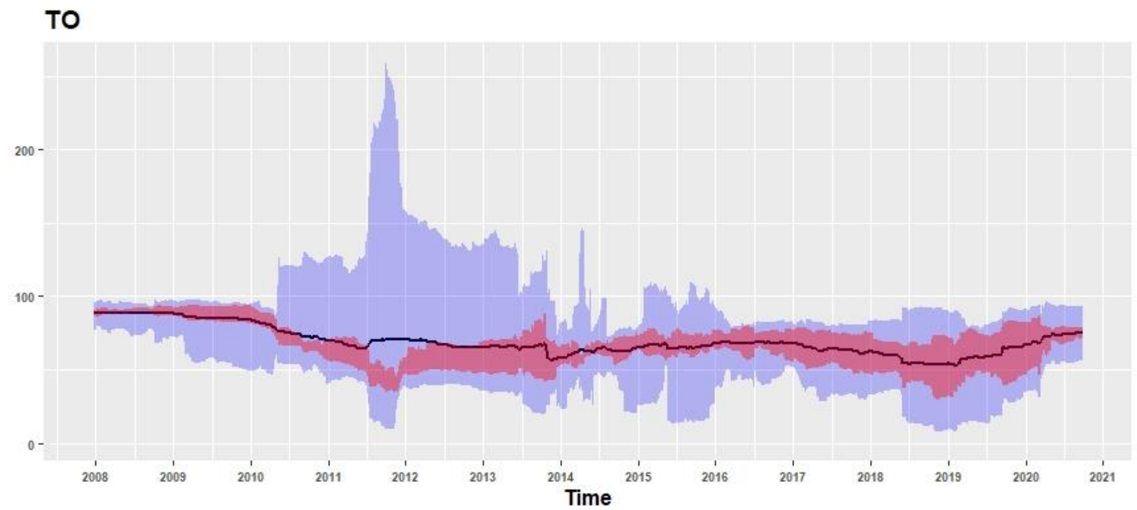


Figure 32 - Rolling Distribution of Total Directional Connectedness to others, together with the min-max range (blue band), interquartile range (red band) and mean (black line).

Leaving again detailed graphs on the dynamic evolution of directional pairwise connectedness country-by-country for the *Appendix B, Figure 31-32* below show the rolling degree distribution of total directional connectedness, *from* and *to* others. As for the corporate sample, the *from* others connectedness is right-skewed and generally vary much less than the other measure. As opposed to the previous sample, there is not seems to be a specific dynamic for this variation, that is almost constant overtime after 2010. Before this latter date, the variance was progressively augmenting from an initial level where tails and interquartile range were almost not even distinguishable. That period was the one right after the subprime crisis, with an abnormal level of total connectedness. Also, the *to* distribution is closer to its mean value at the beginning of the timeline. This behavior makes sense: in times when, total connectedness is as high as 86% or more, the interrelation of the system is so dense that even granular pairwise connections align in magnitude. Over a certain amount of interrelation, the network is just heavily correlated going probably towards multicollinearity and pairwise relations do not make much sense anymore. Connectedness *to* others tends to be right-skewed as well during standard times. During crisis periods this latter measure, shows a very long right tail, anyway the interquartile range is almost ever under the mean value during times with a larger variance of the total connectedness measure. The dynamic just presented can be translated into the fact that, during crisis times relatively more than non-crisis times, there are few firms transmitting very much, while on the receiving side all actors tend to be

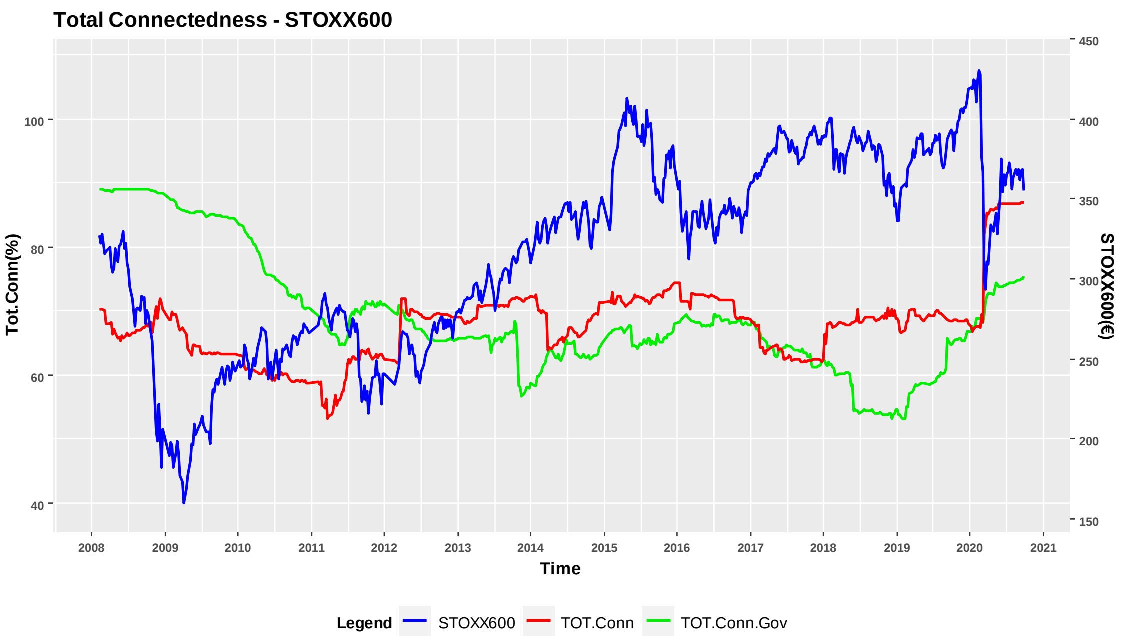


Figure 33 - Dynamic Total Connectedness of the Corporate sample together with the one of the Government one (2Y) and the historical prices of the STOXX 600 index.

always varying around the mean value, with a constant presence of independent countries with little received connectedness.

Even if a strong similarity in the total connectedness's path, dynamically computed over the first two samples has been noticed, the correlation between the just presented measure and the European markets shortfall is not so evident. This is confirmed by looking at *Figure 33* plotting the STOXX 600 index's historical price evolution over time together with the total connectedness measure exposed in *5.2.1* and *5.2.2*.

5.2.3 Ten-year government bonds

Figure 34 below, shows the dynamic estimation of network's total connectedness through time, for the long-term rates of the government bonds sample. The analysis of the rolling total connectedness confirms the first relative feature noted during the static estimation of the model: the 10-year treasury yields constitute the most interrelated network between the three samples analyzed. In fact the

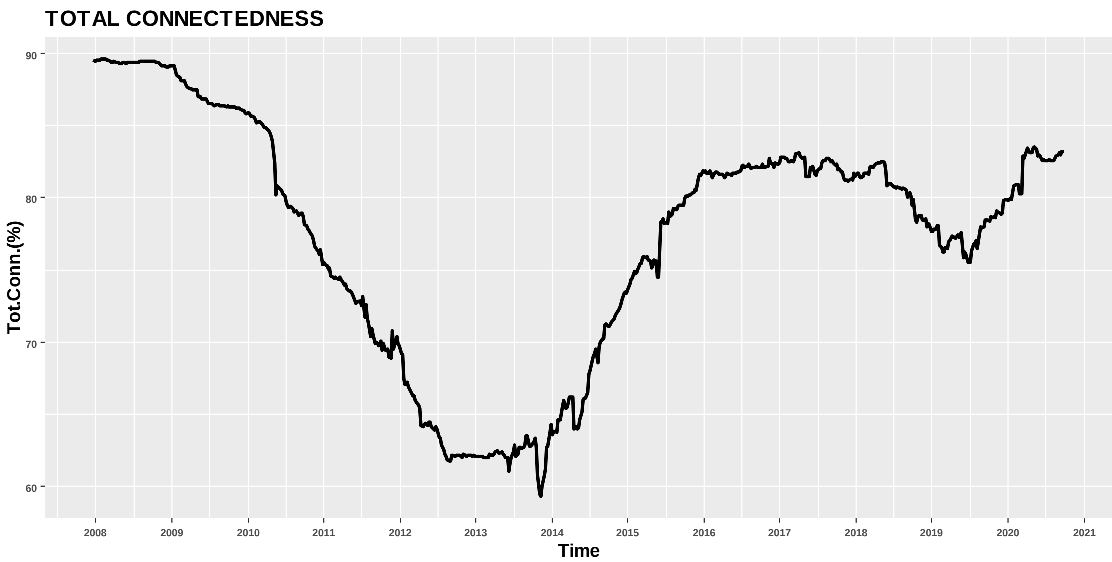


Figure 34 - Total Connectedness through time via dynamic estimation, w=100, h=2, Government Bonds sample (10-year rates).

interrelation measure is never been computed with a final value under about 60% during the period considered. Actually the total connectedness of long-term rates for 10 out of the 12 years analyzed has always been over 70%. The connectedness of this last sample has always evolved at a high rate of changing, but maintaining a smooth path over time. In fact no major crisis-related changes can be read through time, except maybe for the "*U*" shape taken during the period of Trump Administration trade tariffs inclusion, and the followed global trade war. Neither the sovereign debt crisis nor the Covid-19 related one, seem to have caused major trajectory changes of the total connectedness through time, but as noticed for the short-term network, the period during and after the subprime crisis was characterized by very high interrelation. Total connectedness was in fact near 90% for all 2008, and then started a rapidly decreasing path, remaining anyway over 80% until June 2010.

The path followed by long-term rates network's total connectedness seems to be cyclical with two periods of high connectedness and two of relative low interrelation. As can be seen from *Figure 35* below, rolling total connectedness of the short-term and long-term sample, share the same shape. The only difference is in the period of the sovereign debt crisis, where the short-term network suffered

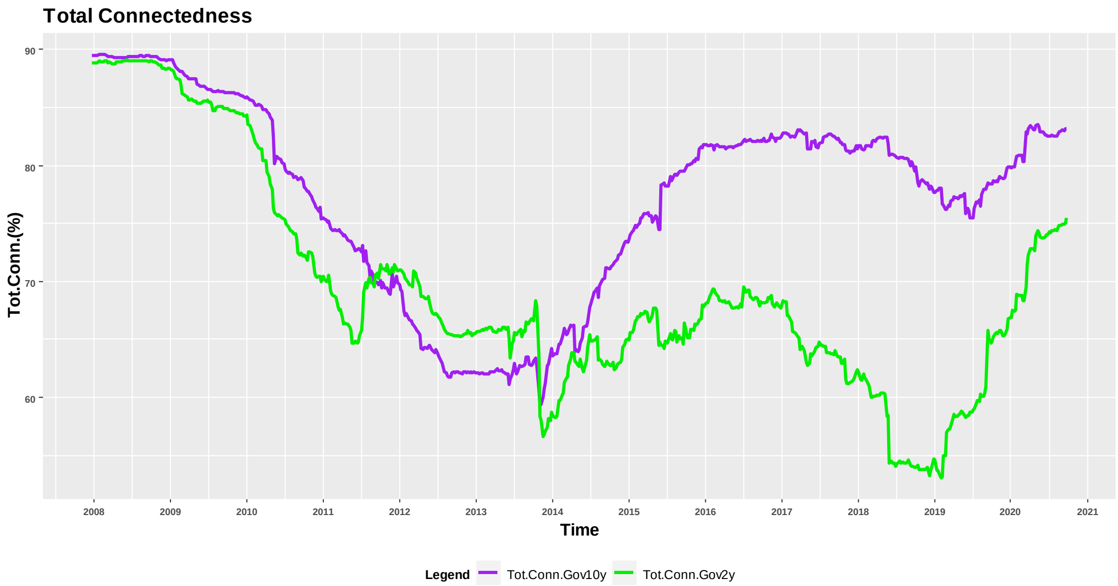


Figure 35 – Rolling Total Connectedness of the long-term Government sample, together with the short term one.

abrupt changes while the long-term system did not. Despite the same shape, magnitude of total connectedness differs quite a lot, with, as just said, overall interrelation of the long-term network always above the one of the short-term one (except for the just mentioned period following the half of 2011). That is long-term rates are always more interrelated as a network, reflecting interdependency of the Euro area countries, that share monetary policies, and economic policies oriented to the long-term evolution of individual economies. This makes sense, since one of the main scopes of the European Central Bank, is the convergency of economic systems in terms of efficiency, structure, and stability, and the long-term targets and estimated outcomes of policies are reflected by the rates at which each country raise financial resources.

Further considerations of differences between long-term and short-term treasury rates networks are skipped to the comparison *Sub-paragraph* (*5.2.4*).

In addition to the global trade war of 2018 and 2019, major events that seem to have shaped the total connectedness path, are the ones derived from the policy persecuted by the European Central Bank between 2014 and 2015. Specifically, the major solutions that ECB adopted in those years were the Targeted Longer-Term Refinancing Operations (TLTRO) and the Quantitative Easing (QE) program. The massive financing operations derived from these programs, and the enormous amount of liquidity injected into the European economic system, seem to have signed a turnover point for the total connectedness path by the beginning of 2014. The interrelation measure was steeply decreasing since the subprime crisis and then started to increase at a high evolution rate after the ECB declared and started unified financial stimulus targeted to reach the real economy through financial institution intermediation. The timing of rolling total connectedness big turnover could so mean that the long-term rates network connectedness reaction to a crisis, is strongly lagged and does not depend on markets shocks in terms of capitalization shortfalls and panic-related financial drawbacks, meanwhile the just mentioned programs drove interdependency between countries, more than the first occurrences. In fact, long-term rates seem to do not be impacted in connectedness by temporary shocks, and it is plausible to think that a prolongation of a shock or the consolidation of its consequences are assumptions due for connectedness structural changes. If this is true, and the horizon of a shock is an essential aspect of reaction in connectedness, in relation to the tenor of the instrument analyzed, it makes sense that enormous monetary programs like TLTRO and QE, with usually markets reaction based on the long-term benefits, had more impact than the occurrence of the crisis in the first place. The over mentioned programs, together with the Fiscal Compact treaty of 2012, marked European monetary policy path, with a very long horizon, leaving more space for economies concertation, and this raised interrelation among European economic systems (further considerations on this concept are left for the comparison *Sub-paragraph 5.2.4*). Even if this theory would be true, it would imply a feature that makes the proposed connectedness measure, maybe interesting ad concrete, but quite useless during crisis times, as a risk management tool (applied on long-term government yields).

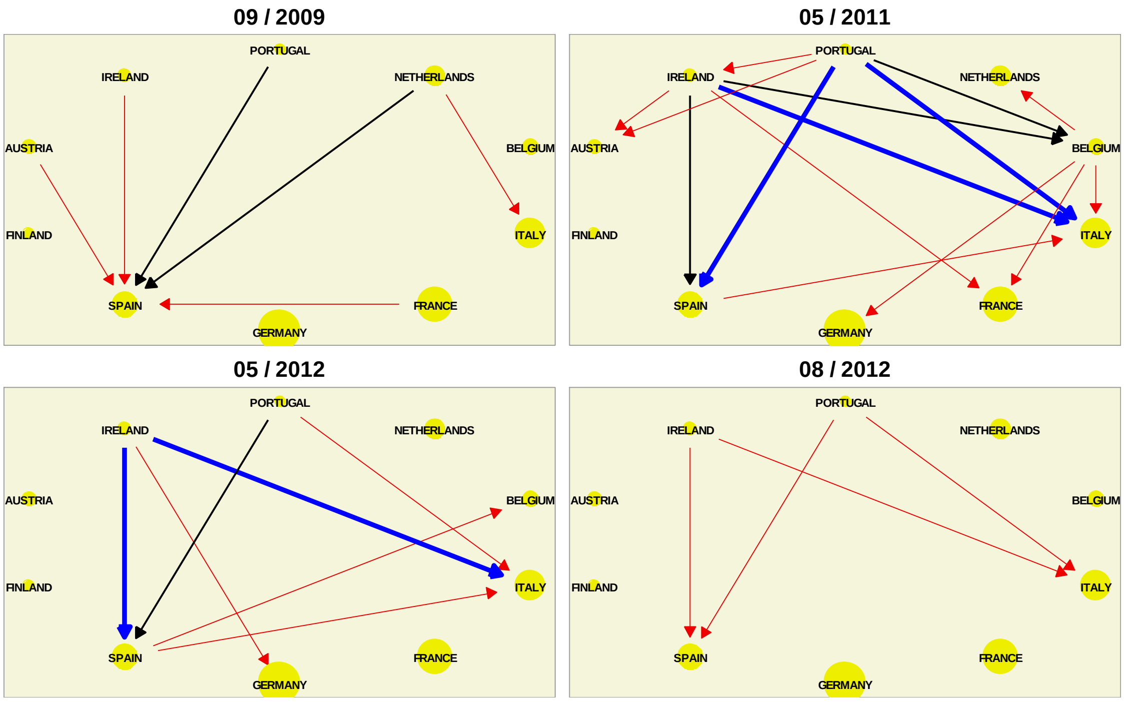


Figure 36 - Government Bond (10Y) pairwise links greater than the 99th (blue) 95th (black) and 90th (red) percentile over the ones computed on the last 50 periods.

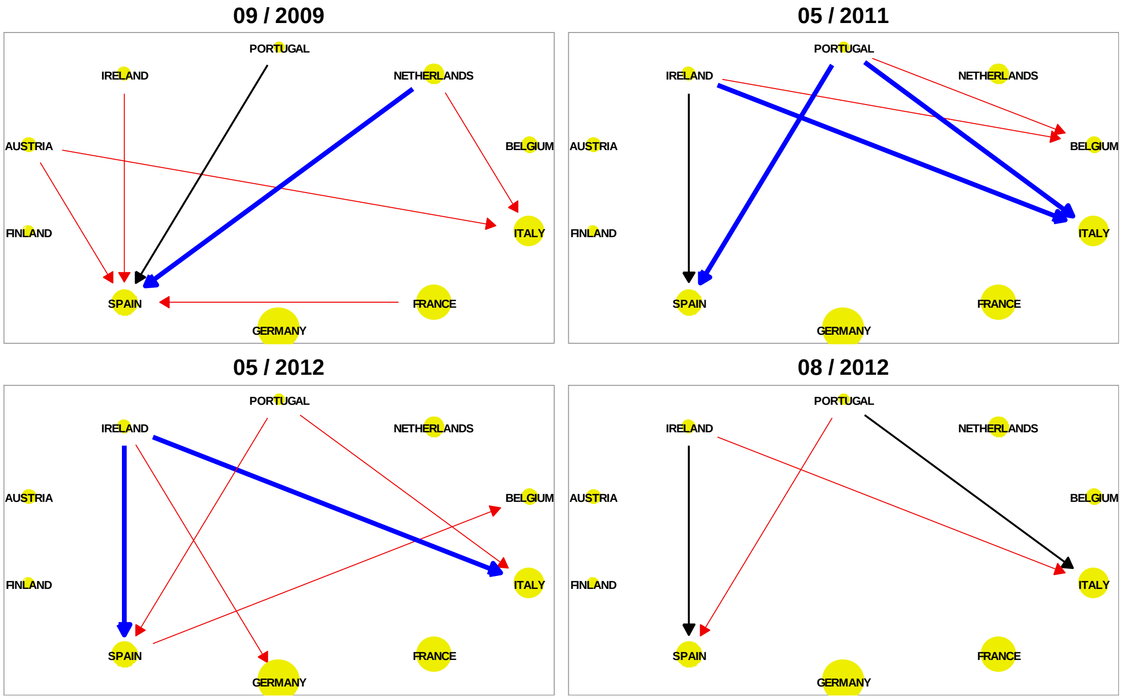


Figure 37 - Government Bond (10Y) pairwise links greater than the 99th (blue) 95th (black) and 90th (red) percentile over the ones computed on the last 15 periods.

