Measuring interconnectedness across institutions and sectors

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Resumen

En este artículo se analiza la transmisión del riesgo tanto en los mercados de deuda soberana y de renta variable del área del euro como en los sectores financiero y no financiero de España. Para ello, el estudio se basa en la metodología propuesta por Diebold y Yilmaz (2009) para medir la conectividad, que se centra en las descomposiciones de la varianza de los errores de predicción a partir de modelos vectoriales autorregresivos. Los resultados indican que los índices de desbordamiento *(spillover)* que utilizan esta metodología identifican períodos durante la crisis de deuda soberana del área del euro y durante la actual pandemia de COVID-19 en los que se generaron efectos de desbordamiento entre los sectores y los mercados financieros.

Palabras clave: efectos de desbordamiento, transmisión de riesgo, contagio, mercados financieros, conectividad.

Abstract

This article analyzes the transmission of risk across euro area sovereign debt markets, euro area equity markets, and financial and non-financial sectors in Spain. To this end, the study draws on the connectedness methodology proposed by Diebold and Yilmaz (2009), which focuses on forecast error variance decompositions from vector autoregressive models. The results indicate that the spillover indices using this methodology identify periods during the euro area sovereign debt crisis and the current COVID-19 pandemic when spillovers were generated across financial markets and sectors.

Keywords: spillovers, risk transmission, contagion, financial markets, connectedness.

1 Introduction

The COVID-19 pandemic has revived interest in understanding how contagion spreads in financial markets, which received much attention during the Great Financial Crisis and the euro area sovereign debt crisis. One central concept to understanding contagion, and more broadly, financial stability, is the concept of interconnectedness, or the strength of ties between different market players. It figures prominently in key aspects of market risk (e.g., return and portfolio interconnectedness), counterparty risk (e.g., bilateral and multilateral contracts), and systemic risk (e.g., system-wide interconnectedness). As an example of how central interconnectedness is, it has been argued that the pandemic has strengthened the "nexus" between sovereigns, banks and the non-financial sector,[1] thereby intensifying the transmission of risk across these sectors. This implies that if vulnerabilities arise in one sector, then spillovers to other sectors may become more likely, with potentially devastating effects.

The purpose of this article is to shed light on the transmission of risk across the main euro area sovereign debt and equity markets, focusing on the contribution of Spanish financial markets to the transmission of shocks to other markets and vice versa. The study then turns to the impact across the non-financial and financial sectors in Spain. To do so, market prices are used at a weekly frequency to estimate the direction and intensity of spillovers in each area. In particular, the analysis systematically uses the connectedness methodology first introduced in Diebold

1 See Schnabel (2021).

and Yilmaz (2009),[2] which is based on forecast error variance decompositions calculated from vector autoregressive models. This technique generates a measure of system-wide interconnectedness called spillover index, and associated concepts such as directional interconnectedness and net interconnectedness. The main advantage of the technique, as opposed to other approaches of measuring the contribution to systemic risk of specific institutions [e.g., Adrian and Brunnermeier (2016) and Brownlees and Engle (2017)], is that it permits a unified approach for empirically measuring interconnectedness at a variety of levels, from pairwise interconnectedness to system-wide interconnectedness. Moreover, the measures have a clear connection to network concepts.

The results indicate that the spillover indices are able to track events in the GFC, the euro area sovereign debt crisis, and the COVID-19 pandemic quite well. In particular, with respect to the euro area sovereign debt market, it is found that the spillover index is able to track the decoupling of peripheral and core sovereign bond markets during the 2010-2014 period. Another finding is that both equity market return spillovers and equity market volatility spillovers sharply increased at the onset of the COVID-19 pandemic. It is also shown that Spanish equity markets mainly receive contagion from core equity markets, while they transmit contagion to peripheral equity markets.[3]

The analysis looks at cross-sectoral stock market spillovers within Spain, with a focus on the channels of contagion during the COVID-19 pandemic. It is found that contagion spread from the non-financial sector to both the financial sector and the Spanish sovereign debt market from the outset of the COVID-19 pandemic onwards. These results can possibly be traced to the increase in vulnerabilities and risks within the non-financial sector and the increase in government exposures to the non-financial sector as a result of the over-all fiscal policy response to the crisis.

The rest of the paper is organized as follows. Section 2 provides a brief literature review of existing approaches to measure systemic risk. Section 3 describes the Diebold and Yilmaz connectedness methodology, and its empirical implementation. Section 4 shows the empirical analysis. Finally, Section 5 concludes.

2 Diebold and Yilmaz (2009) seminal paper spawned a wide literature that refines the measurement and estimation of connectedness to take into account relevant financial institutions via large-scale vector autoregressive models (VARs) with functions that distinguish the key financial institutions [e.g., Demirer et al. (2018) and Gross and Siklos (2020)], more explicit identification schemes based on heteroscedasticity [e.g., De Santis and Zimic (2018)] or structural VAR approaches [e.g., Boeckelmann and Stalla-Bourdillon (2021)].

3 This article adopts the same nomenclature as in previous literature and refers to Greece, Ireland, Italy, Portugal and Spain as “peripheral countries” and the rest as “core countries”.

2 Systemic risk measures: a brief primer

The global financial crisis resulted in changes in approaches to monitoring financial stability. Prior to this crisis, financial regulation and stability measures were micro-prudential in nature, and focused on individual risk measures, such as Value-at-Risk (VaR). The new view, however, stresses the importance of interrelationships between financial institutions. Due to this, new measures were developed to capture systemic risk, spillovers from one financial institution to another (and vice-versa), and other phenomena.

There are four broad categories of systemic risk measures: i) tail measures; ii) network-based models of the financial system; iii) contingent claims analysis, and iv) dynamic stochastic macroeconomic models. The more popular measures are tail-based measures, and network-based measures of the financial system, which are the focus of this article. Tail-risk based measures [see e.g., ΔCoVAR of Adrian and Brunnermeier (2016), Marginal Expected Shortfall of Acharya et al. (2017), and the SRISK index of Brownlees and Engle (2017)] focus on co-dependence in the tails of returns of financial institutions. In particular, these measures are closely linked to Value-at-Risk type approaches; the main difference, though, is that these approaches are able to distinguish the impact of firm-specific disturbances from disturbances to the entire financial sector. Value-at-Risk, however, is institution-specific, and does not take into account the interrelationships of different firms.

Network-based models, meanwhile, focus on the propagation of contagion, the interconnectedness between different firms/sectors, and spillovers from one sector to another. Ideally, to pursue this type of analysis, one would want to observe network data. That is, one would like to observe actual financial exposures of firms to one another. This is not often the case, though. In this regard, several procedures have been developed to measure connectedness across financial institutions in the absence of such information; most of these measures are based on financial market prices. Billio et al. (2012), for example, propose to measure interconnectedness through a method that is based on pairwise Granger causality. A disadvantage of this approach, however, is that the method might be unstable over time, and that it is essentially bivariate in nature. An alternative approach pursued in this article is the interconnectedness approach proposed by Diebold and Yilmaz (hereafter referred to as DY) in a series of papers [see e.g., Diebold and Yilmaz (2009) and Demirer et al. (2018)], which is essentially based on vector autoregressive models (VAR).

The advantage of this approach over Billio et al. (2012) is that it permits to study contagion and spillovers across several firms or sectors. Moreover, it also permits the analysis of contagion from firm-level to a system-wide level. A drawback, however, as opposed to Billio et al. (2012), is the need for identifying assumptions, as the methodology is essentially based on variance decomposition analysis.[4]

3 Measuring interconnectedness using the Diebold-Yilmaz approach

The starting point for measuring interconnectedness of financial institutions using the DY approach is the estimation of vector autoregressive models, which capture the relationship between several variables as they change over time. In particular, DY build their connectedness index from the variance decomposition matrix associated with an N-variable vector autoregressive model. The variance decomposition matrix indicates the contribution of each financial institution to shocks to other financial institutions in the system being modelled. DY augment the variance decomposition matrix obtained from the estimation of the VAR model with rows and columns that indicate total contributions of all other institutions to a particular financial institution. Hence, this permits the calculation of different measures that can be computed, which are presented from the following schematic of the connectedness in Table 1. The procedure is more formally explained in the Annex.