Even if the dynamically estimated total connectedness measure does not seem to be strongly related to crises times and major markets shocks, *net* pairwise relations show a dynamic coherent with the sovereign debt crisis occurrences. *Figure 36-37* below report the already presented network relations through time, during crucial moments of the 2010-2012 crisis. An analysis based on those pairwise relations shows a dynamic not different from the one of the short-term sample. Again Ireland and Portugal had the role of major influencers, role increased in centrality as the crisis took hold. Further confirmation of the progressivity of connectedness directionality change during crises can be derived by the fact that the main intermediate influenced actors were Italy and Spain. Here the peak in pairwise interrelations was reached early, compared to the first two samples: during the rating cut season start, instead than after the Fiscal Compact treaty constitution. Changes in net pairwise connectedness related to the Covid-19 crisis have not been presented, in fact, as said before, the change in total connectedness at the

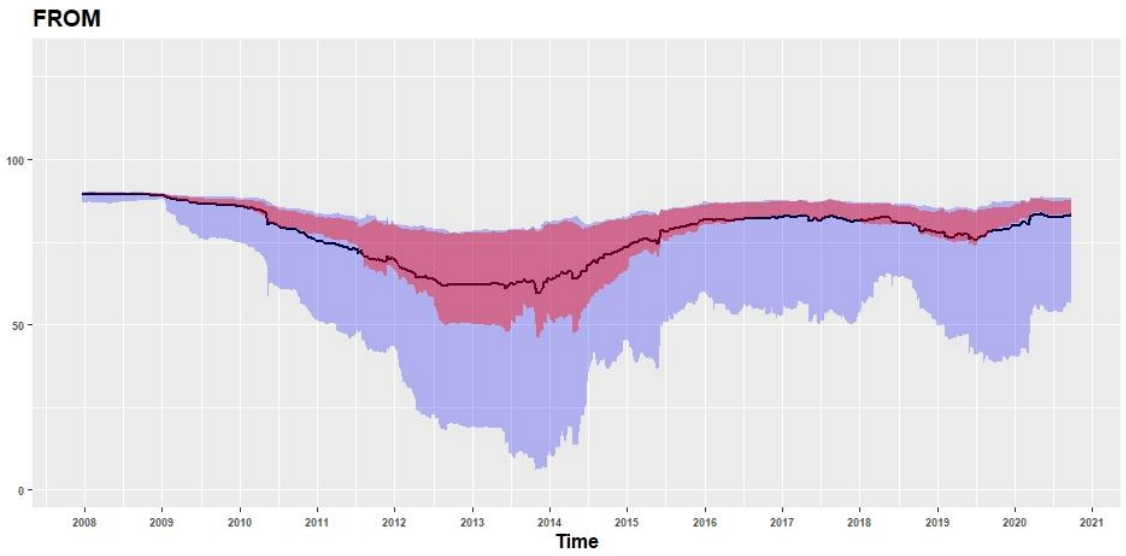


Figure 38 - Rolling Distribution of Total Directional Connectedness from *others, together with the min-max range (blue band), interquartile range (red band) and mean (black line).*

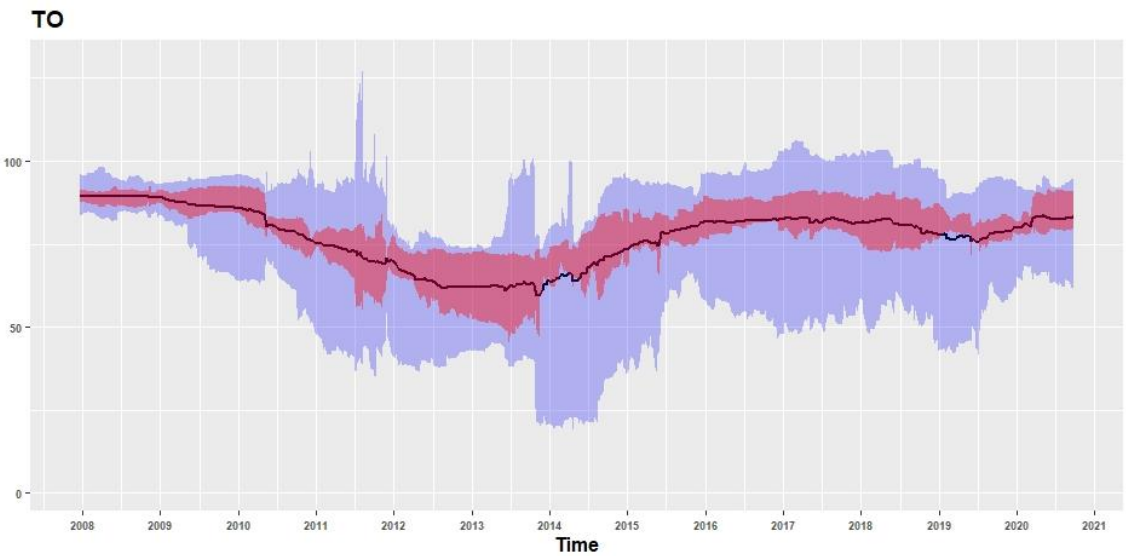


Figure 39 - Rolling Distribution of Total Directional Connectedness to others, together with the min-max range (blue band), interquartile range (red band) and mean (black line).

beginning of 2020 was not differing at all from the previous path's evolution, and pairwise relations didn't show explanatory power as well.

Leaving as before individual evolutions of pairwise connectedness for *Appendix B*, *Figure 38-39* show the rolling degree distribution of total directional connectedness, *from* and *to* others. In contrast to the other two samples, the variation of both measures is here very similar in range. However, the *to* others distribution is really more constant in variation, while the *from* others measure stretched a lot its left tail during periods of relative low connectedness. Furthermore, the former measure is almost ever centred around its mean, except for abrupt turnover points in total connectedness path, where it is left-skewed. In contrast, the *from* others degree distribution is usually left-skewed, with a very long left tail, except that for the sovereign debt crisis's period, and the following years, when it became almost centred, with an even longer left tail. The distribution shape of the *from* others connectedness does not seem to contain useful information, since it is described just in function of the connectedness level. That is, generally, with a high total connectedness value, the majority of network actors receive more than the mean value, with few countries being very independent, with extremely low values of received connectedness. Instead in periods of relative low connectedness, as it would be rational to think, the measure gets lower for many countries and is distributed around its mean, while the probably before isolated countries, become even more isolated. *To* others connectedness distribution, instead, have the strange feature of becoming left-

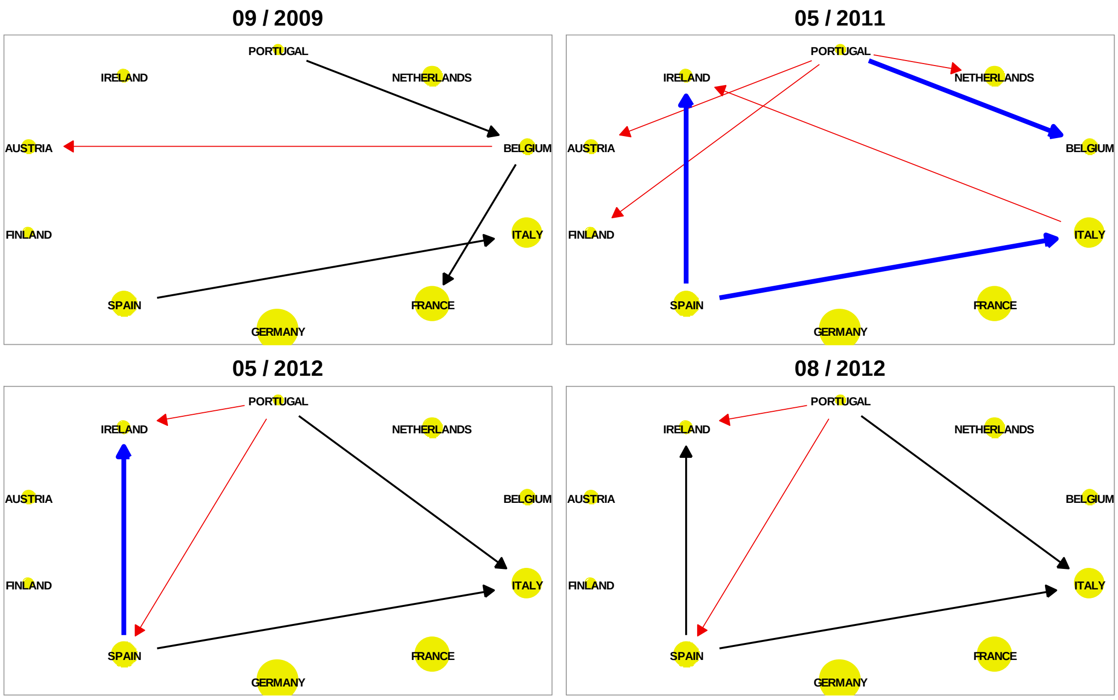


Figure 40 - Government Bond (10Y) pairwise links greater than the 99th (blue) 95th (black) and 90th (red) percentile over the ones computed on the last 15 periods.

skewed during changes in path, and this could be linked to the fact that a few institutions drive the connectedness turnover.

A further investigation of this phenomenon has been carried on, observing changes in *net* pairwise structure, at turnover point, where the degree distribution heavily changes its shape. *Figure 40* shows frames of the network net relations with the usual selection procedure applied on the connections. It is evident how the structure of the system has changed during the path swerve of connectedness, with Spain and Portugal taking the lead in influencing. The previously isolated Italy and Ireland became their main victims of connectedness spread, while Belgium France and Austria exited the high pairwise connection circle. This latter consideration could be read in line with the role that those countries had during the sovreign crisis, and the centrality of economic policy actuated to save weak economies and avoid a general domino effect. There is so much further confirmation about the source of connectedness change, but the interrelation measures as estimated, for timing and magnitude of response, seem again to have little explanatory power for crisis spread related deductions.

To summarize, even if major economic events and their repercussions can be read through the analysis of connectedness estimations, the 10-year government bonds sample seems to produce a non-sensitive measure. Historically speaking the shape of total connectedness is too smooth and cyclical to reflect idiosyncratically each crisis. The disadvantage of this last sample related measure was noted already in the static estimation *Paragraph* (*5.1*), where even a granular net pairwise analysis did not show a delineated framework of any sort of utility for contagion events-related structure prediction or risk management considerations.

5.2.4 Comparative analysis

Figure 41 below shows the rolling estimation of total connectedness for the three samples analyzed, all together.

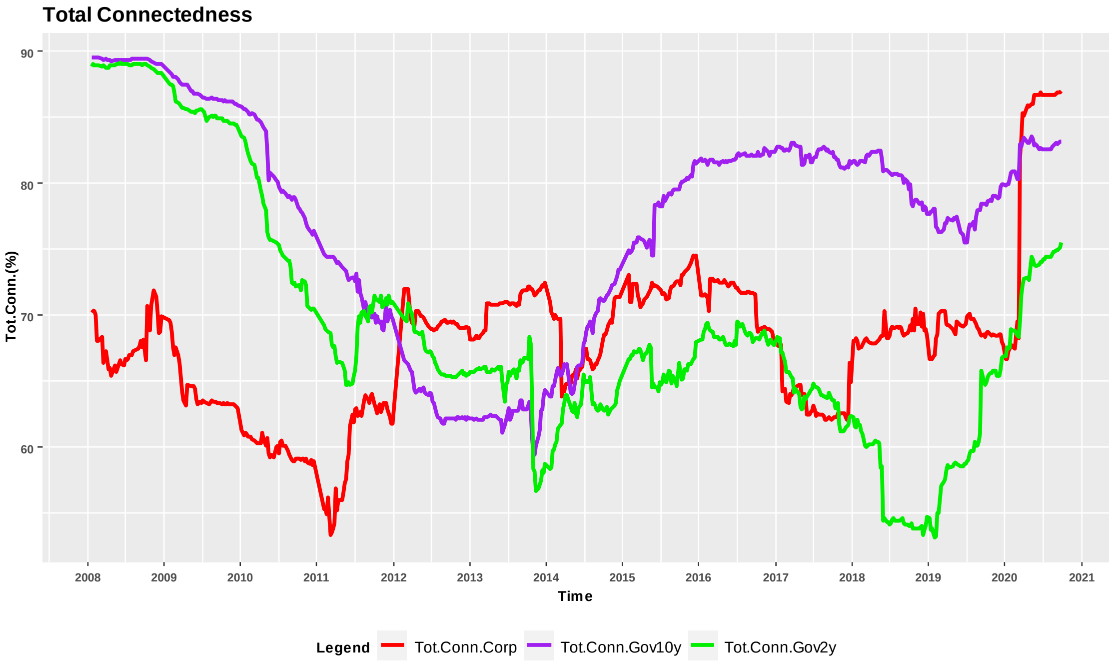


Figure 41 – Rolling total connectedness of the three analysed networks.

The first notable feature that comes out reading the *Graph*, is the exchange in level that occurred after the beginning of 2012, between the corporate sample and the short-term government one. In fact, the first 4 years out of the 12 for which the models have been estimated, are characterized by a total connectedness level of the government sample, way above the one of the corporate network. This has a clear meaning: European financial institutions have become more interrelated than national economies, on a short-term basis, after the sovereign crisis. Connectedness jumps related to crises have always been bigger for the corporate network, compared to the other two samples, but the two-step jump that occurred after the 2010-2012 crisis, signed a breakpoint in connectedness level. Furthermore, after that event, the corporate interrelation measure shows a cyclical behavior, with macro-oscillations around the subprime crisis levels. This switch could be due to a structural change in one, or both networks. Given the fact that the short-term system was before closely related to the long-term one, in path and level, and after 2011 it followed more the corporate network behavior, it would be reasonable to think that main changes have occurred in the structure of the 2-year government bonds system.

The sovereign debt crisis highlighted the possible fragility of the recently created Euro currency, and the monetary Union derived from it. A variety of the criticism against the Euro, on its first times, and even now, are based on differences in economies and debt structures of each European country. Discussions about the pro and cons of a single monetary Union in the European territories are behind the scope of this thesis, but it is worth mentioning that market operators' concerns and expectations over the first years of the Euro were related to the frequently doubted success of a monetary Union.

Looking at the *Graph* it is clear that, despite the level of connectedness, variability of the overall interrelation measure is always greater for the corporate sample, and this difference was neater in the 2008-2011 period. This concept was brought on already in the unconditional analysis and is quite obvious since corporations are more fragile institutions whit respect to governments. Given this, a quicker change in financial firms' performances and stability forecasts is clearly reflected by a more rapid total connectedness response to economic occurrences. The structural change regarding the short-term system, could have so partially aligned market operators' expectations on financial firms and governments (on a short-term basis). This has given the short-term connectedness a structure and properties (in terms of response and changes), linkable to more fragile institutions. The event of a crisis related to the sovereign debt creditworthiness in the Euro area, seem so to have broken the resilience to small shocks and happenings before proper of the short-term government network.

The corporate network remains anyway the most sensible to occurrences, varying the most, and as the quickest, during crises events and after economic policies consolidations. A further proof of this aspect is the rapidity with which the corporate sample reacted after the trade war begin (almost a year before governments networks). There are anyway strong evidences to make the assumption of a structural change on a short-term government basis. This concept was already introduced in *Chapter 3* where, describing the yield-to-maturity times series used to estimate the models, a difference in the general behavior of the series before and after 2011 was noted. In practice, as said before, there was a sort of convergence to a mean value, even with the variance caused by the subprime crisis. Anyway, after 2011, yield times series came back converging around a common path, but with much more differences between themselves.

The thesis of a structural change can be supported even for the long-term network. It has been pointed out already, for all three samples, that total connectedness follows a cyclical path, and the one of the 10-year yields network is the most marked and smoother, taking the shape of a *sine* function. Macro-oscillations of connectedness, for the long-term system, have anyway started to drastically reduce in width at the end of the considered period. There are however probably not enough data, on a time level, to assert in a more descriptive way this phenomenon, given the length of cyclical changes in connectedness (that are only three in the period analyzed).

Total connectedness of corporate bonds has almost always been less than the one of the long-term government ones. As just said the dynamic of the former reflects frequent structural changes of the system, that occur more commonly. Speaking of shocks, this mechanism can be read also on a threshold level: it seems so that maybe even small and temporary shocks affect with little changes connectedness of the corporate network, while just big market structural changes, or major shocks, affect long-term government bonds connectedness. Big differences between corporate and long-term government networks are as well in the paths, that rarely reflect common direction or levels.

To summarize, no notable common features bind these two samples, and between them, the largest explanatory power in term of crisis-related shocks, is definitely given by the financial corporation network.

Even if a change in the response sensibility of total connectedness between long-term and short-term government networks has occurred, as pointed out before, the measures of the two systems share a common path. As said, this excludes the sovereign debt period: the only period where the short-term system was more interrelated than the long-term one. Actually, the paths of the two measures were

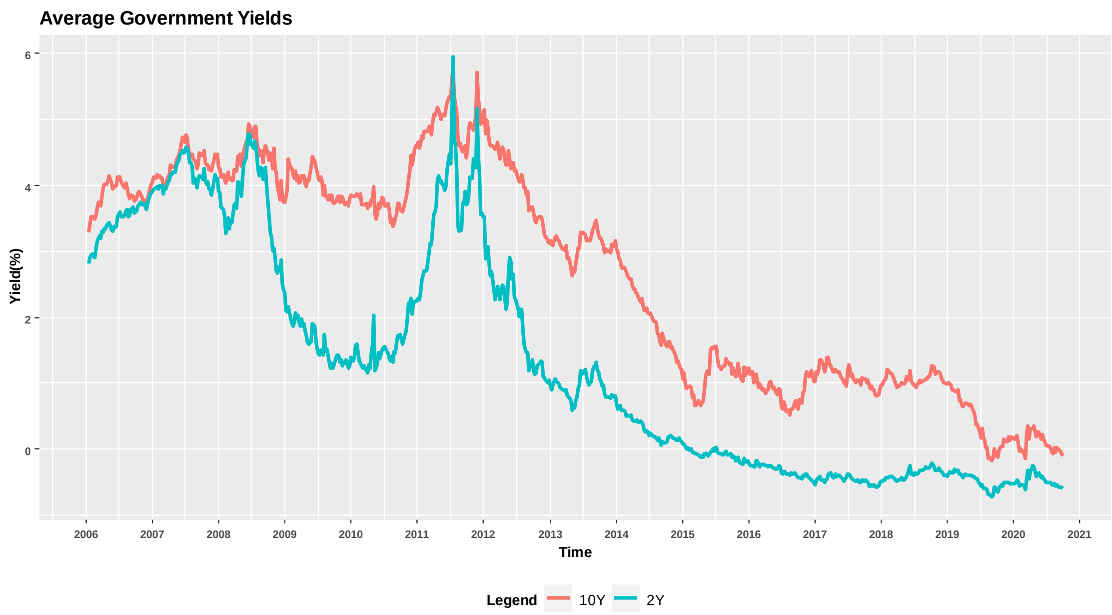


Figure 42 – Average Government treasury yields in the Euro area (for Governments in the sample).

similar but very different in jumps: the short-term connectedness previously diverging from the long-term one, made a rude increase, re-joining path and level (even more as said) of the latter system.

As known treasury yields curve's shape reflects expectations about the future in term of risk, inflation and so on. During crisis periods yields curve tend to take a flatter shape, and sometimes even to invert (becoming decreasing in tenors). During the half of 2011, when the total connectedness of the short-term system jumped, the average yields curve on the euro area (for the countries in the sample) was flat, even inverted for a couple of weeks. This happened mostly for major sell-off of short-term bonds, that for buy moves on the longer-term securities (eventually made for expectations about the imminent probable lowering of interest rate by central banks). This scheme can be easily noted by *Figure 42*, representing the average value of both samples (2-year and 10-year government bond yields). The distance between the two curves represents the steepness of the yield curves in the euro area (on average terms): the greater the distance, the steeper the curve.

It is easy to notice how through time, total connectedness of the short-term network got closer or even higher than the one of the long-term system only with a flat yield curve. During the sovereign crisis, the 2-year system interrelation surely surpassed the 10-year one, but a lookout at the first left part of *Figure 40*, insinuates the doubt that before 2008, the situation was the same. An equal deduction can be carried out for the latest total connectedness estimations (2020), that show the two measures to moving towards convergence. These three periods have in common to be massive global crises of course, and also to have a flat treasury yield curve (on average).

A further investigation of this dynamic highlighted the fact that iteratively, during periods with a flat yield curve, total connectedness of the two government samples tend to converge in level and path. Moreover, periods with a steeper yield curve, "leave" the connectedness measure of the short-term network, varying a lot and more independently. That is, during crisis times, or just before them, when market operators forecast an imminent change in interest rates or an expansionary fiscal policy, the connectedness on a government level tend to converge despite the tenor of the instrument analyzed. This latter concept reflects the uncertainty about the future that is spread to all government activities, and it is also associated with a relative high in connectedness for the short-term network. During standard times (in terms of yields curve shape), anyway, the short-term government network showed flexibility in response to economic occurrences. A feature worth to be mentioned is that level of long-term connectedness seems to not be related to the above exposed dynamic but its cyclical turnover points can be associated with yield curve flattening events.

As said before long-term network derived measures alone are not useful and reactive tools, but the interpretation of them together with the short-term ones could give useful hints for risk management analysis.

This last theory does not break the one of a structural change in short-term connectedness but strengthen it. In fact, could be that the structure of connectedness changes over crisis periods, becoming aligned at a government level;

it then changes again after crucial moments of crises. So structural changes could have been even more than the one hypothesized before during the time considered. Substantially the 2-year government network, oscillates in properties and structure, bouncing between the features proper of the long-term system and the ones of the corporate financial network.

A final comparison statement regards a phenomenon confirmed by the three analysis: the polarization occurred for every network during crisis periods, on a *net* directional connectedness level. This frameworks' structure was already pointed out in the unconditional analysis in *Paragraph 5.1*, where directional connectedness was seen polarizing around the weakest institutions as channels towards the other ones. This has been noted in a neater way in the corporate sample, while in a progressive way in the two government ones, where very small and weak countries influence the bigger but weak as well, and then connectedness is spread towards the "top" economies in the system. A polarized structure has been so noted also in the dynamical analysis, observing the strongest pairwise relations via the selection procedure based on percentiles. In fact, rolling estimation highlighted that along the path bringing to a crisis explosion and the reaching of its peak, the very same pairwise framework of unconditional estimation was iteratively formed.