The main upper left block of the interconnectedness table contains the variance decomposition matrix,[5] which we will denote by $D^H = \left[d_{ij}^H\right]$, where i is the row variable, j is the column variable, and H is the time horizon from which we computed the matrix. The connectedness table augments the variance decomposition matrix with an additional row that contains row sums, an additional column that contains column sums, and an additional cell in the bottom-right containing an average for all cases, for each $i \neq j$.

From the connectedness perspective, the measures of relevance are the off-diagonal elements of the matrix D^H, as they provide measures of pairwise directional connectedness. The pairwise directional connectedness from j to i is defined as:

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

Sometimes, one might be interested in net pairwise directional connectedness, which is simply the following difference:

$$C_{i \leftrightarrow j}^H = C_{j \leftarrow i}^H - C_{i \leftarrow j}^H$$

4 As explained in the Annex, the spillover index is computed from the forecast error variance decompositions coming from the estimation of a vector autoregressive model. As reduced-form shocks are rarely orthogonal in nature, one would need to proceed with some scheme to identify the uncorrelated “structural” shocks from the correlated orthogonal shocks.

5 One can obtain the variance decomposition matrix by rewriting the VAR system that is specified earlier to a moving average representation, compute H step ahead forecasts, and the corresponding forecast errors and obtain its covariance matrix.

Table 1
INTERCONNECTEDNESS TABLE

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

SOURCE: Own elaboration.

From the pairwise connectedness measures, one can define aggregate measures of interconnectedness. For example, the row sum of the off-diagonal elements provides the amount of the H step forecast error variance of variable i coming from shocks arising from other variables can be expressed as the following quantity:

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

Meanwhile, the total directional connectedness to others from j can be described as the following quantity, which is the column sum of the off-diagonal elements:

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

Finally, one can compute a grand total of all of the off-diagonal elements of the elements in the variance decomposition matrix. This measure is what DY call the *total directional connectedness*:

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

The total directional connectedness measure can then be thought of as a measure of total system-wide connectedness.

3.1 Model implementation

The aim is to study spillovers across European sovereign bond yields, stock market indices, and Spanish financial and non-financial sectors using market data at a weekly frequency. The rationale behind this choice (as opposed to using e.g. daily frequency) is to avoid the possibility of stale prices.[6] In particular, the analysis draws on Wednesday-to-Wednesday returns, as these are less susceptible to day-of-the-week effects.[7]

To implement the DY methodology, one needs to specify the predictive horizon H and the dynamics of the variables, as represented by the number of lags p. In addition, time-varying interconnectedness allows to move away from the completely static procedure implicitly assumed thus far. Allowing for time-varying interconnectedness is especially important as the dynamics of the variables one is interested in may vary with the business or the financial cycle, or it may evolve slowly e.g. with the structure of the financial system.

A predictive horizon of $H = 1$ week is chosen, similar to Diebold and Yilmaz (2009) and Boeckelmann and Stalla-Bourdillon (2021). To compute the optimal number of lags p, the analysis needs to rely on standard information criteria, such as the Akaike information criterion and the Bayesian information criterion. The information criteria reveal that for each of the areas, the most adequate model is one that has $p = 1$. Finally, to allow for time-varying interconnectedness, the analysis relies on a rolling window estimation, with a one-sided rolling window of 103 weeks (approximately two years). In the robustness exercises, attention is given to how the spillover index changes when the predictive horizon or the rolling window are changed.

4 Empirical analysis

This section shows the empirical application of the connectedness methodology. First, the data used for the empirical analysis is described, followed by the dynamic analysis of interconnectedness.

4.1 Data

Interconnectedness is studied under three different settings: sovereign bond markets and equity markets of major European countries, respectively, and non-financial and

6 Prices are stale when current prices do not reflect actual market information.

7 With Friday-to-Friday returns the results are quite similar.

financial sectors in Spain. To pursue this analysis, information from Datastream is used. The type of information in each setting is outlined below.

— Sovereign bond markets: Weekly information is obtained on 10-year sovereign bond yields from Austria, Belgium, France, Germany, and the Netherlands (core), Greece, Ireland, Italy, Portugal and Spain (periphery). The main variables for this estimation are weekly changes in sovereign bond yields, and the corresponding volatilities, calculated via one-month rolling windows of standard deviations of yield changes.

— Equity markets: Weekly information is obtained on the main equity indices on the countries mentioned above. This estimation uses weekly log changes in equity price indexes, and the corresponding volatilities, which were calculated via one-month rolling windows of the standard deviations of equity returns.[8]

— Sectoral indices: Weekly information is obtained on sectoral indices based on the different constituent firms in the Madrid Stock Exchange. The sectors included in the stock exchange are: petroleum, construction, consumer goods, leisure and tourism, retail, transportation and distribution, banks, insurance, telecommunications, and real estate. In the subsequent empirical analysis, sectoral indices are aggregated into financial and non-financial sectors via a weighted average, with the market capitalizations as the weights. In a subsequent analysis, the non-financial sectors are further divided into vulnerable and non-vulnerable sectors, following the classification in Blanco et al. (2021).[9] The corresponding volatilities, which are rolling windows of one month, are also calculated.

The data used for the empirical analysis spans January 2001 to July 2021 for sovereign bond yields and equity indices, and from January 2008 to July 2021 for sectoral indices (due to data availability).

4.2 Results

The results of each of the empirical analyses are described below.

8 Similar results are obtained when computing the spillover index via the corresponding squares of the returns.

9 Blanco et al. (2021) divide the sectors into three groups: severely vulnerable, moderately vulnerable, and non-vulnerable. Because the analysis pursued here only allows to observe broader sectors as opposed to the more detailed sector classifications in Blanco et al. (2021), only two groups are considered, wherein severely and moderately vulnerable sectors are combined into one group. Vulnerable sectors are power, basic materials, industry and construction, consumer goods, leisure and transportation. Non-vulnerable sectors are retail trade, telecommunications and real estate.

4.2.1 Sovereign debt markets

The blue line of Chart 1.1 plots the total connectedness of sovereign bond yields over a two-year rolling window. The chart shows two main patterns. First, it indicates that prior to the debt crisis, sovereign bonds were highly interconnected. In particular, one finding is that close to 90 % of forecast error variance comes from spillovers to different sovereign bonds. However, as the sovereign debt crisis unfolded, the spillover index decreased to less than 50 % in 2014. The drop in spillovers can be associated to the decoupling of sovereign bonds of the peripheral countries and the core countries, a fact that can be observed from the moving average correlations of sovereign bond yields plotted in Chart 1.2, which turned to be negative at around the same period. Connectedness of the sovereign bonds increased afterwards, which can be attributed to bailout packages and other policies targeted at ensuring financial stability of the euro area. The proportion of forecast error variance decompositions were relatively stable at 70 % up until 2019. Finally, there was a sharp increase in 2020, which coincided with the COVID-19 pandemic and subsequent measures to contain it. As documented in Corradin, Grimm and Schwaab (2021), at the onset of the COVID-19 pandemic, there was an increase in sovereign bond yields in countries like Italy and Spain, which prompted the announcement of the PEPP on 18 March 2020, which is precisely the week where we observe the spike in the spillover index. The announcement of this program led to a lowering of sovereign bond yields in all euro area countries.