Chapter VI. Final overview

In this section, I present a final comparison of all the constructed networks, with an overview of the main common features and the principal differences noted on both, a static and a dynamic estimation level. The results shown below outline interesting dynamics, and widely support the main thesis of the current analysis.

6.1 Main common networks features

The unconditional estimation carried out in *Paragraph 5.1* highlighted some common features of the three samples. All three networks are in fact very interrelated since the static estimation showed a total connectedness level of more than 58% even for the most "independent" system. Furthermore, geographical factors seem to be relevant neither for connectedness directionality nor for its magnitude.

A last shared feature of the three systems analysed (from a static estimation perspective) is in the directionality source. It is in fact clear how connectedness is always spread among all actors: every network is conformed as a net, linking all institutions in the system without leaving any node isolated. However, an analysis base on an ordinal perspective (in magnitude terms) highlights a common neat path of relations. Both financial corporations and governments spread connectedness according to their financial structures, with dimensionality (market capitalization or GDP level) and financial health (credit ranking) as main drivers. The path is clear: troubled nodes in the system direct connectedness to the healthier actors. Furthermore, the weaker the institution greater is the connectedness directed.

Rolling estimation highlighted the fact that every network shows a cyclical path of total connectedness over time. However, only the corporate and the short-term systems share common cycles, except for a below addressed period of 2 years (i.e.

2018-2020). Although these cycles are not aligned the total connectedness paths have multiple turnover points in common through time.
Another common feature on a dynamical level is in the polarization mechanism iterated over crisis periods. In fact, the already mentioned pairwise structure became neater every time a crisis event occurs, with different institutions acting as main influencers (depending on each crisis and each relative conditions of these actors at the time). It is very clear how this happened for every crisis considered and every network constructed. Not only directional connectedness tends to aggregate around some specific nodes, but also the magnitude of the polarized relations increased in crisis periods, reinforcing the effect of this phenomena on the system.
A final common feature of dynamical estimation outcomes is in the degree distribution of total directional connectedness, which is never centred around its mean through time. This is translated in network frameworks that are never homogeneous but always polarized around some extreme influencers or influenced institutions.

6.2 Main networks differences

Despite the outlined common features, the three constructed networks differ in some interesting aspects. As already said those systems are all very interrelated, regardless the issuer or the maturity of the bonds, in general, government networks present a higher degree of total connectedness. As shown above, this is not constant over time (dynamic estimation), except for the long-term system that is almost always more interconnected than the others.
Another difference in connection, in an unconditional perspective, is in the pairwise relations. Despite the fact that systems with the higher value of overall connectedness have greater pairwise relations (for construction the diagonal elements are not included in total connectedness computation), those set off each

other more frequently in strongly interconnected networks. This translates into a sort of magnitude symmetry in the elements of the connectedness matrix. Such a phenomenon suggests the existence of an inverse relation between total connectedness and pairwise *net* connections.

A last notable difference between the three networks is in the pairwise directionality mechanism. In fact, as outlined in *Sub-paragraph 5.1.4* government bonds reflect some kind of progressivity in *net* relations spread. Corporate firms, following the logic of the weak institution that influences the strong one, act in a more "drastic" way, having small and troubled institutions directly influencing the biggest and best-ranked ones. Meanwhile, government bonds tend to present a middle step in connectedness, with a "pyramidal" framework characterized by small and troubled countries influencing the medium ones (in GDP and credit score terms), and then overall connections that are spread among all actors.

One main difference in the historical path of total connectedness can be seen in the response to crisis events or market shocks of the three overall measures. This is clearly different on two fronts: the magnitude and the timing. For sure the financial corporations network reacts in a neater manner to crisis events, making jumps usually almost double of the size the ones of the short-term system. Also, the timing of these jumps always precedes the one of the latter network, with a lag related to each event (e.g. less than one month during the sovereign debt crisis, while almost a year for the global trade war). However, as already pointed out the long-term system does not show marked jumps related to crisis events.

As just mentioned, a very different behaviour has been noted for total connectedness in the three networks during the global trade war period. In fact, not only the timing but also the path followed by the overall interrelation measure, were different in reaction. The corporate bonds measure suffered in fact a significant turnover, jumping instantaneously after the first tariffs introductions, meanwhile, government bonds reacted one year later in an alike significant manner, but without a neat jump in total connectedness.

Conclusions

Given the considerations on the static and dynamic behaviour of the three systems, exposed in the previous section, it is clear how the corporate and the short-term estimated networks are the ones producing the more useful and dialoguing connectedness measures. In fact, both the financial corporation and the short-term government samples, showed a peculiar granular framework of *net* pairwise relations and a neat path of total connectedness, varying according to economic events. An analysis based on connectedness measures derived from these two systems can so be useful in order to assess dependencies among institutions and operate on a risk management level, constructing ad hoc recommendations aimed to preserve the financial stability of related actors. Furthermore, monitoring activity on the total connectedness level of these networks could be functional to shocks evaluations and the production of related considerations on financial drawbacks.

Regarding the 10-year treasury rates network, none of the analyses showed neat dynamics or peculiar pairwise relations. Static estimation on a net pairwise level showed a system framework very interrelated as a whole, but almost independent from a granular perspective. Even the analysis carried on the historical path of total connectedness reflected a behaviour of the system almost independent from economic occurrences. For sure the constructed network is very interrelated (the most connected) but given the estimated relations among actors and the simultaneous reactions of the system to economic events, it seems to be useless to conduct accurate evaluations of dynamics between institutions. This could be given by the nature of the network itself, but as pointed out, there seems to be an inverse relation between total connectedness and the magnitude of net pairwise relations. It could be so possible that this last system is so interrelated to converge in behaviour. As in fact already exposed, degree distributions of total directional connectedness tend to almost lose their tail over a certain level of total connectedness, so it would be plausible to think that in a very interrelated system, each actor suffers shocks and economic cycles in a symmetric way, without a spread of connectedness in a peculiar manner. This, anyway, does not justify the almost independent path of total connectedness through time for the 10-year bonds. For this reason, the just exposed concept has not been deepened.

Despite the lack of useful features of the 10-year system connectedness measures, some considerations arose in *Sub-paragraph 5.2.4* leave space for applications of these tools. There is in fact a relationship between the steepness of treasury yield curves (on average terms) and the relative level of long-term and short-term networks' total connectedness. Specifically, as said, periods characterised by a flatter yield curve seen the two connectedness measures to converge, or even the short-term one to surpass the long-term one (an exceptional event, historically speaking). Recalling one of the main reasons for which two kinds of government bonds samples were included in the current analysis (i.e. the closer reflection of market operators' expectations by the long-term yields), the above mentioned phenomenon could give useful insights. In fact, a flattening of treasury yields curve reflects low confidence and bad expectations on markets about the future. So, even without directly using the 10-year yields derived connectedness measures alone, for concrete analytical purposes, a lookout of the two government-based measures together could increase their explanatory power. Following this approach, the 2-year connectedness measures should be followed and analysed for general analysis and considerations, while the relative level compared to the 10-year one, could reflect not only network's structure, and shock dissipation paths, but also the effect of these phenomena on an expectations level. That is, during crisis periods, evaluations of the short-term network alone could help understand the magnitude of a crisis and the dynamic of its repercussions, but long-term total connectedness relative level, could constitute a threshold, that, when surpassed, indicates long-term repercussion in market operators' expectations, giving further alarms about a crisis or a shock impact magnitude.

To sum up, the evidence obtained by the analysis carried out strongly supports the thesis of the current project. It is in fact clear how connectedness, on a system-wide level, changes during crisis times, with a neat increase after events of negative economic relevance. However, despite this clear path, there is not a direct relation with markets capitalization growth or volatility decrease. For sure high volatility periods and crisis events, bringing to market capitalization shortfalls, are followed and/or preceded by jumps and increase in connectedness, but the inverse relation is not so strong. Specifically, times of economic growth or low volatility periods do not match a system-wide connectedness decrease. Furthermore, the cyclical component seems to be strong and not directly (or at least perfectly) related to economic cycles. This anyway does not weaken the power of the derived connectedness measures for risk management purposes.

At the end, not only a clear dynamic of connectedness has been observed, but also an important structural change that followed the sovereign debt crisis has been defined. It is evident how this recent crisis has reflected in a different manner on corporate and short-term government bonds, with the former suffering an enormous connectedness change in a very little time compared to the latter. This different reaction must not be evaluated only on a magnitude level, but also, and primarily, on a structural one. In fact, the occurrences of the 2010-2012 crisis led to a relative swap in interrelation, making the corporate bonds system to become more interconnected than the 2-year government one. Surely the debt component of the crisis had something to do with this phenomenon, as well as the centrality of European countries (despite the global repercussions).

As already pointed out, since the crisis arose from sovereign debt instruments, it is likely that a structural change has occurred for the government system rather than for the corporate one, that as already shown, usually suffers quicker and bigger changes in connectedness during crises.

As remarked in the previous section (*6.2*) there seems to be an inverse relationship between total connectedness level and strength of net pairwise relations, so, even if the short-term system became relatively less interrelated than the corporate one, its granular links could have been defined with a neater structure. This latter is a direct consequence of the crisis. Exceptional country defaults in the modern era were already part of market operators' background in 2010 (e.g. Argentina), and the sudden realization of a similar scenario in Europe, amplified by a domino effect, probably broke short-term government bonds connectedness structure, making it to converge to the corporate one, instead than to the long-term framework. Even the resilience of short-term government securities on small events seems to have been broken. In fact, the change in level in comparison to the corporate network brought also more volatility in the interrelation measure of the 2-years government system.

Despite the thesis of a structural change in the short-term government network is easily addressable, it is likely that an important structural commutation occurred also for the corporate system. Not only operations of European financial institutions heavily depend on the union countries' economic health, but also balance sheets of these kinds of firms are strongly bonded to sovereign debt. In fact, historically, major European countries have the greatest portion of their debts, owned by domestic banks, citizens, and other union banks and institutions (situation exponentially intensified after the QE program). Given this, a clear explanation for a structural change in the corporate system could be that the total connectedness "portion" sourced by balance sheets codependencies among governments and banks in Europe, drastically augmented.

Independently from these structural changes' sources and dynamics, such an event as a permanent commutation in the total interrelation level between two financial systems would surely have to trigger risk management practices and economic policies adjustments and considerations.

Finally, also on the polarization side, strong evidence has been produced. The European financial system shows in fact a polarized framework even on an unconditional level, with some institutions having the role of main influencers with respect to others that suffer connectedness spread from few institutions. Among the formers, UniCredit Bank and Deutsche Bank showed a constant central role, while solid institutions as ABN Amro, Rabobank and Nordea Bank mainly received connectedness spread from them and in an overall manner. This structure has been observed as dynamically changing over time, with institutions swapping roles depending on their relative structure according to time periods. Furthermore, events of historical importance seen those frameworks' structures to increase in definitions, with more polarization and some actors as strong protagonists of financial dynamics and shocks repercussions. Specifically, UniCredit played an increasing central role during the times preceding the sovereign debt crisis with the strongest connections realized at the crisis peak. Deutsche Bank had the same role in the network during the pandemic-related economic crisis, but with a little less definition in its connectedness *to* others.

A very similar dynamic has been observed in the government networks, where Portugal and Ireland, similarly to UniCredit and Deutsche Bank, were constantly the main influencers in the system. Italy and Spain are indeed their main victims, but this framework suffered a swap during the Coronavirus-related crisis, where Italy took the role of main influencer in the early times.

The main drivers of these phenomena have been clearly addressed and consist in economic relevance (market capitalization or GDP production), and creditworthiness. Unexpectedly geographical components play a very marginal role in connectedness' structure definition, on a polarized conformation level. However, between the corporate and the government networks, there is an interesting difference in the functioning of these drivers. In fact, corporate institutions follow the rule of the small and fragile firm influencing the big and solid one. As opposed the government frameworks are characterized by an intermediate step, with the weakest and smallest countries directly influencing the intermediate ones (on a GDP and credit rating level). The latter are then connected in an overall manner to top institutions.

Further proof of this aspect is certainly given by the behaviour of Belgium – properly the median country in the system, in terms of driver's values – receiving strong connections from all the mentioned countries: Portugal, Ireland, Italy and

Spain, and then connected in an overall manner to all other actors, with important pairwise relations.

Appendix A. Quantitative insights

A.1 Generalised Impulse Response Function

Dynamic analysis of vector autoregressive (VAR) models is often carried out using the orthogonalized impulse responses. This approach implies that the underlying shocks to the VAR model are orthogonalized using the *Cholesky decomposition*, before computing impulse response function (IRF), or forecast error variance decompositions (FEVD). This methodology is not, however, invariant to the ordering of the equations in the model. An alternative approach that does not has the above shortcoming, is the so called the Generalized Impulse Response Analysis (GIRF), proposed by Pesaran and Shin in 1997[25]. Those authors proposed a linear version of what just described, building on the non-linear multivariate framework, proposed by Koop et al. (1996)[26]. Anyway, since the applications shown in the current analysis are on linear models, just the framework of interest will be presented.

The first step to understand the generalized impulse measures is to consider the VAR(p) model presented in *Paragraph 4.1*, for simplicity reported without the constant term $\boldsymbol{\phi_0}$:

$$x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t \tag{A.1.1}$$

where given $\boldsymbol{m}$ as the number of time series for each sample, $\boldsymbol{x_t}$ is a m-dimensional multivariate time series, $\boldsymbol{\Phi}$ is a $\boldsymbol{m} \times \boldsymbol{m}$ matrix, and $\{\boldsymbol{\varepsilon_t}\}$ is a sequence of serially uncorrelated random vectors with zero mean and covariance matrix Σ .

The following standard assumptions have then to be made:

[25] Pesaran M.H. & Shin Y. (1997); "Generalized Impulse Response Analysis in Linear Multivariate Models"; Economics Letters.

[26] Koop G., Pesaran M.H. & Potter S.M. (1996); "Impulse response analysis in nonlinear multivariate models"; Journal of Econometrics.

i. $E(\varepsilon_t) = 0$, $E(\varepsilon_t \varepsilon_t') = \Sigma$ for all t, where $\Sigma = \{\sigma_{ij}, i, j = 1,2, \dots, m\}$ is an $m \times m$ positive definite matrix, $E(\varepsilon_t \varepsilon_t') = 0$ for all $t = t'$.

ii. All the roots of $|\sum_{i=1}^{p} \Phi_i z^i| = 0$ fall outside the unit circle.

iii. $x_{t-1}, x_{t-2}, \dots x_{t-p}$, t =1,2,...T, are not perfectly collinear.

Under assumption (i) and (ii), $\boldsymbol{x_t}$ would be covariance-stationary, and rewritable in the infinite Moving Average (MA) representation already exposed:

$$x_t = \sum_{i=0}^{\infty} \mathrm{A}_i \, \varepsilon_{t-i} \tag{A.1.2}$$

Where the $\boldsymbol{m} \times \boldsymbol{m}$ coefficients matrices $\mathbf{A}_{\boldsymbol{i}}$ obey to the recursion:

$$\mathrm{A}_i = \sum_{j=1}^{p} \Phi_j \mathrm{A}_{i-j} \tag{A.1.3}$$

Whit $\mathbf{A_0}$ a $\boldsymbol{m} \times \boldsymbol{m}$ identity matrix and $\mathbf{A}_{\boldsymbol{i}} = 0$ for $\boldsymbol{i} < 0$.

It can be now defined an *impulse response function*, as a function measuring the time profile of the effect of shocks at a given point in time on the expected future values of variables in a dynamical system. The best way to describe an impulse response is to view it as the outcome of a conceptual experiment in which the time profile of the effect of an $\boldsymbol{m} \times \mathbf{1}$ vector of shocks of size $\boldsymbol{\delta} = (\delta_1, \delta_2, \dots \delta_m)'$, that hit the economy at time t, is compared with a base-line profile at time $t + n$, given the economy's history.

There are three main issues:

i. the types of shocks hitting the economy at time $\boldsymbol{t}$;

ii. the state of the economy at time $\boldsymbol{t-1}$ before being shocked;

iii. the types of shocks expected to hit the economy from $\boldsymbol{t+1}$ to $\boldsymbol{t+n}$.

Denoting the known history of the economy up to time $\boldsymbol{t-1}$ by the non-decreasing information set $\boldsymbol{\Omega_{t-1}}$, the generalized impulse response function of $\boldsymbol{x_t}$ at horizon $\boldsymbol{n}$, advanced in Koop et al. (1996), is defined by:

$$\mathrm{GI}_x(n,\delta,\Omega_{t-1}) = E(x_{t+n}|\varepsilon_t=\delta,\Omega_{t-1}) - E(x_{t+n}|\Omega_{t-1}) \tag{A.1.4}$$

Using (*A.1.4*) in (*A.1.2*) then $\mathbf{GI}_{\boldsymbol{x}}(\boldsymbol{n},\boldsymbol{\delta},\Omega_{\boldsymbol{t-1}}) = \mathbf{A}_{\boldsymbol{n}}\boldsymbol{\delta}$, wich is independent respect to $\boldsymbol{\Omega_{t-1}}$, but depends on the value of shocks defined by $\boldsymbol{\delta}$.

The appropriate choice of the shocks vector $\boldsymbol{\delta}$, is central to the properties of the impulse response function. The traditional approach, depending to the ordering of the variables, is to resolve the problem surrounding the choice of $\boldsymbol{\delta}$ by using the *Cholesky decomposition* of Σ:

$$\boldsymbol{PP'} = \Sigma \tag{A.1.5}$$

Where $\mathbf{P}$ is an $\boldsymbol{m}$ x $\boldsymbol{m}$ lower triangular matrix.

Then (*A.1.2*) can now be rewritten as:

$$x_t = \sum_{i=0}^{\infty}(A_iP)(P^{-1}\,\varepsilon_{t-i}) = \sum_{i=0}^{\infty}(A_iP)\boldsymbol{\xi}_{t-i}\ , t = 1,2,\ldots T \tag{A.1.6}$$

Such that $\boldsymbol{\xi_t} = \boldsymbol{P^{-1}\varepsilon_t}$ are the orthogonalized errors, i.e. $\boldsymbol{E}(\boldsymbol{\xi_t\xi_t}') = \Sigma_\xi = \boldsymbol{I_m}$.

Hence the $\boldsymbol{m}$ x $\mathbf{1}$ vector of orthogonalized IRF of a *unit* shock to the $\boldsymbol{j}$-th equation on $\boldsymbol{x_{t+n}}$ is given by:

$$\psi_j^0(n) = \mathrm{A}_nPe_j\ , n = 0,1,2,\ldots \tag{A.1.7}$$

Where $\boldsymbol{e_j}$ is an $\boldsymbol{m}$ x $\mathbf{1}$ selection vector with unity as its $\boldsymbol{j}$-th element and zeros elsewhere.

An alternative approach would be to use (*A.1.4*) directly, but instead of shocking all the elements of $\boldsymbol{\varepsilon_t}$ we could choose to shock only one element, say its j-th element, and integrate out the effects of other shocks using an assumed (or the historically observed) distribution of the errors. Following this path we would have:

$$\mathrm{GI}_x(n, \delta_j, \Omega_{t-1}) = E(x_{t+n}|\varepsilon_{jt} = \delta_j, \Omega_{t-1}) - E(x_{t+n}|\Omega_{t-1}) \qquad \text{(A.1.8)}$$

Assuming then, that $\boldsymbol{\varepsilon_t}$ has a multivariate normal distribution, it can be proved that:

$$E(\varepsilon_t|\varepsilon_{jt} = \delta_j) = (\sigma_{1j}, \sigma_{2j}, \dots, \sigma_{mj})'\sigma_{jj}{}^{-1}\delta_j = \Sigma e_j \sigma_{jj}{}^{-1}\delta_j \qquad \text{(A.1.9)}$$

Hence the $\boldsymbol{m} \times \mathbf{1}$ vector of the unscaled generalized impulse response of the repercussion of a shock in the j-th equation at time $\boldsymbol{t}$ on $\boldsymbol{x_{t+n}}$ is given by:

$$\left(\frac{\mathrm{A}_n \Sigma e_j}{\sqrt{\boldsymbol{\sigma_{jj}}}}\right)\left(\frac{\delta_j}{\sqrt{\boldsymbol{\sigma_{jj}}}}\right), n = 0,1,2,\dots \qquad \text{(A.1.10)}$$

By finally setting $\delta_j = \sqrt{\boldsymbol{\sigma_{jj}}}$ we obtain the scaled generalized impulse response function, reported below:

$$\psi_j^G(n) = \sigma_{jj}{}^{-1/2}\, \mathrm{A}_n \Sigma e_j\, , n = 0,1,2,\dots \qquad \text{(A.1.11)}$$

which measures the effect of one standard error shock to the j-th equation at time $\boldsymbol{t}$ on expected values of $\boldsymbol{x}$ at time $\boldsymbol{t+n}$.