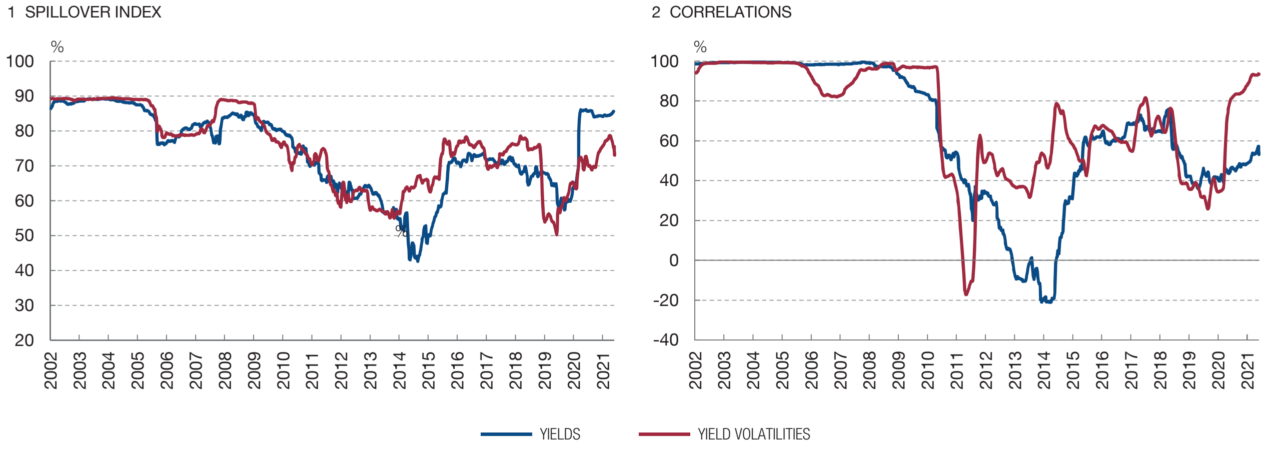
The red line of Chart 1.1, meanwhile, plots the total connectedness of sovereign bond yield volatilities. As can be observed, the patterns of bond yield volatilities are similar to that of bond yield changes. The correlation dynamics also follow a similar pattern, as can be observed in Chart 1.2.

To understand whether the fluctuations in connectedness are general or specific for certain groups of countries, the spillover index for core countries (blue line of Chart 2) and the spillover index for peripheral countries (red line of Chart 2) are computed. The chart for core countries shows that there is almost no variation in the spillover index, which hovers slightly above 80 % throughout the sample period. Meanwhile, the chart for peripheral countries indicates the wide variation observed in the total spillover index for all countries. This result suggests that the movements in the spillover index are driven by peripheral countries and not by core ones.

The results of the study of how Spain contributes to the variation in sovereign bond yields are in Chart 3, which shows the net connectedness of Spain to the core and peripheral countries, respectively. A positive measure of net connectedness implies that Spain is a net receiver of shocks, while a negative measure implies that Spain is a net transmitter of shocks. As can be observed, with respect to core countries, the Spanish sovereign market in general influenced sovereign bond yields in core

Chart 1

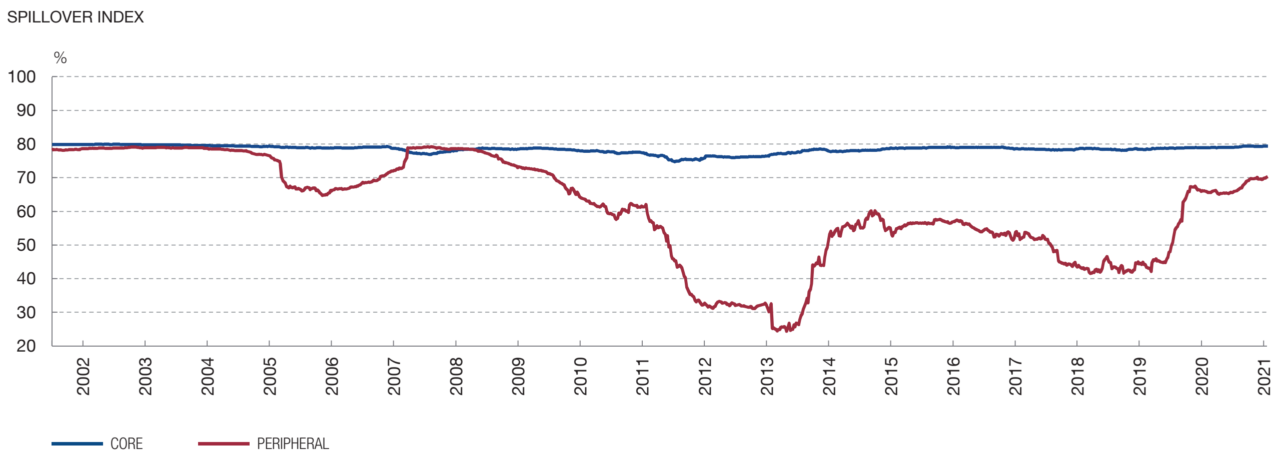
SPILLOVER INDICES IN EURO AREA SOVEREIGN DEBT MARKETS