A.2 Generalised Forecast Error Variance Decomposition

The GIRF in *(A.1.11)* can now be used in the derivation of the forecast error variance decomposition, defined as the proportion of the H-step ahead forecast error variance of variable $\boldsymbol{j}$ which is accounted for by the innovations in variable $\boldsymbol{m}$ in the VAR(p) model.

Recalling (*A.1.6*) with orthogonal white noise innovations, and replacing $\boldsymbol{A_i P}$ with $\boldsymbol{\Theta_i}$ for sake of notation simplicity, we have:

$$x_t = \sum_{i=0}^{\infty} \theta_i \xi_{t-i} \tag{A.2.1}$$

Where $\boldsymbol{\xi_t} = \boldsymbol{P^{-1}\varepsilon_t}$ are the orthogonalized errors, i.e. $\boldsymbol{E(\xi_t \xi_t')} = \Sigma_\xi = \boldsymbol{I_m}$. Given *(A.2.1)* the error of the optimal H-step forecast is:

$$x_{t+H} - x_t(H) = \sum_{i=0}^{H-1} \theta_i \xi_{t+H-i} \tag{A.2.2}$$

Then denoting the mn-th element of $\boldsymbol{\Theta_i}$ by $\boldsymbol{\theta_{mn,i}}$, the H-step ahead forecast error of the j-th component of $\boldsymbol{x_t}$ is:

$$x_{j,t+H} - x_{j,t}(H) = \sum_{i=0}^{H-1} (\theta_{j1,i}, \xi_{1,t+H-i} + \cdots + \theta_{jM,i}\, \xi_{M,t+H-i}) \tag{A.2.3}$$

That is also:

$$x_{j,t+H} - x_{j,t}(H) = \sum_{m=1}^{M} (\theta_{jm,0}, \xi_{m,t+H} + \cdots + \theta_{jm,h-1}\, \xi_{m,t+1}) \tag{A.2.4}$$

Thus, the forecast error of the j-th component potentially consists of all the innovations $\boldsymbol{\xi_{1t}, \ldots \xi_{Mt}}$. Since the $\boldsymbol{\theta_{mn,i}}$ are orthogonalized and have unit variances, the mean square error (MSE) of $\boldsymbol{x_{j,t}(H)}$ is:

$$E(x_{j,t+H} - x_{j,t}(H))^2 = \sum_{m=1}^{M} (\theta^2{}_{jm,0} + \cdots + \theta^2{}_{jm,h-1}) \tag{A.2.5}$$

and so:

$$\theta^2{}_{jm,0} + \cdots + \theta^2{}_{jm,h-1} = \sum_{i=0}^{h-1} (e_j' \Theta_i e_m)^2 \tag{A.2.6}$$

could be interpreted as the contribution of innovations in variable $\boldsymbol{m}$ to the forecast error variance or MSE of the *h*-step forecast of variable $\boldsymbol{j}$. Here $\boldsymbol{e_m}$ is the *m*-th column of $\boldsymbol{I_m}$.

Finally, is easy to see that dividing *(A.2.6)* by (*A.2.5*), we obtain the proportion of the *H*-step forecast error variance of variable $\boldsymbol{j}$, accounted for by $\boldsymbol{\xi_{mt}}$ innovations, and if $\boldsymbol{\xi_{mt}}$ can be associated with variable $\boldsymbol{m}$, $\boldsymbol{\xi_{jm,h}}$ represents the proportion of the *H*-step forecast error variance accounted for by innovations in variable $\boldsymbol{m}$.

After some substitutions and with the use of a selection vector $\boldsymbol{e_j}$, it can be proved that the orthogonalized FEVD of variable $\boldsymbol{j}$ respect to variable $\boldsymbol{m}$ ($\boldsymbol{d_{jm}^{O\,H}}$ for sake of notation alignment) can be expressed as:

$$d_{jm}^{O\,H} = \frac{\sum_{h=0}^{H-1} (e_j' A_h P e_m)^2}{\sum_{h=0}^{H-1} (e_j' A_h \Sigma A_h{}' e_j)} \tag{A.2.7}$$

At the end, given the intuition of (*A.1.9-10*), we can express GFEVD ($\boldsymbol{d_{jm}^{G\,H}}$), that allowed for shock correlation, while simultaneously accounting for it (historically observed values and under normality assumptions), as:

$$d_{jm}^{gH} = \frac{\sigma_{mm}^{-1} \sum_{h=0}^{H-1} (e_j' A_h \Sigma e_m)^2}{\sum_{h=0}^{H-1} (e_j' A_h \Sigma A_h{}' e_j)} \tag{A.2.8}$$

Appendix B. Extra data

Below, in *Figure 43*[27], a granular legend of the *Figure 4* of *Paragraph 2.2* is presented. Each element constitue an asset category of the ECB consolidated balance sheet.

It follows the presentation of dynamic estimates of total pairwise connectedness for each firm and for each country of the three samples. Net total pairwise connectedness, obtained as the difference between connectedness spread *to* thers, and the one received *from* others, has been marked with a red line on the zero value.

Figure 43 - Legend for the ECB consolidated balance sheet graph (Figure 4 – Paragraph 2.2).

[27] Source: ECB

B.1 Dynamic pairwise connectedness

B.1.1 Corporate bonds

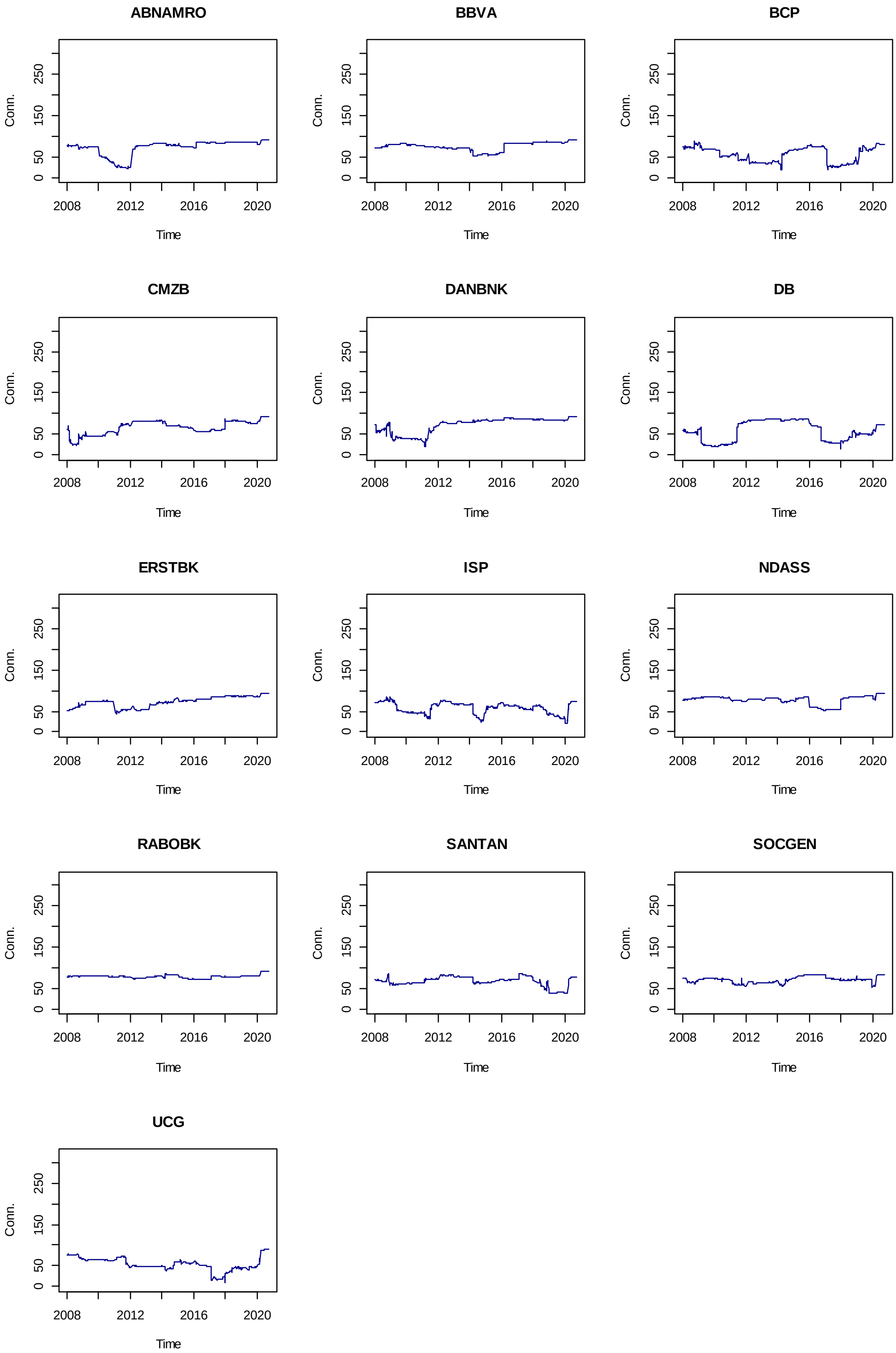


Figure 44 – Rolling total directional connectedness from others.

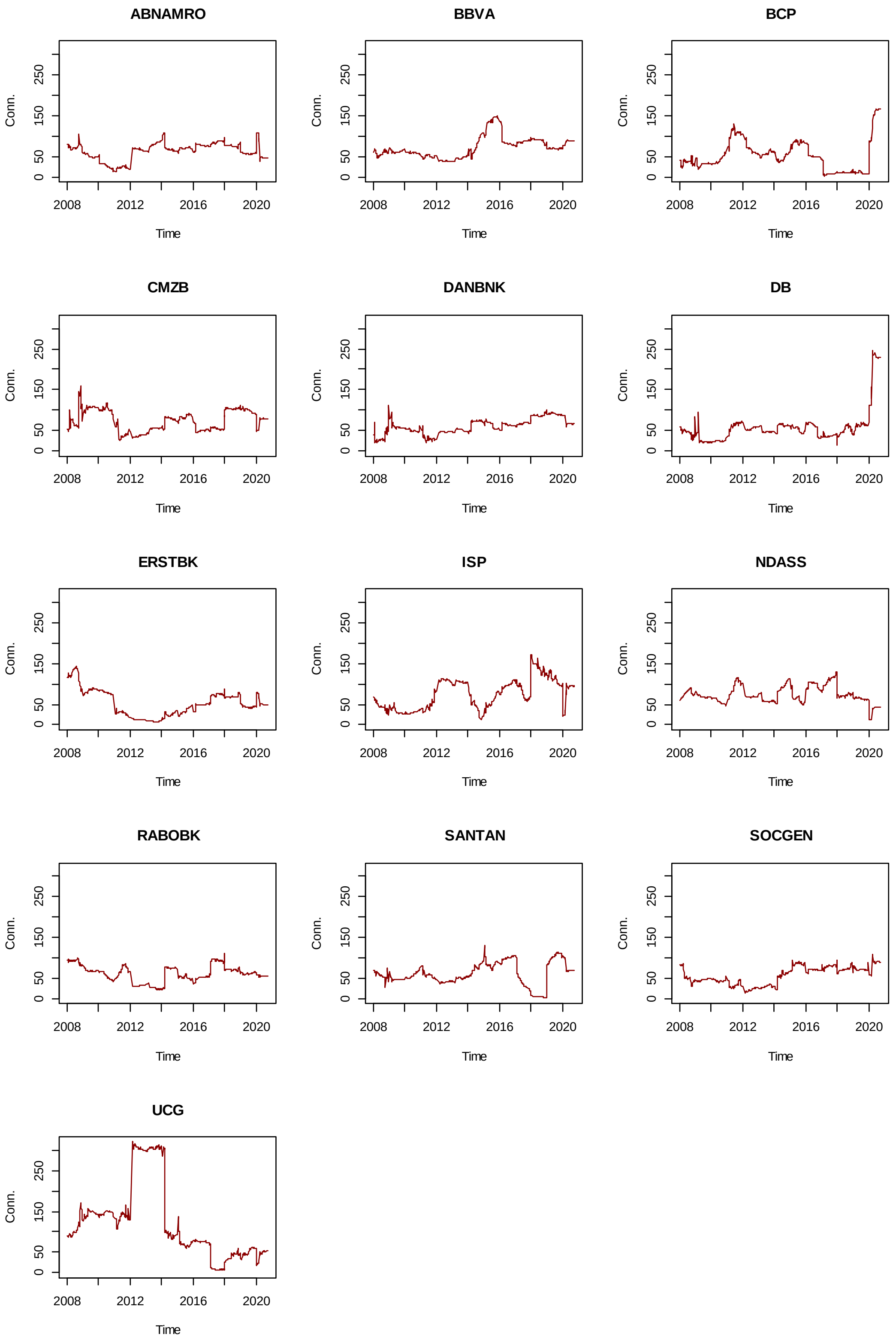


Figure 45 – Rolling total directional connectedness to others.

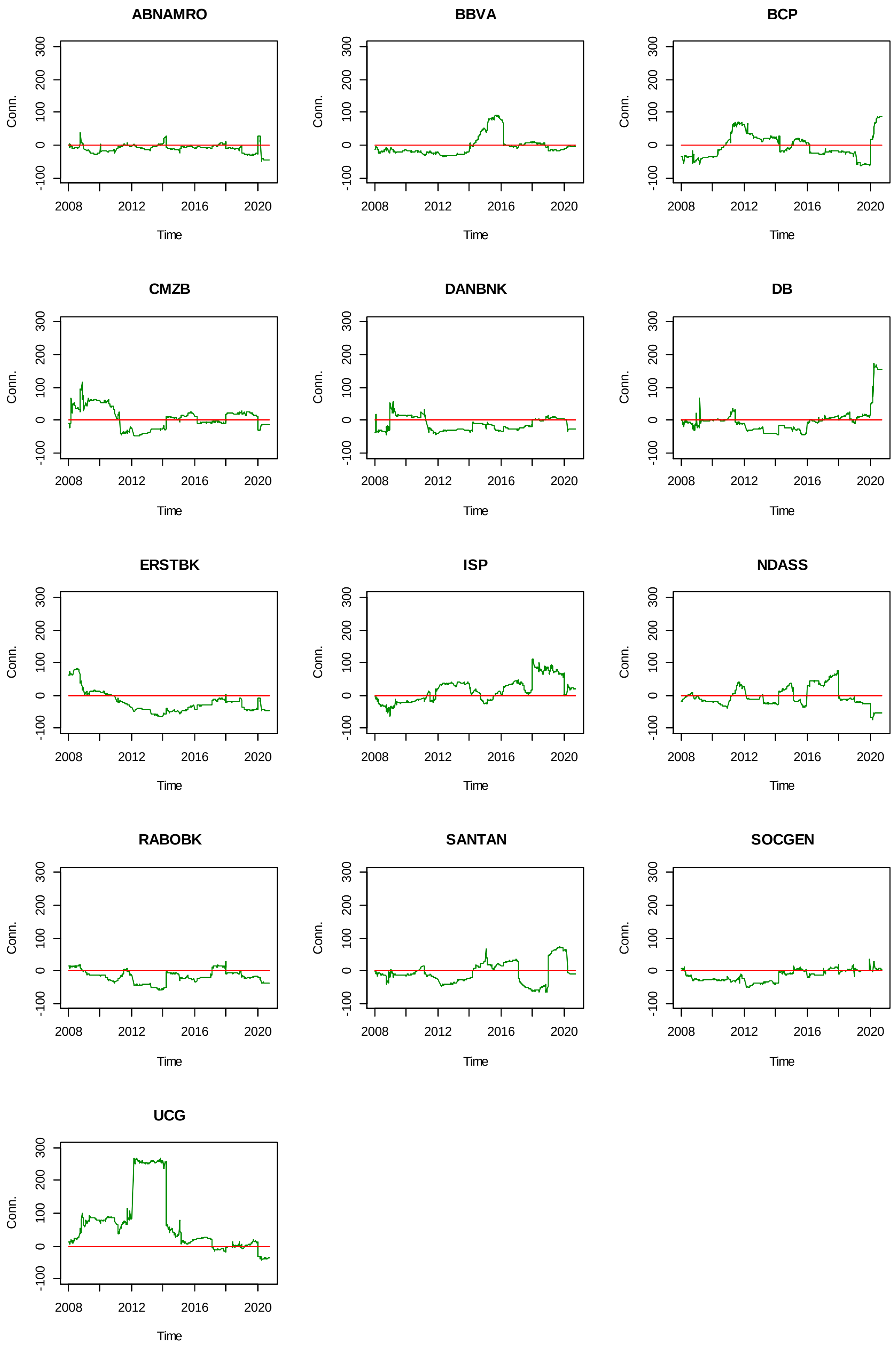


Figure 46 – Rolling total net directional connectedness.

B.1.2 Two-year government bonds

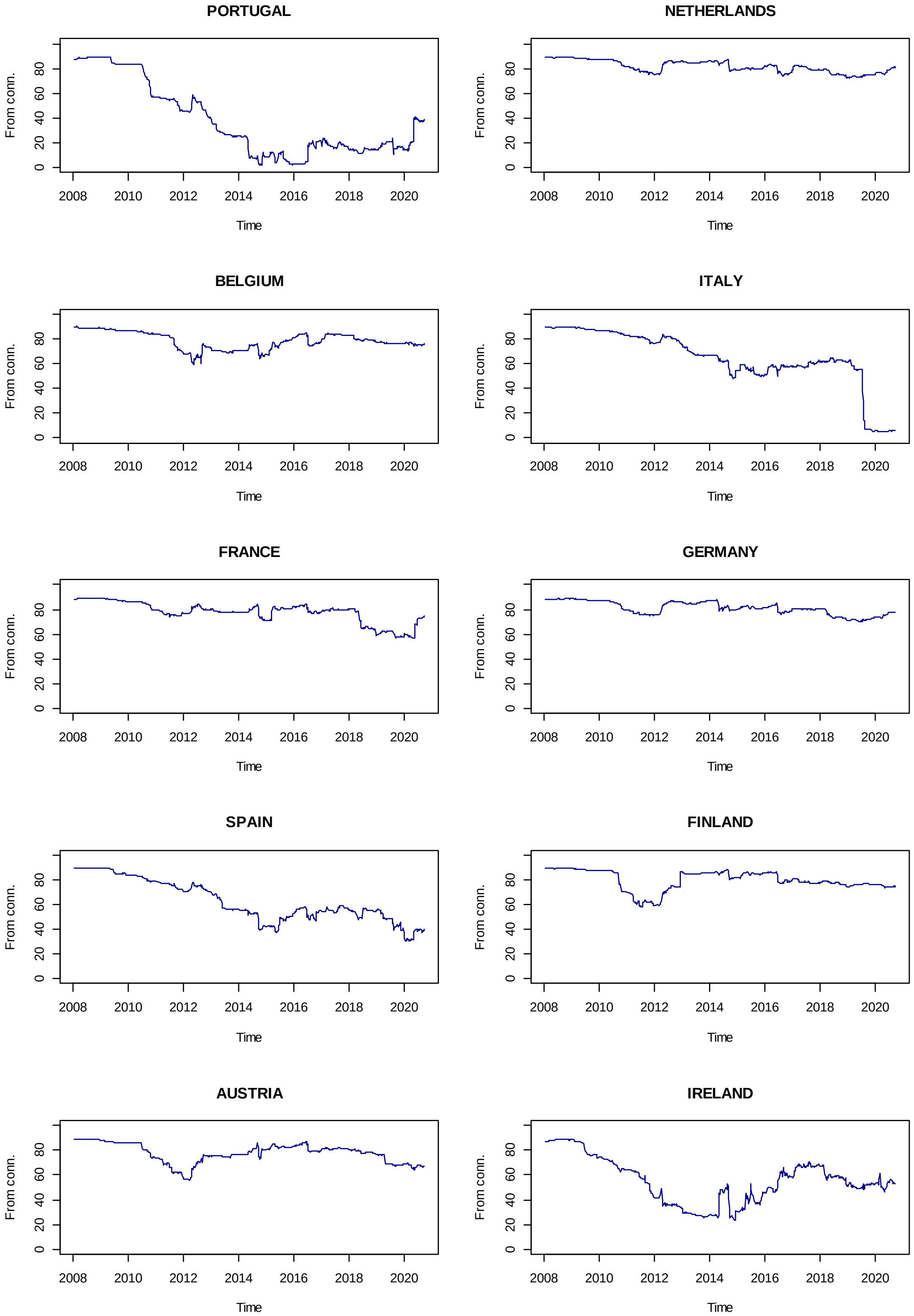


Figure 47 – Rolling total directional connectedness from others.

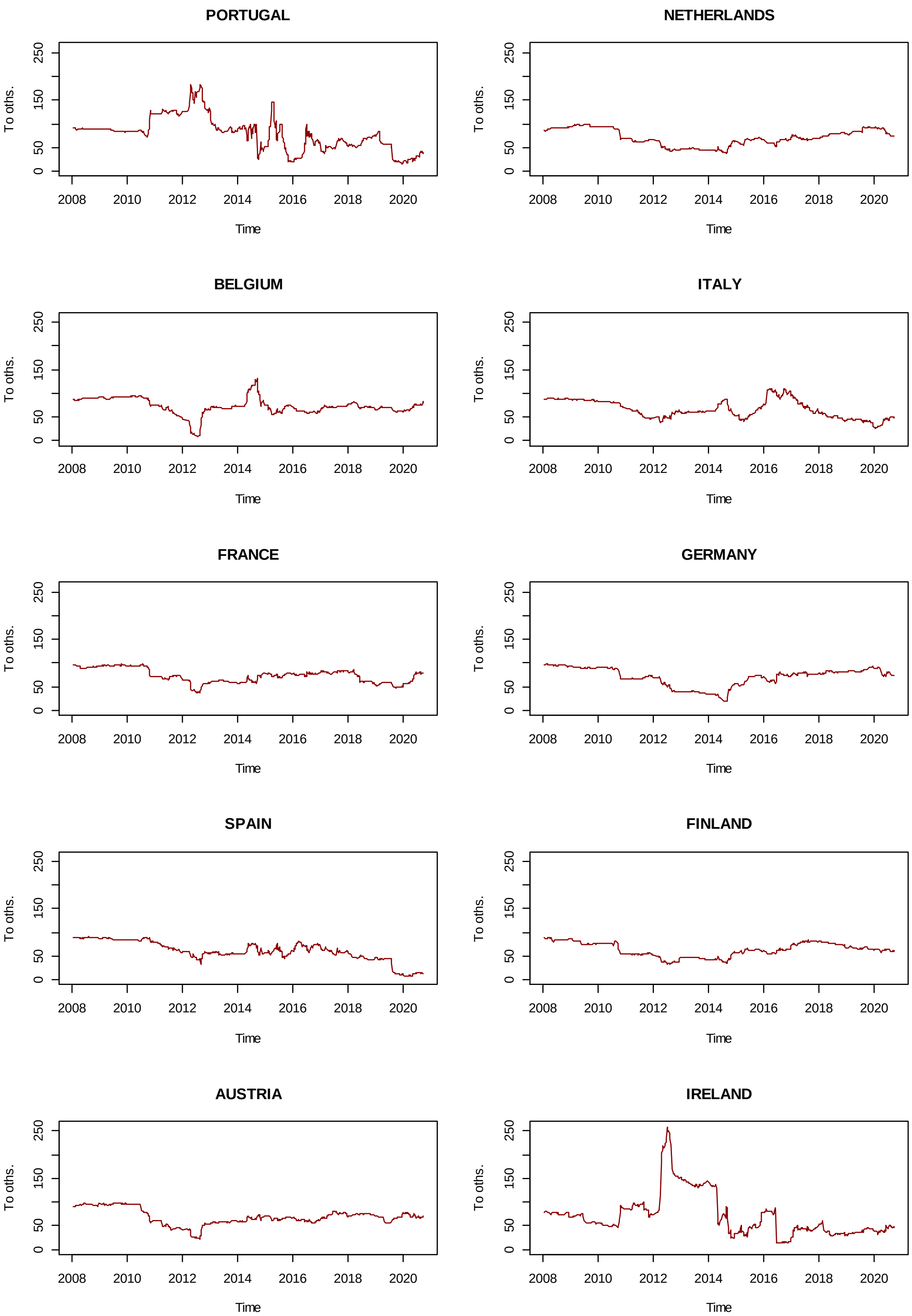


Figure 48 – Rolling total directional connectedness to others.

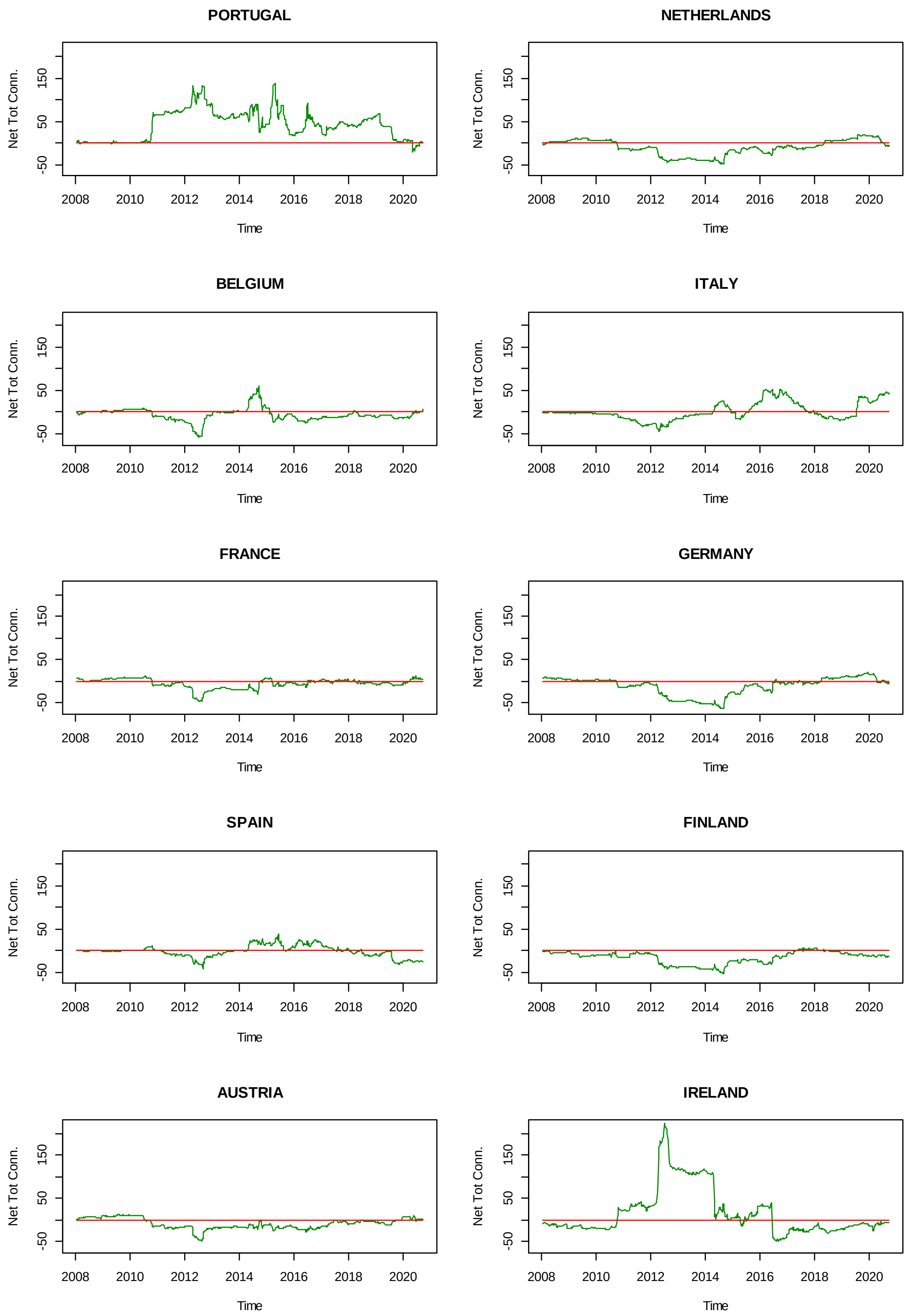


Figure 49 – Rolling total net directional connectedness.

B.1.3 Ten-year government bonds

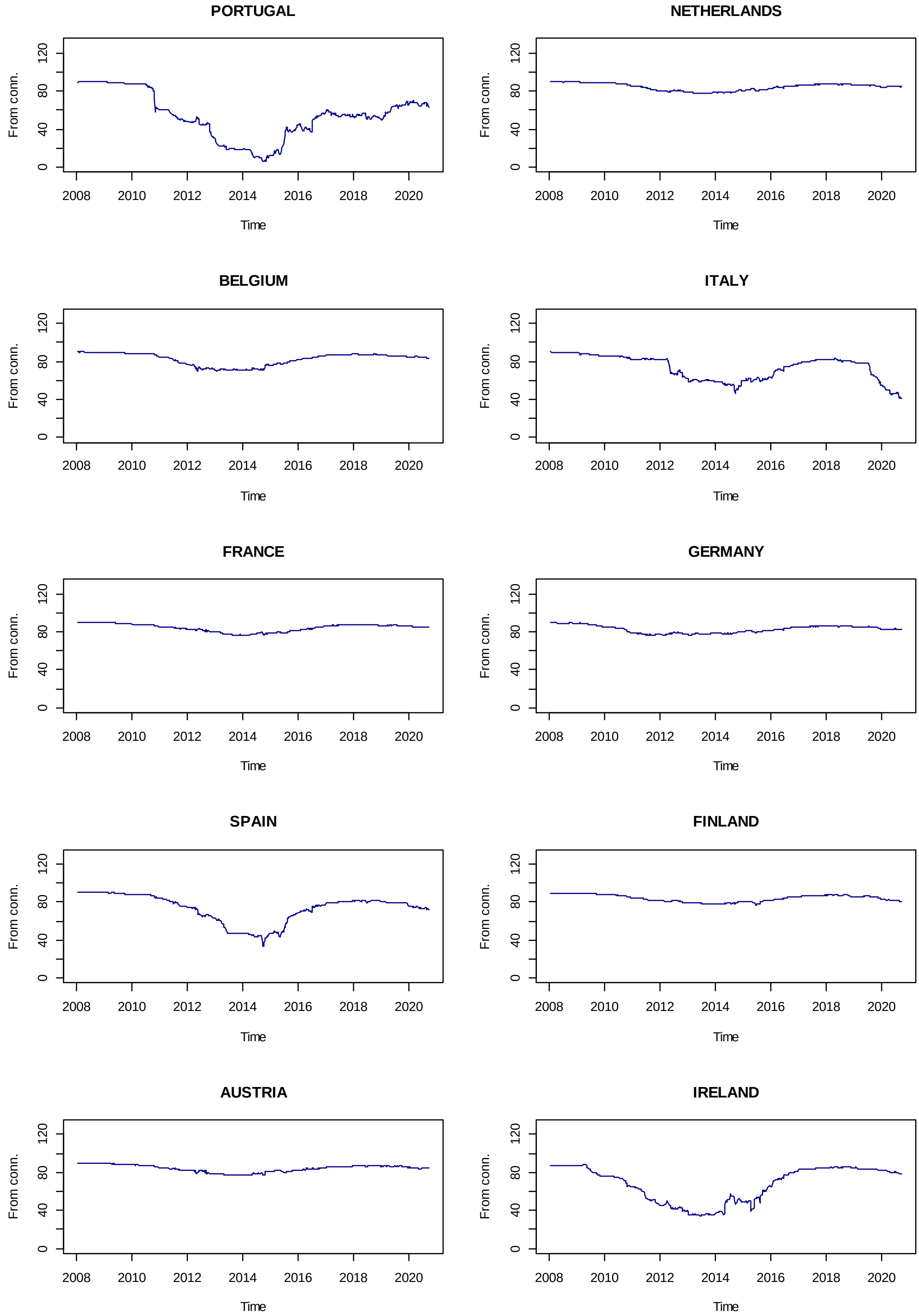


Figure 50 – Rolling total directional connectedness from others.

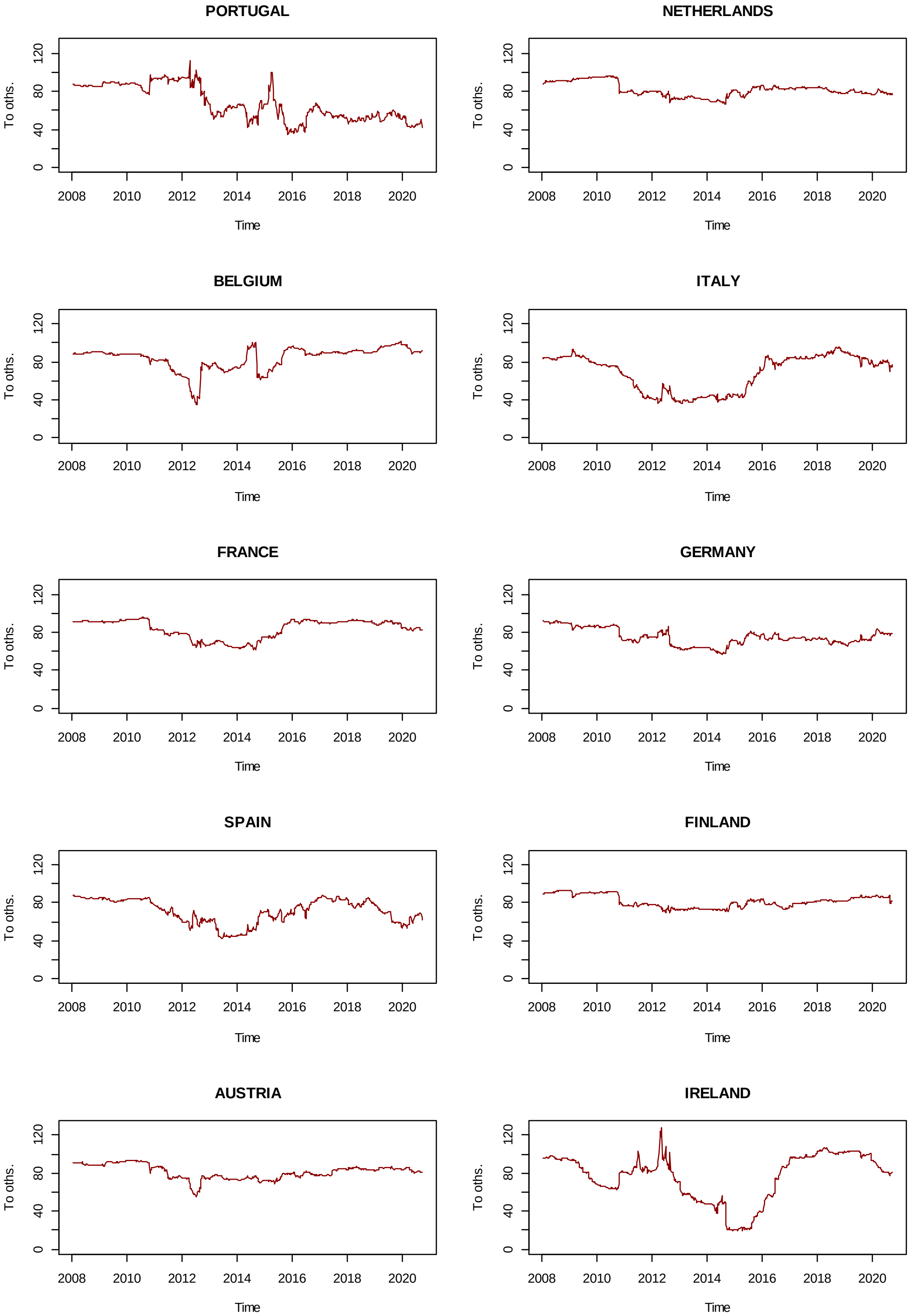


Figure 51 – Rolling total directional connectedness to others.

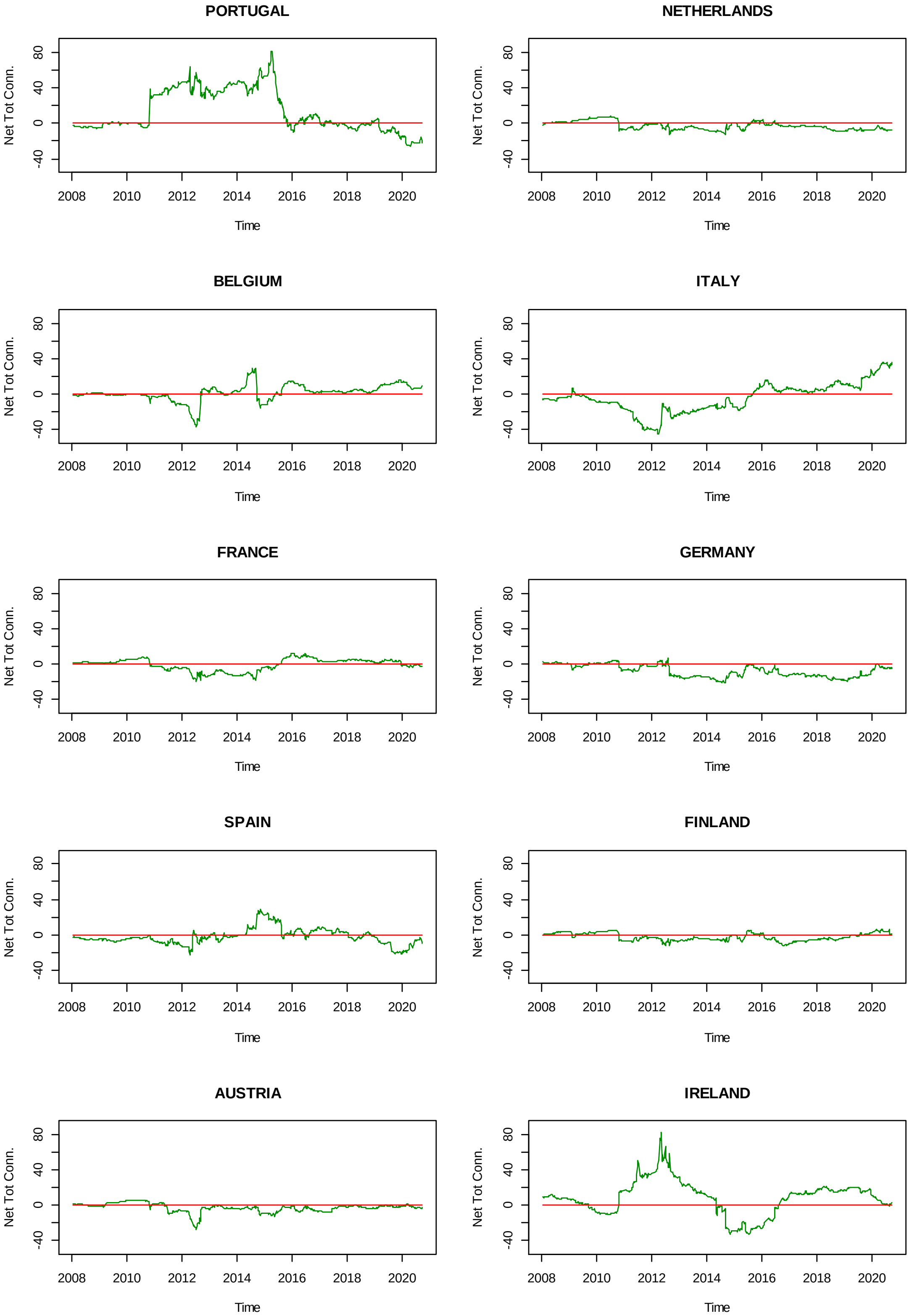


Figure 52 – Rolling total net directional connectedness.

B.2 Robustness assessment

Finally, this section concludes with a discussion of the robustness of the parameters chosen. I plotted the total connectedness for alternative values of the rolling window width w (in addition to $w = 100$ weeks, I considered sample windows of 95, 90, 105 and 110 weeks), and for alternative forecast horizons (in addition to $H = 2$ weeks, I considered 3 and 4 weeks). The results are presented in *Figure 53-62.*

All connectedness measures are more sensitive and varying when the window width is smaller and become smoother as the window width increases. Furthermore, rolling window width determine a lag in measures reactions. This is due to the dropping of data for the estimation that happens before with small windows, and later with large ones. Conversely, a shorter forecast horizon H implies much variation and sensitivity of the measures. However, path and levels of total connectedness measures are very close to the ones analysed in the thesis. To summarize, the dynamic behaviour of the overall interrelation measures is robust to the choice of alternative sample window lengths and forecast horizons.

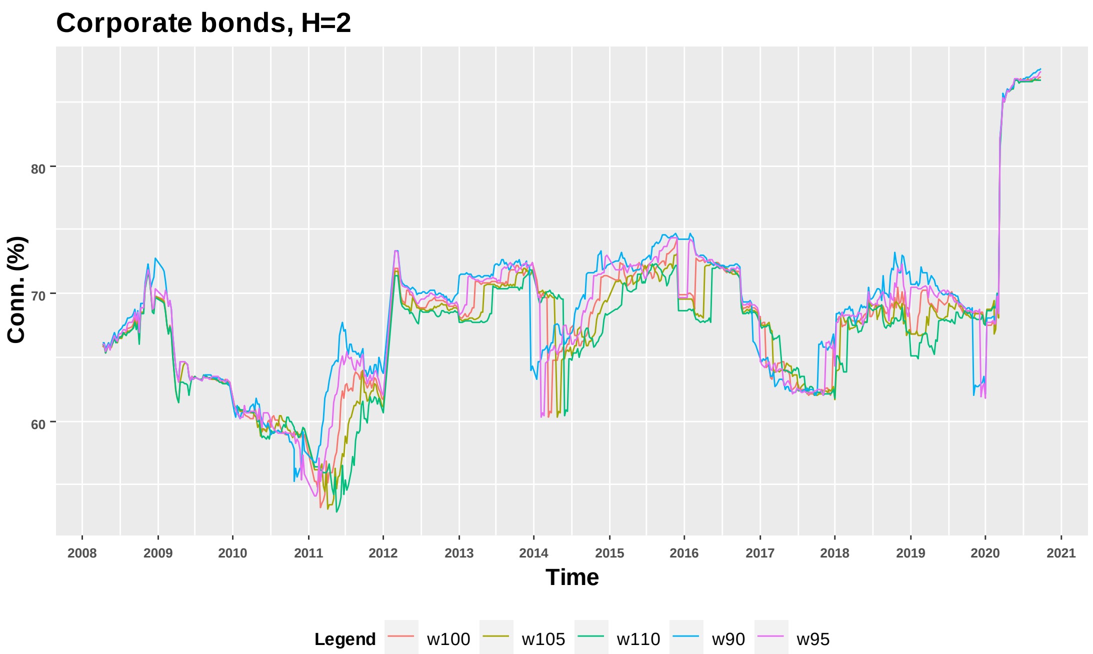


Figure 53 – Corporate Bonds robustness assessment.