SOURCES: Datastream and own elaboration.
NOTE: The charts above show the total spillover index for changes in sovereign bond yields (see Chart 1.1), and sovereign bond yield volatilities (see Chart 1.2). The spillover indices are defined as the sum of all variance decomposition "contributions to others". The values of the index are from 0 to 100, and can be thought of as percentages. The charts are estimated from a VAR(1) model with a two-year rolling window, and a predictive horizon of one week.

Chart 2

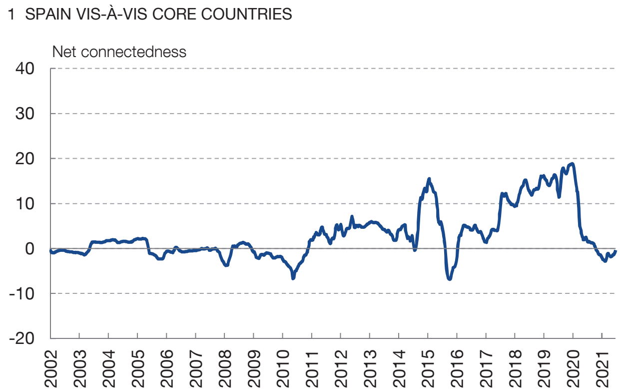
SPILLOVER INDICES OF SOVEREIGN BOND YIELDS IN CORE AND PERIPHERAL COUNTRIES

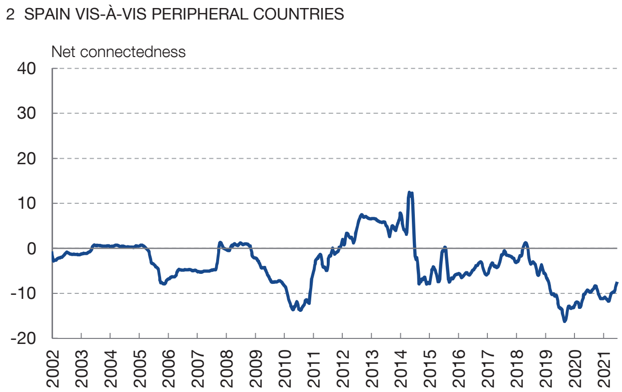


SOURCES: Datastream and own elaboration.
NOTE: The chart above shows the total spillover index of changes in sovereign bond yields of core countries (blue), and peripheral countries (red). The spillover indices are defined as the sum of all variance decomposition "contributions to others". The values of the index are from 0 to 100, and can be thought of as percentages. The chart is estimated from a VAR(1) model with a two-year rolling window, with a predictive horizon of one week.

countries during the 2006-2010 period, and in 2011-2014 (although there were brief spikes wherein Spain was a net receiver of contagion). From 2015 onwards, however, the Spanish sovereign market was influenced more by movements in the core countries. This can be related to the end of the sovereign debt crisis, when the Spanish economy started its economic recovery, and improved its competitiveness