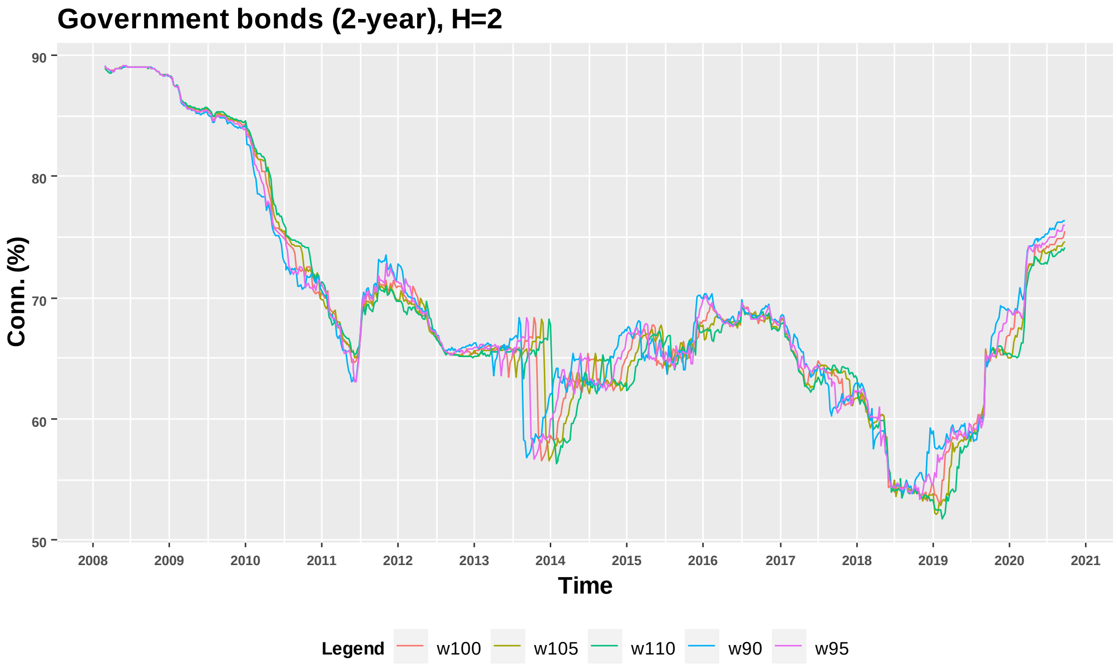


Figure 54 – 2-Years Government Bonds robustness assessment.

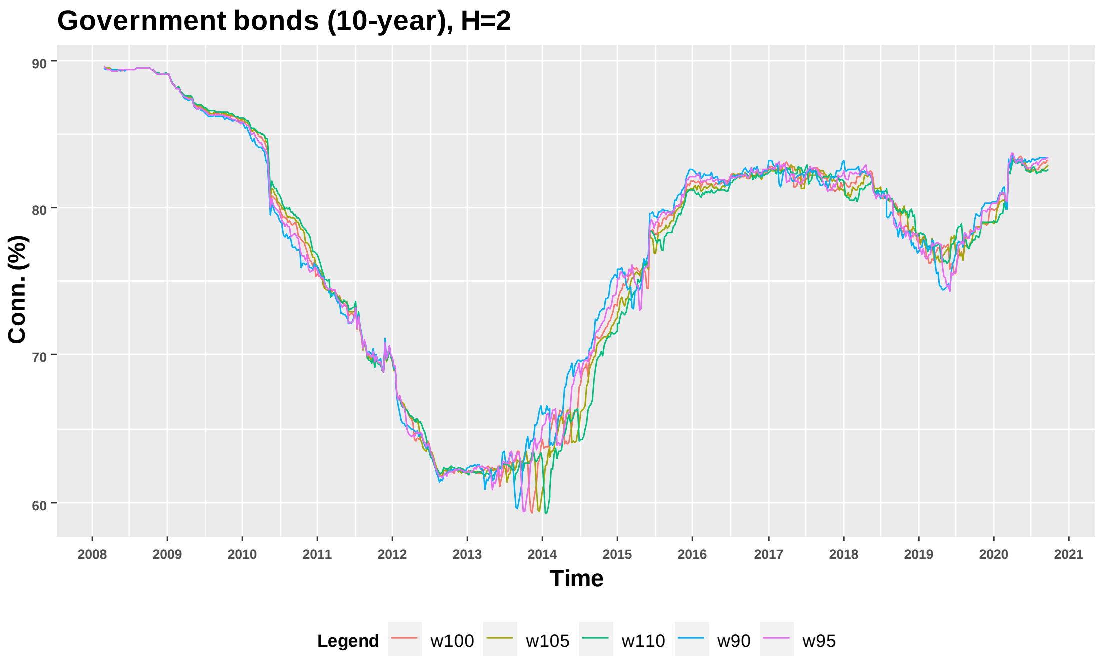


Figure 55 – 10-Years Government Bonds robustness assessment.

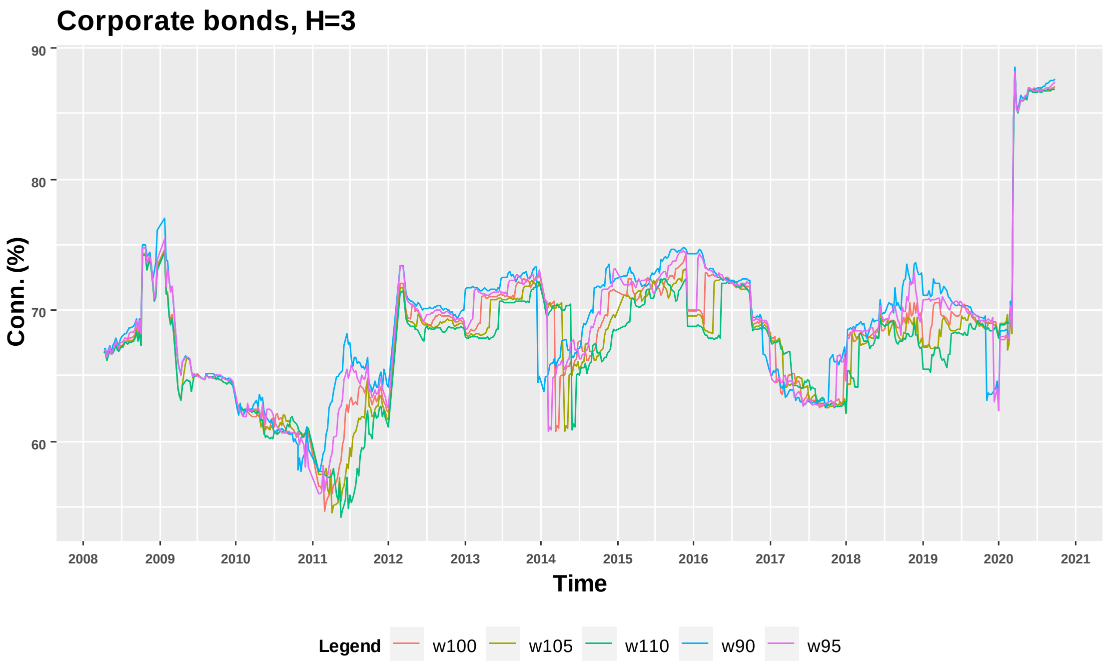


Figure 56 – Corporate Bonds robustness assessment.

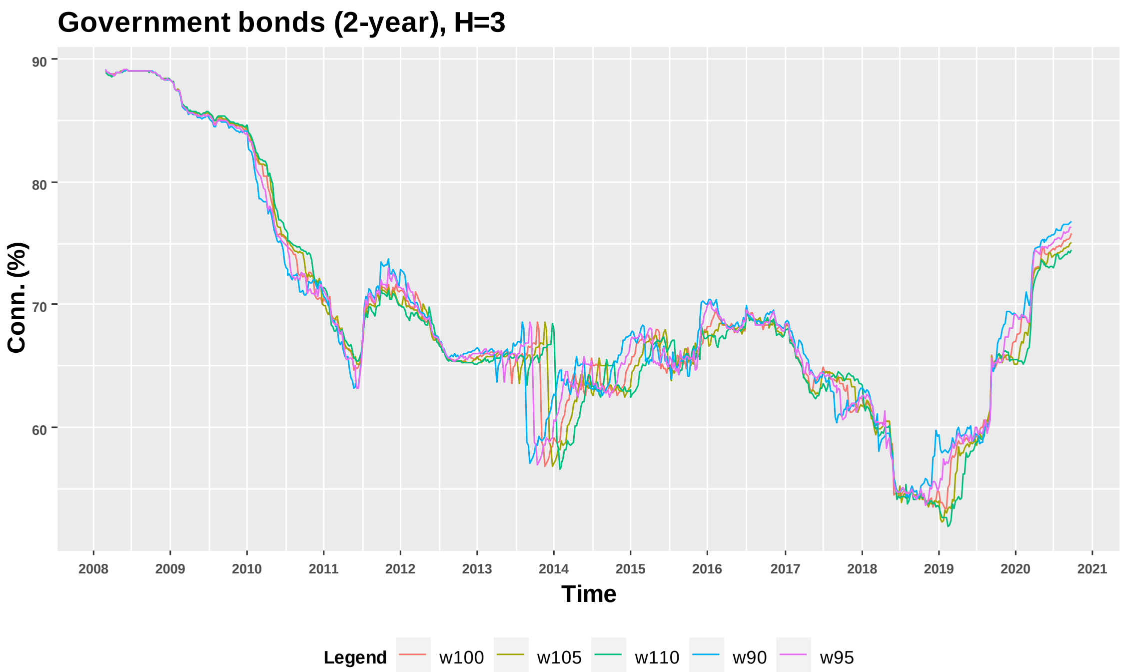


Figure 57 – 2-Years Government Bonds robustness assessment.

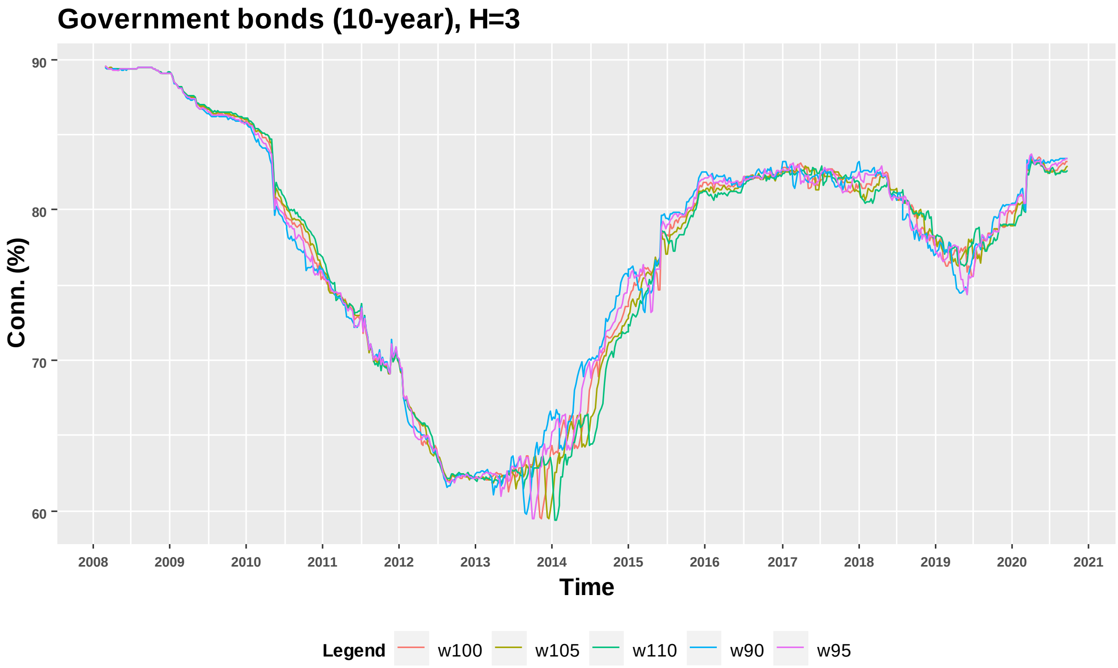


Figure 58 – 10-Years Government Bonds robustness assessment.

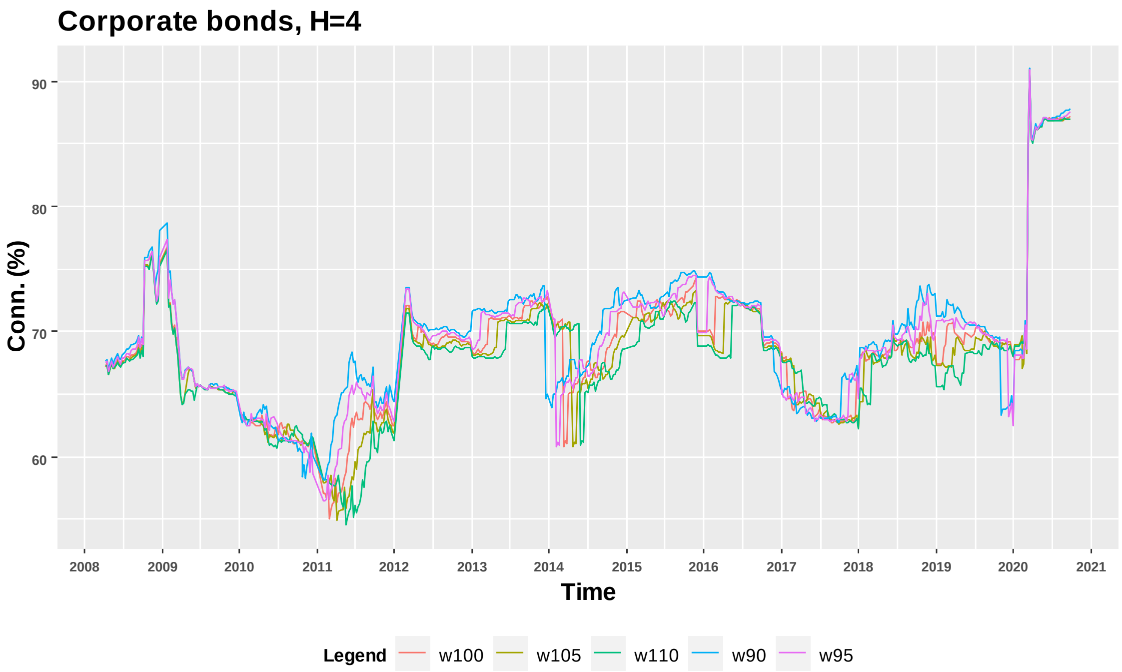


Figure 59 – Corporate Bonds robustness assessment.

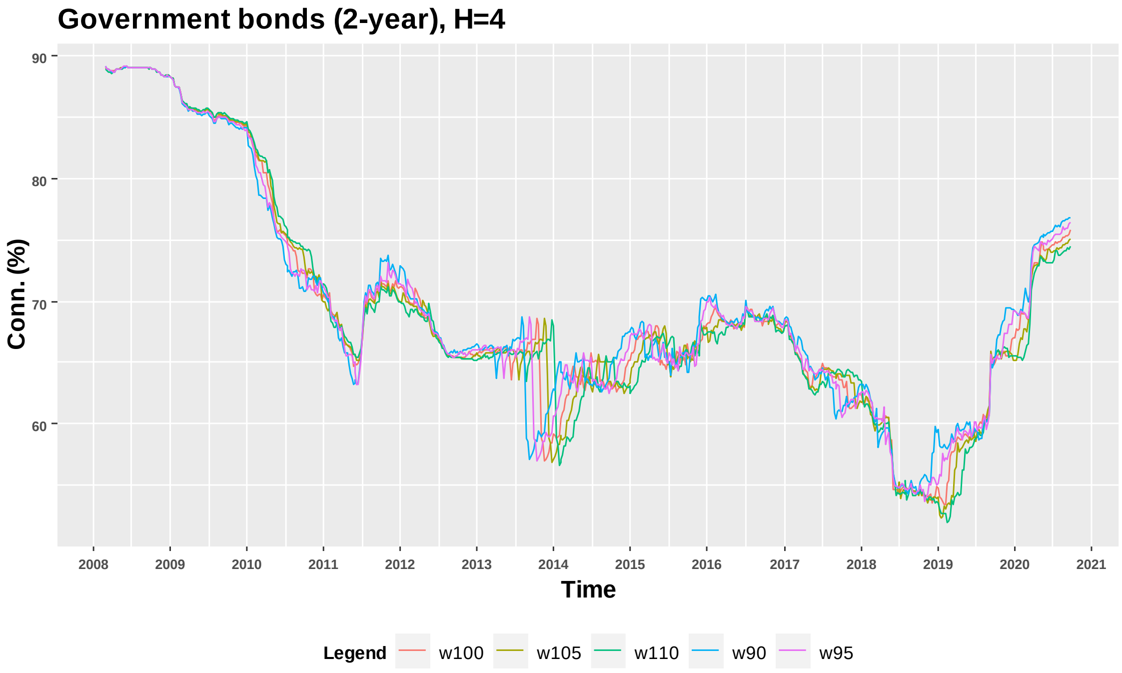


Figure 60 – 2-Years Government Bonds robustness assessment.

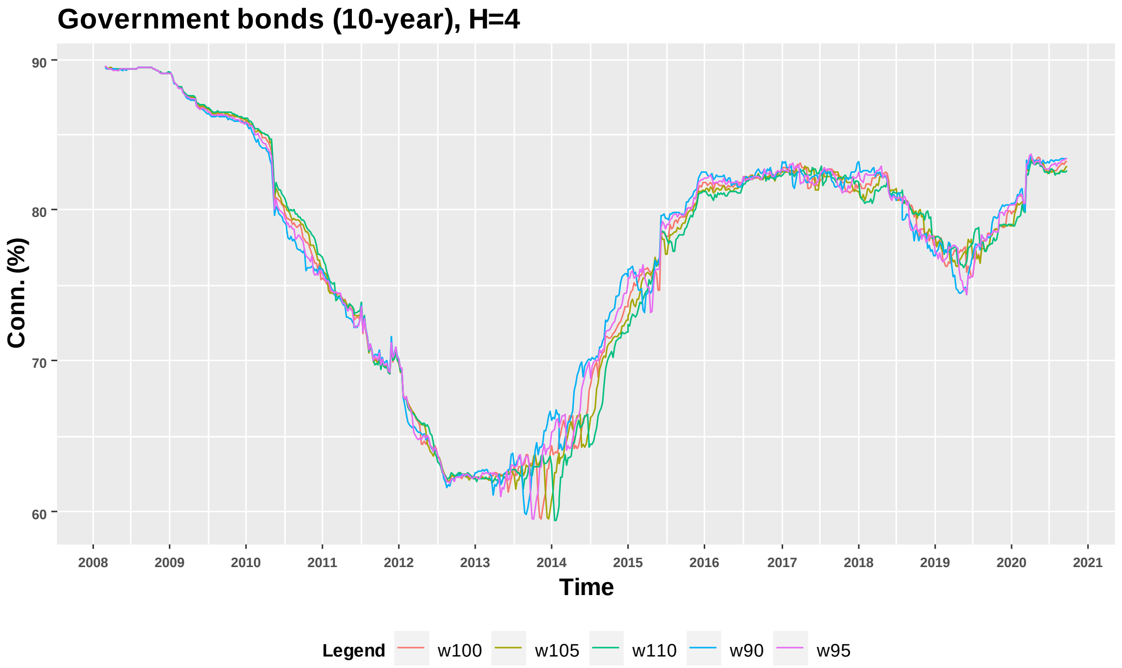


Figure 61 – 10-Years Government Bonds robustness assessment.

Appendix C. Code and Tools

This section presents the code written in the *R programming language* in order to handle the data and to make statistical computations (including data modelling and the production of descriptive statistics). Given the complexity of some graphical representations, also parts of the code developed with pure graphical purposes will be shown.
Despite the multitude of *scripts* (or *R-type* files) iteratively or subsequently executed by the software interpreter for the results production, four main categories of the overall code can be identified:

i. dataset construction and data handling;
ii. *ad hoc* created functions;
iii. data modelling and statistical computations;
iv. graphic representations.

The current *Appendix* is so structured in order to separately present each category-related part of the overall code.
Before this presentation it is reported a list of open-source standardized functional *R-libraries*, which functionalities have been used to perform from (i) to (iv), in addition to the functions created by me for this thesis's specific applications:

- `BigVAR`
- `dplyr`
- `ExPosition`
- `GGally`
- `ggplot2`
- `network`
- `readxl`
- `rlist`
- `sna`

- stats
- tidyr
- tseries
- vars

C.1 Dataset construction and data handling

The following code has been produced in order to concatenate the times series of bond yields, taking the time-related values corresponding to the tenor aimed to be analysed. It is an automatization whose function it is only to avoid a manual composition of each times series, reducing operational risks and reducing time of large dataset evaluations. It does so, by reading all the files in a directory and discriminating them by the name (that has to contain the Ticker and the time gap-related to yields). It produces it the end a singular file containing the time series of bond yields of a single institution through time, a plot of the time series, and a prospect on eventually missing values.

```
output = '.csv' #File name to be printed in output
temp = list.files(pattern = "*.csv")
#Creation of the first Dataframe to which concatenate the others
#via the subsequent FOR LOOP
data = read.csv(temp[length(temp)])
names(data) = c('date', 'YTM')
data = data[9:nrow(data), 1:2]
data[, 2] = as.double(data[, 2])
names(data) = c('date', temp[length(temp)])
rownames(data) <- NULL
data[, 1] = as.character(as.Date(data[, 1], format = '%m/%d/%Y'))

ref.d = toString(colnames(data)[2])[1]
ref.d = toString(strsplit(ref.d, '.csv'))
ref.d = (substr(ref.d, (nchar(ref.d) - 4), nchar(ref.d) - 3))
stop = 0
for (u in 1:nrow(data)) {
  check.d = substr(as.character(data[u, 1]), 3, 4)
  if (check.d < ref.d) {
    stop = u - 1
    break()
  }
}
data = data[1:stop, ]

#Mentioned FOR LOOP
for (i in (length(temp) - 1):1) {
  df = read.csv(temp[i])
  df = df[9:nrow(df), 1:2]
  df[, 2] = as.double(df[, 2])
  names(df) = c('date', temp[i])
  rownames(df) <- NULL
  df[, 1] = as.character(as.Date(df[, 1], format = '%m/%d/%Y'))
```

```
  #Setting reference indexes for concatenating the period of competence
  ref.d = toString(colnames(df)[2])[1]
  ref.d = toString(strsplit(ref.d, '.csv'))
  ref.d = (substr(ref.d, (nchar(ref.d) - 1), nchar(ref.d)))
  ref.s = toString(colnames(df)[2])[1]
  ref.s = toString(strsplit(ref.s, '.csv'))
  ref.s = (substr(ref.s, (nchar(ref.s) - 4), nchar(ref.s) - 3))
  stop = 0
  start = 0

  #Logical driven concatenation
  for (u in 1:nrow(df)) {
    check.d = substr(as.character(df[u, 1]), 3, 4)
    if (check.d == ref.d) {
      stop = u
      break()
    }
  }
  for (v in 1:nrow(df)) {
    check.d = substr(as.character(df[v, 1]), 3, 4)
    if (check.d < ref.s) {
      start = v - 1
      break()
    }
  }
  if (start == 0) {
    start = nrow(df)
  }
  df = df[stop:start, ] #because the order of data is inverse (in time)
  rownames(df) <- NULL
  colnames(df) = colnames(data)
  data = rbind(data, df)
  rownames(data) <- NULL
}
data = apply(data, 2, rev)
rownames(data) <- NULL
missing.obs = matrix(0, nrow = 15, ncol = 1)
miss.obs = matrix(0, nrow = 15, ncol = 1)
# Creating an index for missing observations of each year
missing.obs[, 1] = c('06',
                     '07',
                     '08',
                     '09',
                     '10',
                     '11',
                     '12',
                     '13',
                     '14',
                     '15',
                     '16',
                     '17',
                     '18',
                     '19',
                     '20')

for (p in 1:nrow(data)) {
  year = substr(as.character(data[p, 1]), 3, 4)
  for (t in 1:nrow(missing.obs)) {
    if (year == missing.obs[t, 1]) {
      miss.obs[t, 1] = miss.obs[t, 1] + 1
    }
  }
}
################## CHECK ON MISSING VALUES ###############################
data = as.data.frame(data[complete.cases(data), ])
data[, 1] = as.Date(data[, 1])
data[, 1] = as.Date(data[, 1], format = '%Y/%m/%d')
data[, 2] = as.double(data[, 2])
colnames(data) = c('date', 'Y')
setwd('C:/ ')
write.csv(data, file = output)
#Getting back an allert with details about missing observations
allert = cbind(missing.obs, miss.obs)
allert[which.min(allert[, 2]) , ]
```

The following code was developed in order to concatenate each time series previously created in a unique array for each sample. It also crates an additional array containing the first differences of the series, and some extra objects with aesthetics useful for graphic purposes (like dates and dimensions).

```
##################### CORPORATE BONDS ########################
#Setting working directory
setwd('C:/')
temp = list.files(pattern = "*.csv")
temp2 = strsplit(temp, ".csv")
temp2 = as.character(temp2)
#Creation of a first array to which concatenate all time series via FOR LOOP
data = read.csv(temp[1])
data = data[, 2:3]
names(data) = c('date', 'YTM')
data = data[8:nrow(data), 1:2]
data[, 2] = as.double(data[, 2])
names(data) = c('date', temp[1])
#Mentioned FOR LOOP
for (i in 2:length(temp)) {
  df = read.csv(temp[i])
  df = df[, 2:3]
  df = df[8:nrow(df), 1:2]
  df[, 2] = as.double(df[, 2])
  names(df) = c('date', temp[i])
  data = full_join(data, df, by = 'date')
}
data = data[complete.cases(data),]
dates = as.matrix(data$date)
rownames(data) = data$date
data2 = as.data.frame(data)
data2[, 1] = as.character(data2[, 1])
# Taking weekly observations (just the one occurred on Friday days)
day.rid = matrix(0, nrow = nrow(data), ncol = 1)
for (s in 1:nrow(data2)) {
  if (weekdays(as.Date(data2$date[s])) != "venerdì") {
    day.rid[s] = s
  }
}
day.rid = day.rid[day.rid != 0]
for (y in 1:length(day.rid)) {
  if (day.rid[y] != 0) {
    data2 = data2[-(day.rid[y]),]
    day.rid = day.rid - 1
  }
}

dates = as.matrix(as.character(as.Date(data2$date)))
data = as.matrix(data2[, 2:ncol(data)])
colnames(data) = temp2
cut = nrow(data)

################# GOVERNMENT BONDS - 2Y ####################
datagov = read_excel("2y.xlsx")
datagov2 = as.data.frame(datagov)
datagov2[, 1] = as.character(datagov2[, 1])

day.rid = matrix(0, nrow = nrow(datagov), ncol = 1)
for (s in 1:nrow(datagov2)) {
  if (weekdays(as.Date(datagov2$dates[s])) != "venerdì") {
    day.rid[s] = s
```

```
  }
}
day.rid = day.rid[day.rid != 0]
for (y in 1:length(day.rid)) {
  if (day.rid[y] != 0) {
    datagov2 = datagov2[-(day.rid[y]),]
    day.rid = day.rid - 1
  }
}
rownames(datagov2) <- NULL
datesgov = as.matrix(as.character(as.Date(datagov2$dates)))

datagov = as.matrix(datagov2[, 2:ncol(datagov)])

################## GOVERNMENT BONDS - 10Y ###################
datagov10 = read_excel("10y.xlsx")
datagov2.10 = as.data.frame(datagov10)
datagov2.10[, 1] = as.character(datagov2.10[, 1])

day.rid2 = matrix(0, nrow = nrow(datagov10), ncol = 1)
for (s in 1:nrow(datagov2.10)) {
  if (weekdays(as.Date(datagov2.10$dates[s])) != "venerdì") {
    day.rid2[s] = s
  }
}
day.rid2 = day.rid2[day.rid2 != 0]
for (y in 1:length(day.rid2)) {
  if (day.rid2[y] != 0) {
    datagov2.10 = datagov2.10[-(day.rid2[y]),]
    day.rid2 = day.rid2 - 1
  }
}
rownames(datagov2.10) <- NULL
datesgov2 = as.matrix(as.character(as.Date(datagov2.10$dates)))
datagov10 = as.matrix(datagov2.10[, 2:ncol(datagov10)])

############## DATASET ALLIGNMENT IN TIME ####################
data = data[1:704,]
datagov = datagov[315:nrow(datagov),]
datagov10 = datagov10[315:nrow(datagov10),]
dates = as.matrix(dates[1:704])
datesgov = as.matrix(datesgov[315:length(datesgov)])
datesgov2 = as.matrix(datesgov2[315:length(datesgov2)])
rownames(datagov) <- NULL
rownames(datagov10) <- NULL
rownames(data) <- NULL
############### TAKING FIRST DIFFERENCES #####################
data1 = diff(data)
data2 = diff(datagov)
data3 = diff(datagov10)
```

C.2 *Ad hoc* created functions

The central instrument for connectedness measures computations used was as said GFEVD, anyway despite the great diffusion of this technique, a specific function for the computation of the Generalised version is not included in standard statistical *R*-libraries. I so developed two functions computing the above mentioned measures, and giving back a matrix-form output, with standardized results. The need of two functions arose just for the handling differences of two input formats (one from the OLS VAR(p) estimation, and one from Elastic Net model). Basically, the second function has jus the additional task to perform the inversion of the VAR(p) model with a customized procedure. They are both presented below:

OLS estimation input

```
GFEVD_vars = function(model, data, step) {
  MA2 = as.matrix(as.data.frame(Phi(model, nstep = 50)))
  residuals = residuals(model)
  epsilon = cov(residuals)

  fevd_gen = matrix(0, nrow = ncol(data), ncol = ncol(data))
  sumup = 0
  sumdw = 0

  for (m in 1:ncol(data)) {
    ei = matrix(0, nrow = ncol(data), ncol = 1)
    ei[m, 1] = 1
    for (n in 1:ncol(data)) {
      sigma = sqrt(epsilon[n, n])
      ej = matrix(0, nrow = ncol(data), ncol = 1)
      ej[n, 1] = 1
      for (h in seq(1, (((step - 1) * ncol(data)) + 1), by = ncol(data))) {
        PHI = MA2[, h:(h + (ncol(data) - 1))]
        sumup = sumup + ((t(ei) %*% PHI %*% epsilon %*% ej) ^ 2)
        sumdw = sumdw + (t(ei) %*% PHI %*% epsilon %*% t(PHI) %*% ei)
      }
      fevd_gen[m, n] = ((sigma ^ -1) * sumup) / sumdw
      sumup = 0
      sumdw = 0
    }
  }
  colnames(fevd_gen) = colnames(data)
  rownames(fevd_gen) = colnames(data)
  fevd = fevd_gen

  #Standardization of the results
  for (q in 1:ncol(fevd)) {
    for (w in 1:nrow(fevd)) {
      fevd[w, q] = fevd_gen[w, q] / sum(fevd_gen[w, ])
    }
  }
  return(fevd)
}
```

Elastic Net estimation Input

```
GFEVD_BigVars = function(model, data, step) {
  residuals = model@resids
  epsilon = cov(residuals)
  coeff_s = model@betaPred

  #Creation of a "MA_inf CLASS to fill with the matrices of MA representation of the VAR"
  setClass(
    "MA_inf",
    slots = list(
      mu = "vector",
      phi0 = "matrix",
      phi1 = "matrix",
      phi2 = "matrix",
      phi3 = "matrix",
      phi4 = "matrix",
      phi5 = "matrix",
```

```
    phi6 = "matrix",
    phi7 = "matrix",
    phi8 = "matrix",
    phi9 = "matrix",
    phi10 = "matrix",
    phi11 = "matrix",
    phi12 = "matrix",
    phi13 = "matrix",
    phi14 = "matrix",
    phi15 = "matrix",
    phi16 = "matrix",
    phi17 = "matrix",
    phi18 = "matrix",
    phi19 = "matrix",
    phi20 = "matrix"
  )
)
MA = new("MA_inf")
MA@mu = coeff_s[, 1]
MA@phi0 = diag(ncol(data))
a1 = coeff_s[, 2:(ncol(data) + 1)]
MA@phi1 = MA@phi0 %*% a1
MA@phi2 = (MA@phi1 %*% a1)
MA@phi3 = (MA@phi2 %*% a1)
MA@phi4 = (MA@phi3 %*% a1)
MA@phi5 = (MA@phi4 %*% a1)
MA@phi6 = (MA@phi5 %*% a1)
MA@phi7 = (MA@phi6 %*% a1)
MA@phi8 = (MA@phi7 %*% a1)
MA@phi9 = (MA@phi8 %*% a1)
MA@phi10 = (MA@phi9 %*% a1)
MA@phi11 = (MA@phi10 %*% a1)
MA@phi12 = (MA@phi11 %*% a1)
MA@phi13 = (MA@phi12 %*% a1)
MA@phi14 = (MA@phi13 %*% a1)
MA@phi15 = (MA@phi14 %*% a1)
MA@phi16 = (MA@phi15 %*% a1)
MA@phi17 = (MA@phi16 %*% a1)
MA@phi18 = (MA@phi17 %*% a1)
MA@phi19 = (MA@phi18 %*% a1)
MA@phi20 = (MA@phi19 %*% a1)

MA2 = cbind(
  MA@mu,
  MA@phi0,
  MA@phi1,
  MA@phi2,
  MA@phi3,
  MA@phi4,
  MA@phi5,
  MA@phi6,
  MA@phi7,
  MA@phi8,
  MA@phi9,
  MA@phi10,
  MA@phi11,
  MA@phi12,
  MA@phi13,
  MA@phi14,
  MA@phi15,
  MA@phi16,
  MA@phi17,
  MA@phi18,
  MA@phi19,
  MA@phi20
)

fevd_gen = matrix(0, nrow = ncol(data), ncol = ncol(data))
sumup = 0
sumdw = 0

for (m in 1:ncol(data)) {
  ei = matrix(0, nrow = ncol(data), ncol = 1)
  ei[m, 1] = 1
```

```
    for (n in 1:ncol(data)) {
      sigma = sqrt(epsilon[n, n])
      ej = matrix(0, nrow = ncol(data), ncol = 1)
      ej[n, 1] = 1
      for (h in seq(1, (((step - 1) * ncol(data)) + 1), by = ncol(data))) {
        PHI = MA2[, (h + 1):(h + (ncol(data)))]
        sumup = sumup + ((t(ei) %*% PHI %*% epsilon %*% ej) ^ 2)
        sumdw = sumdw + (t(ei) %*% PHI %*% epsilon %*% t(PHI) %*% ei)
      }
      fevd_gen[m, n] = ((sigma ^ -1) * sumup) / sumdw
      sumup = 0
      sumdw = 0
    }
  }
  colnames(fevd_gen) = colnames(data)
  rownames(fevd_gen) = colnames(data)
  fevd = fevd_gen
  #Standardization of the results
  for (q in 1:ncol(fevd)) {
    for (w in 1:nrow(fevd)) {
      fevd[w, q] = fevd_gen[w, q] / sum(fevd_gen[w,])
    }
  }
  return(fevd)
}
```

C.3 Data modelling and statistical computations

In this section is reported the code developed to compute the unconditional model via Elastic Net estimation. The final arrays constructed for each model are denominated as:

i. *"FEVD" – corporate bonds;*
ii. *"FEVD_2" – 2 years government bonds;*
iii. *"FEVD_10" – 10 years government bonds;*

and then used for a direct matrix representation, and the network plots of net pairwise relations already exposed. The estimation of the models and the cross-validation on parameters has been executed with the *BigVAR* R-library, inspirated by the work of Nicholson et al. (2017) on VARX-L models.

```
################################################################################
                           # STATIC MODELLING #
################################################################################

# PARAMETERS SET UP: F.E. HORIZON (H)
```

```
step = 2 #setting the forecast window
alpha = 0.1 #alpha parameter for the Elastic Net estimation

### 1 CORPORATE ###
count_s_corr = 0

mod_s = constructModel(
  data1,
  p = 1,
  "BasicEN",
  alpha = alpha,
  gran = c(150, 10),
  RVAR = FALSE,
  h = 1,
  cv = "Rolling",
  MN = FALSE,
  verbose = TRUE,
  IC = TRUE,
  intercept = FALSE
)

model_static = cv.BigVAR(mod_s) #performing Cross-validation
residuals_s = model_static@resids
plot(model_static)
SparsityPlot.BigVAR.results(model_static)

#Checking for residuals correlation
for (k in 1:ncol(residuals_s)) {
  test = Box.test(residuals_s[, k], lag = 1, type = "Ljung-Box")
  if (test$p.value < 0.01) {
    print("AT LEAST ONE ERRORS T.S. IS AUTOCORRELATED")
    count_s_corr = count_s_corr + 1
    defect[count_s_corr, 1] = i
  }
  else {
  }
}

#Computing GFEVD
fevd_s = GFEVD_BigVars(model_static, data, step)

fevd_comput = fevd_s * 100 #reporting in (%) scale
diag(fevd_comput) = 0
FEVD = cbind(rbind(fevd_s, 'TO' = 0, 'NET' = 0), 'FROM' = 0) * 100
for (i in 1:(ncol(FEVD) - 1)) {
  for (j in 1:(nrow(FEVD) - 2)) {
    if (j != i) {
      FEVD['TO', i] = FEVD['TO', i] + FEVD[j, i]
      FEVD[j, 'FROM'] = FEVD[j, 'FROM'] + FEVD[j, i]
    }
  }
}
FEVD['NET', 1:(ncol(FEVD) - 1)] = FEVD['TO', 1:(ncol(FEVD) - 1)] - FEVD[1:(nrow(FEVD) -
                                                                              2), 'FROM']
FEVD['TO', 'FROM'] = sum(fevd_comput) / ncol(data1)


### 2 GOV-2Y ###
count_s_corr = 0

mod_s = constructModel(
  data2,
  p = 1,
  "BasicEN",
  alpha = alpha,
  gran = c(150, 10),
  RVAR = FALSE,
  h = 1,
  cv = "Rolling",
  MN = FALSE,
  verbose = TRUE,
  IC = TRUE,
  intercept = FALSE
)
```

```
model_static = cv.BigVAR(mod_s) #performing Cross-validation
residuals_s = model_static@resids
plot(model_static)
SparsityPlot.BigVAR.results(model_static)

#Checking for residuals correlation
for (k in 1:ncol(residuals_s)) {
  test = Box.test(residuals_s[, k], lag = 1, type = "Ljung-Box")
  if (test$p.value < 0.01) {
    print("AT LEAST ONE ERRORS T.S. IS AUTOCORRELATED")
    count_s_corr = count_s_corr + 1
    defect[count_s_corr, 1] = i
  }
  else {
  }
}

#Computing GFEVD
fevd_s_gov.2 = GFEVD_BigVars(model_static, datagov, step)

fevd_comput = fevd_s_gov.2 * 100 #reporting in (%) scale
diag(fevd_comput) = 0
FEVD_2 = cbind(rbind(fevd_s_gov.2, 'TO' = 0, 'NET' = 0), 'FROM' = 0) * 100
for (i in 1:(ncol(FEVD_2) - 1)) {
  for (j in 1:(nrow(FEVD_2) - 2)) {
    if (j != i) {
      FEVD_2['TO', i] = FEVD_2['TO', i] + FEVD_2[j, i]
      FEVD_2[j, 'FROM'] = FEVD_2[j, 'FROM'] + FEVD_2[j, i]
    }
  }
}
FEVD_2['NET', 1:(ncol(FEVD_2) - 1)] =
  FEVD_2['TO', 1:(ncol(FEVD_2) - 1)] - FEVD_2[1:(nrow(FEVD_2) - 2), 'FROM']
FEVD_2['TO', 'FROM'] = sum(fevd_comput) / ncol(data2)


### 3 GOV-10Y ###
count_s_corr = 0

mod_s = constructModel(
  data3,
  p = 1,
  "BasicEN",
  alpha = alpha,
  gran = c(150, 10),
  RVAR = FALSE,
  h = 1,
  cv = "Rolling",
  MN = FALSE,
  verbose = TRUE,
  IC = TRUE,
  intercept = FALSE
)

model_static = cv.BigVAR(mod_s) #performing Cross-validation
residuals_s = model_static@resids
plot(model_static)
SparsityPlot.BigVAR.results(model_static)

#Checking for residuals correlation
for (k in 1:ncol(residuals_s)) {
  test = Box.test(residuals_s[, k], lag = 1, type = "Ljung-Box")
  if (test$p.value < 0.01) {
    print("AT LEAST ONE ERRORS T.S. IS AUTOCORRELATED")
    count_s_corr = count_s_corr + 1
    defect[count_s_corr, 1] = i
  }
  else {
  }
}

#Computing GFEVD
fevd_s_gov.10 = GFEVD_BigVars(model_static, datagov10, step)
```

```
fevd_comput = fevd_s_gov.10 * 100 #reporting in (%) scale
diag(fevd_comput) = 0
FEVD_10 = cbind(rbind(fevd_s_gov.10, 'TO' = 0, 'NET' = 0), 'FROM' = 0) *
  100
for (i in 1:(ncol(FEVD_10) - 1)) {
  for (j in 1:(nrow(FEVD_10) - 2)) {
    if (j != i) {
      FEVD_10['TO', i] = FEVD_10['TO', i] + FEVD_10[j, i]
      FEVD_10[j, 'FROM'] = FEVD_10[j, 'FROM'] + FEVD_10[j, i]
    }
  }
}
FEVD_10['NET', 1:(ncol(FEVD_10) - 1)] = FEVD_10['TO', 1:(ncol(FEVD_10) -
                                                            1)]                    -
FEVD_10[1:(nrow(FEVD_10) - 2), 'FROM']
FEVD_10['TO', 'FROM'] = sum(fevd_comput) / ncol(data3)
```

It follows now the code developed to compute models via *rolling estimation*. The output consists of different arrays for:

i. total system-wide connectedness;
ii. total connectedness *to* others for each institution;
iii. total connectedness *from* others for each institution;
iv. total *net* connectedness for each institution;

the algorithm adds a *list* for each of these objects, containing the *net pairwise matrix* for each estimation, later used for the dynamically performed selection procedure on network's links.

```
####################################################################################
                               # DYNAMIC MODELLING #
####################################################################################

### 1 - CORPORATE ###
# Parameters selection
window = 100 #rolling estimation window
step = 2 #FEVD step

total_models = nrow(data1) - window
defect = matrix(0, nrow = total_models, ncol = 1)

TOTAL_conn = matrix(0, nrow = total_models, ncol = 2)

TO_conn = matrix(0, nrow = total_models, ncol = ncol(data))
colnames(TO_conn) = colnames(data)

FROM_conn = matrix(0, nrow = total_models, ncol = ncol(data))
colnames(FROM_conn) = colnames(data)
```

```r
NET_conn = matrix(0, nrow = total_models, ncol = ncol(data))
colnames(NET_conn) = colnames(data)

count_s_corr = 0
lista.corp = list(1)

for (i in 1:(total_models)) {
  pval = 0
  roll = data1[(0 + i):(window + i),]

  model = VAR(roll, p = 1)
  residuals = residuals(model)
  for (k in 1:ncol(residuals)) {
    test = Box.test(residuals[, k], lag = 1, type = "Ljung-Box")
    if (test$p.value < 0.01) {
      print("AT LEAST ONE ERRORS T.S. IS AUTOCORRELATED")
      count_s_corr = count_s_corr + 1
      defect[count_s_corr, 1] = i
      break
    }
    else {
    }
  }

  # FEVD
  fevd = GFEVD_vars(model, roll, step)
  diag(fevd) = 0
  TOTAL_conn[i, 2] = sum(fevd) / ncol(data)

  for (g in 1:ncol(data)) {
    FROM_conn[i, g] = sum(fevd[g, ]) * 100
    TO_conn[i, g] = sum(fevd[, g]) * 100
    NET_conn[i, g] = TO_conn[i, g] - FROM_conn[i, g]
  }

  # Computation of net pairwise connectedness matrix "corp"
  #  and storage of each value in a list
  corp = fevd
  for (i in 1:ncol(corp)) {
    for (j in 1:nrow(corp)) {
      if (i != j) {
        if (corp[i, j] > corp[j, i]) {
          corp[i, j] = corp[i, j] - corp[j, i]
          corp[j, i] = 0
        }
        else {
          corp[j, i] = corp[j, i] - corp[i, j]
          corp[i, j] = 0
        }
      }
    }
  }
  lista.corp = list.append(lista.corp, corp)
}

TOTAL_conn[, 1] = dates[(nrow(dates) - nrow(TOTAL_conn) + 1):nrow(dates), ]
TOTAL_conn = as.data.frame(TOTAL_conn)
colnames(TOTAL_conn) = list("Time", "Tot.Conn.Corp")
TOTAL_conn[, 1] = as.Date(TOTAL_conn$Time)
TOTAL_conn[, 2] = (as.double(TOTAL_conn[, 2])) * 100


### 2 - GOVERNMENT 2Y ###

total_models_gov2 = nrow(data2) - window

TOTAL_conn_gov = matrix(0, nrow = total_models_gov2, ncol = 2)

TO_gov2 = matrix(0, nrow = total_models_gov2, ncol = ncol(data2))
colnames(TO_gov2) = colnames(data2)

FROM_gov2 = matrix(0, nrow = total_models_gov2, ncol = ncol(data2))
colnames(FROM_gov2) = colnames(data2)
```

```r
NET_gov2 = matrix(0, nrow = total_models_gov2, ncol = ncol(data2))
colnames(NET_gov2) = colnames(data2)

count_s_corr = 0
lista.gov2 = list(1)

for (i in 1:(total_models_gov2)) {
  roll = data2[(0 + i):(window + i),]

  model = VAR(roll, p = 1)
  residuals = residuals(model)
  for (k in 1:ncol(residuals)) {
    test = Box.test(residuals[, k], lag = 1, type = "Ljung-Box")
    if (test$p.value < 0.01) {
      print("AT LEAST ONE ERRORS T.S. IS AUTOCORRELATED")
      count_s_corr = count_s_corr + 1
      defect[count_s_corr, 1] = i
      break
    }
    else {
    }
  }

  # FEVD
  fevd = FEVD_vars(model, roll, step)
  gfevd = GFEVD_vars(model, roll, step)
  fevd=gfevd

  diag(fevd) = 0
  diag(gfevd) = 0
  TOTAL_conn_gov[i, 2] = sum(gfevd) / ncol(data2)


  for (g in 1:ncol(data2)) {
    FROM_gov2[i, g] = sum(gfevd[g, ]) * 100
    TO_gov2[i, g] = sum(gfevd[, g]) * 100
    NET_gov2[i, g] = TO_gov2[i, g] - FROM_gov2[i, g]
  }

  # Computation of net pairwise connectedness matrix "corp"
  #  and storage of each value in a list
  corp = gfevd
  for (i in 1:ncol(corp)) {
    for (j in 1:nrow(corp)) {
      if (i != j) {
        if (corp[i, j] > corp[j, i]) {
          corp[i, j] = corp[i, j] - corp[j, i]
          corp[j, i] = 0
        }
        else {
          corp[j, i] = corp[j, i] - corp[i, j]
          corp[i, j] = 0
        }
      }
    }
  }
  lista.gov2 = list.append(lista.gov2, corp)
}
TOTAL_conn_gov[, 1] = datesgov[(nrow(datesgov) - nrow(TOTAL_conn_gov) +
                                  1):nrow(datesgov), 1]
TOTAL_conn_gov = as.data.frame(TOTAL_conn_gov)
colnames(TOTAL_conn_gov) = list("Time", "Tot.Conn.Gov2y")
TOTAL_conn_gov[, 1] = as.Date(TOTAL_conn_gov$Time)
TOTAL_conn_gov[, 2] = as.double(TOTAL_conn_gov[, 2]) * 100


### 3 - GOVERNMENT 10Y ###

total_models_gov10 = nrow(data3) - window

TOTAL_conn_gov10 = matrix(0, nrow = total_models_gov10, ncol = 2)

TO_gov10 = matrix(0, nrow = total_models_gov10, ncol = ncol(data3))
```

```r
colnames(TO_gov10) = colnames(data3)

FROM_gov10 = matrix(0, nrow = total_models_gov10, ncol = ncol(data3))
colnames(FROM_gov10) = colnames(data3)

NET_gov10 = matrix(0, nrow = total_models_gov10, ncol = ncol(data3))
colnames(NET_gov10) = colnames(data3)

count_s_corr = 0
lista.gov10 = list(1)

for (i in 1:(total_models_gov10)) {
  roll = data3[(0 + i):(window + i),]

  model = VAR(roll, p = 1)
  residuals = residuals(model)
  for (k in 1:ncol(residuals)) {
    test = Box.test(residuals[, k], lag = 1, type = "Ljung-Box")
    if (test$p.value < 0.01) {
      print("AT LEAST ONE ERRORS T.S. IS AUTOCORRELATED")
      count_s_corr = count_s_corr + 1
      defect[count_s_corr, 1] = i
      break
    }
    else {
    }
  }

  # FEVD
  fevd = FEVD_vars(model, roll, step)
  gfevd = GFEVD_vars(model, roll, step)
  fevd=gfevd

  diag(fevd) = 0
  diag(gfevd) = 0
  TOTAL_conn_gov10[i, 2] = sum(gfevd) / ncol(data3)

  for (g in 1:ncol(data3)) {
    FROM_gov10[i, g] = sum(gfevd[g, ]) * 100
    TO_gov10[i, g] = sum(gfevd[, g]) * 100
    NET_gov10[i, g] = TO_gov10[i, g] - FROM_gov10[i, g]
  }

  # Computation of net pairwise connectedness matrix "corp"
  #  and storage of each value in a list
  corp = gfevd
  for (i in 1:ncol(corp)) {
    for (j in 1:nrow(corp)) {
      if (i != j) {
        if (corp[i, j] > corp[j, i]) {
          corp[i, j] = corp[i, j] - corp[j, i]
          corp[j, i] = 0
        }
        else {
          corp[j, i] = corp[j, i] - corp[i, j]
          corp[i, j] = 0
        }
      }
    }
  }
  lista.gov10 = list.append(lista.gov10, corp)
}
TOTAL_conn_gov10[, 1] = datesgov2[(nrow(datesgov2) - nrow(TOTAL_conn_gov10) +
                                     1):nrow(datesgov2), 1]
TOTAL_conn_gov10 = as.data.frame(TOTAL_conn_gov10)
colnames(TOTAL_conn_gov10) = list("Time", "Tot.Conn.Gov10y")
TOTAL_conn_gov10[, 1] = as.Date(TOTAL_conn_gov10$Time)
TOTAL_conn_gov10[, 2] = as.double(TOTAL_conn_gov10[, 2]) * 100



#####  PLOTS of all three total connectedness through time  #####

tot.c = full_join(TOTAL_conn, TOTAL_conn_gov, TOTAL_conn_gov10, by = "Time")
```

```
tot.c = full_join(tot.c, TOTAL_conn_gov10, by = "Time")
tot.c = tot.c[complete.cases(tot.c), ]
tot.plot = pivot_longer(tot.c,
                        cols =
                          c("Tot.Conn.Corp",
                            "Tot.Conn.Gov2y",
                            "Tot.Conn.Gov10y"))

ggplot(tot.plot, aes(
  x = Time,
  y = value,
  group = name,
  color = name
)) +
  geom_line(lwd = 1.2) +
  ggtitle('Total Connectedness') +
  labs(y = "Tot.Conn.(%)", x = "Time", color = 'Legend') +
  scale_x_date(date_breaks = '1 year', date_labels = "%Y") +
  scale_colour_manual(values = c("red","purple","green2")) +
  theme(
    legend.title = element_text(size = 8),
    legend.position = "bottom",
    title = element_text(size = 10, face = 'bold'),
    axis.title = element_text(size = 8, face = 'bold'),
    axis.text = element_text(size = 7, face = 'bold'),
  )
```

Finally, is reported the selection procedures performed on net pairwise relations, in order to understand the dynamic of networks' connections during crisis periods. The following code performs the selection procedure based on percentiles, and the graphic representation of networks. Some inputs have to be set, in particular the index of the original data matrix, that corresponds to the dates of interest for the selection procedure. Those latter settings are commented and mapped at the top of the code.

```
###  OBSERVATIONS - DATES MAPPING ###
## Sovreign Debt crisis
# 72 - 09/2009 PRE Greek declaration
# 150 - 05/2011 S&P rating cut italia, and Portugal ask help as Ireland
# 190 - 05/2012 Fiscal Compact
# 208 - 08/2012 Whatever it takes DRAGHI

## Covid-19 crisis
# 573 - before
# 579 - after

### Parameters and data input ###
#dates of interest (index)
container = c(72, 150, 190, 208)

#gap for selection procedure over distributions
gap = c(50, 15)

colorss = c('beige', 'white')

#upload time varying data
lista = lista.gov10
```

```
gov.check = 1 #set equal to 1 if the data are government

g.id = 1 #graph counter
c.id = 1 #color counter

#Weigths for network graph
w99 = 1.8
w95 = 1
w90 = 0.4
############

for (l in gap) {
  for (obs in container) {
    nplot = obs #date on wich the netowork have to be plotted
    plus = nplot - 3#pre-crisis gap END
    ref = plus - 1 #gap BEGIN

    quant = c() #will contain all net relations in the GAP
    for (i in ref:plus) {
      corp = lista[[i]]
      quant = append(quant, as.vector(corp[-(which(corp == 0))]))
    }
    q_99 = (as.numeric(quantile(quant, probs = 0.99)))
    q_95 = (as.numeric(quantile(quant, probs = 0.95)))
    q_90 = (as.numeric(quantile(quant, probs = 0.90)))

    net.pairwise = lista[[plus]]
    net.pairwise = net.pairwise * 0

    match = lista[[nplot]]
    for (u in 1:ncol(match)) {
      for (y in 1:nrow(match)) {
        if (match[y, u] >= q_99) {
          net.pairwise[y, u] = w99
        }
        else if (match[y, u] >= q_95) {
          net.pairwise[y, u] = w95
        }
        else if (match[y, u] >= q_90) {
          net.pairwise[y, u] = w90
        }
      }
    }


    ### NETWORK DATA REPRESENTATION ###

    #Setting the weighs of the nodes
    if (gov.check == 0) {
      anag = read.csv('Network_details.csv')

      #Corporate
      anag.size = anag
      rownames(anag.size) = anag[, 1]
      sizer = c()
      for (i in c(colnames(net.pairwise))) {
        sizer = cbind(sizer, anag.size[i, 5])
      }
    }
    else {
      anag = read.csv('Network_details_gov.csv')
      #Government
      rownames(anag) = anag[, 1]
      sizer = c()
      for (i in c(colnames(net.pairwise))) {
        sizer = cbind(sizer, anag[i, 3])
      }
    }


    net = network(
      t(net.pairwise),
      directed = TRUE,
```

```
      ignore.eval = FALSE,
      names.eval = "weights"
    )

    # vertex names
    network.vertex.names(net) = colnames(net.pairwise)
    set.edge.attribute(net,
                       'color',
                       ifelse(
                         net %e% "weights" == w99,
                         "blue",
                         ifelse(net %e% "weights" == w95, "black", "red2")
                       ))


    dynamicVariableName <-
      paste0("n", g.id) #dynamic variable for graph concat.

    assign(
      dynamicVariableName,
      ggnet2(
        net,
        label = TRUE,
        fontface = 'bold',
        edge.color = 'color',
        edge.size = "weights",
        label.color = 'black',
        label.size = 3,
        color = "yellow2",
        arrow.size = 9,
        arrow.gap = 0.07,
        size = as.numeric(sizer),
        max_size = 15,
        mode = "circle"
      ) +
        guides(size = FALSE) + # remove the legend
        theme(title = element_text(size = 14, face = 'bold')) +
        theme(plot.title = element_text(hjust = 0.5))
    )

    g.id = g.id + 1
  }

  col = colorss[c.id]
  b = theme(panel.background = element_rect(color = "grey60", fill = col))

  if (length(container) == 4) {
    gridExtra::grid.arrange(
      n1 + ggtitle("09 / 2009") + b,
      n2 + ggtitle("05 / 2011") + b,
      n3 + ggtitle("05 / 2012") + b,
      n4 + ggtitle("08 / 2012") + b
    )
    g.id = 1
  }
  else {
    g.id = 3
  }
  c.id = c.id + 1
}

if (length(container) == 2) {
  b = theme(panel.background = element_rect(color = "grey60", fill = 'beige'))
  b1 = theme(panel.background = element_rect(color = "grey60", fill = 'white'))
  gridExtra::grid.arrange(
    n1 + ggtitle("02 / 2020 ") + b,
    n2 + ggtitle("03 / 2020") + b,
    n3 + ggtitle("02 / 2020 ") + b1,
    n4 + ggtitle("03 / 2020") + b1
  )
}
```

C.4 Graphic representations

In this final section is reported an overview of the graphical-related parts of the code.

Below it is presented the *R* code producing the network static pairwise representation for each sample, comprehensive of the computations of net relations among the actors.

```
#######################################
### NET PAIRWISE MATRIX PREPARATION ###
#######################################
#Graphic Parameters setting
#(weight to emphasize the links diameter)
w = 3.2

### Setting the weights of the nodes ###
setwd('C:/Users/Lapo/Desktop/CaFoscari/Thesis')
anag = read.csv('Network_details.csv')
anag.gov = read.csv('Network_details_gov.csv')
#Corporate
anag.size = anag
rownames(anag.size) = anag[, 1]
sizer.corp = c()
for (i in c(colnames(fevd_s))) {
  sizer.corp = cbind(sizer.corp, anag.size[i, 5])
}
#Government
rownames(anag.gov) = anag.gov[, 1]
sizer.gov = c()
for (i in c(colnames(fevd_s_gov.10))) {
  sizer.gov = cbind(sizer.gov, anag.gov[i, 3])
}


corp = fevd_s
gov2 = fevd_s_gov.2
gov10 = fevd_s_gov.10


### Computation of NET pairwise Conn Matrix ###
#Corporate
for (i in 1:ncol(corp)) {
  for (j in 1:nrow(corp)) {
    if (i != j) {
      if (corp[i, j] > corp[j, i]) {
        corp[i, j] = corp[i, j] - corp[j, i]
        corp[j, i] = 0
      }
      else {
        corp[j, i] = corp[j, i] - corp[i, j]
        corp[i, j] = 0
      }
    }
  }
}
#Gov 2y
for (i in 1:ncol(gov2)) {
  for (j in 1:nrow(gov2)) {
    if (i != j) {
      if (gov2[i, j] > gov2[j, i]) {
        gov2[i, j] = gov2[i, j] - gov2[j, i]
        gov2[j, i] = 0
```

```r
      }
      else {
        gov2[j, i] = gov2[j, i] - gov2[i, j]
        gov2[i, j] = 0
      }
    }
  }
}
#Gov 10y
for (i in 1:ncol(gov10)) {
  for (j in 1:nrow(gov10)) {
    if (i != j) {
      if (gov10[i, j] > gov10[j, i]) {
        gov10[i, j] = gov10[i, j] - gov10[j, i]
        gov10[j, i] = 0
      }
      else {
        gov10[j, i] = gov10[j, i] - gov10[i, j]
        gov10[i, j] = 0
      }
    }
  }
}

#############################################
######### GGNET2 NETWORK PLOTTING ############
#############################################

#weighting  links
corp = corp * w
gov2 = gov2 * w
gov10 = gov10 * w

diag(corp) = 0
diag(gov2) = 0
diag(gov10) = 0

net.corp = network(
  t(corp),
  directed = TRUE,
  ignore.eval = FALSE,
  names.eval = "weig"
)
net.gov2 = network(
  t(gov2),
  directed = TRUE,
  ignore.eval = FALSE,
  names.eval = "weig"
)
net.gov10 = network(
  t(gov10),
  directed = TRUE,
  ignore.eval = FALSE,
  names.eval = "weig"
)
# setting nodes names
network.vertex.names(net.corp) = colnames(corp)
network.vertex.names(net.gov2) = colnames(gov2)
network.vertex.names(net.gov10) = colnames(gov10)

ggnet2(
  net.corp,
  label = TRUE,
  fontface = 'bold',
  edge.size = "weig",
  label.color = 'black',
  label.size = 4.5,
  color = "yellow2",
  edge.color = 'seagreen3',
  arrow.size = 12,
  arrow.gap = 0.05,
  size = as.numeric(sizer.corp),
  max_size = 15
) +
```

```
  guides(size = FALSE) + #remove the legend
  ggtitle("Corporate Bonds") +
  theme(title = element_text(size = 12, face = 'bold'))

ggnet2(
  net.gov2,
  label = TRUE,
  fontface = 'bold',
  edge.size = "weig",
  label.color = 'black',
  label.size = 4.5,
  color = "darkorange",
  edge.color = 'red2',
  arrow.size = 12,
  arrow.gap = 0.05,
  size = as.numeric(sizer.gov),
  max_size = 18
) +
  guides(size = FALSE) + #remove the legend
  ggtitle("Gov.Bonds - 2Y") +
  theme(title = element_text(size = 12, face = 'bold'))

ggnet2(
  net.gov10,
  label = TRUE,
  fontface = 'bold',
  edge.size = "weig",
  label.color = 'black',
  label.size = 4.5,
  color = "lightpink1",
  edge.color = 'slateblue1',
  arrow.size = 12,
  arrow.gap = 0.05,
  size = as.numeric(sizer.gov),
  max_size = 18
) +
  guides(size = FALSE) + #remove the legend
  ggtitle("Gov.Bonds - 10Y") +
  theme(title = element_text(size = 12, face = 'bold'))
```

Additional parts of the code, producing standard graphics representations or computations (like the contents of *Appendix B*) are here not presented for lack of methodological interest and peculiarity.

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