Chart 3
NET CONTRIBUTION OF SPANISH SOVEREIGN BOND YIELDS TO CORE AND PERIPHERAL COUNTRIES





SOURCES: Datastream and own elaboration.
NOTE: The charts above show the net connectedness of Spain with respect to core countries (see Chart 3.1), and peripheral countries (see Chart 3.2). The charts are estimated from a VAR(1) model with a two-year rolling window. The charts are estimated from a VAR(1) model with a two-year rolling window and a one week prediction horizon. A positive value of the measure indicates that Spain is a net absorber of contagion, while a negative value of the measure indicates that Spain is a net transmitter of contagion.

vis-à-vis other countries in the euro area. Meanwhile, with respect to peripheral countries, it is found that prior to 2011, Spain influenced peripheral sovereign bond yields. The Spanish sovereign market then became a net receiver of contagion coinciding with the sovereign debt market crisis.

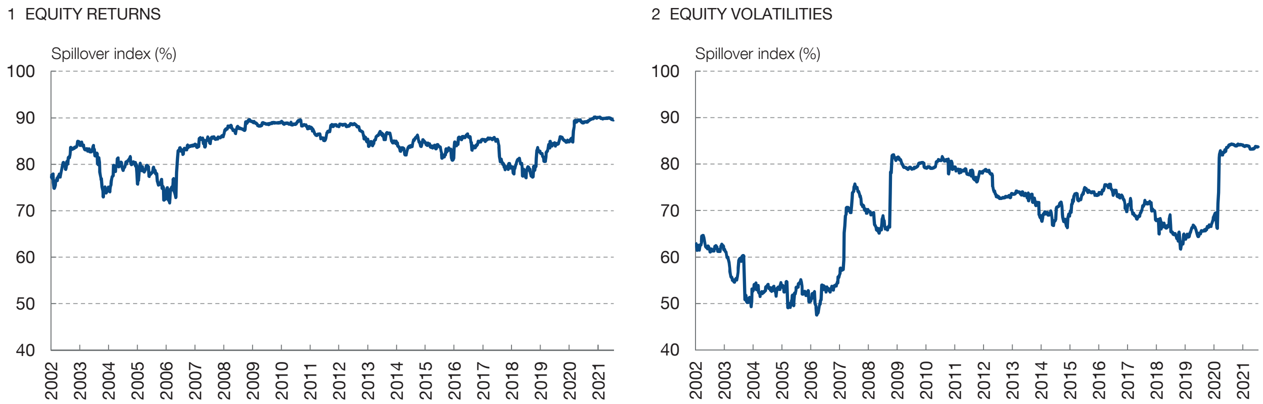
The index increased significantly until July 2012, right around the period of the "whatever it takes" speech by the then ECB President Mario Draghi. This suggests that during the sovereign debt crisis Spanish sovereign yields were highly influenced by developments in the other peripheral countries. There was then a decrease until 2018, wherein Spain is found to become a net transmitter of shocks, although the absolute value of the index was relatively low.

4.2.2 Equity markets

Turning to the study the connectedness of equity markets in the major euro area economies, Chart 4 shows the spillover indices computed for equity index returns (see Chart 4.1) and equity index return volatilities[10] (see Chart 4.2). The charts indicate relatively small movements in equity return spillovers, which fluctuate between 70 % and 90 % of forecast error variance decompositions. These high levels indicate that there is a high degree of system-wide interconnectedness across euro area equity markets. By contrast, with respect to equity index return volatilities, wider movements

10 To compute volatilities, 4-week (1 month) rolling window standard deviations are calculated.

Chart 4
SPILLOVER INDICES OF EURO AREA EQUITY INDEX RETURNS AND EQUITY RETURN VOLATILITIES



SOURCES: Datastream and own elaboration.
NOTE: The charts above show the total spillover index for equity markets (see Chart 4.1) and for equity volatilities (see Chart 4.2) across major European countries. The spillover indices are defined as the sum of all variance decomposition "contributions to others". The values of the index are from 0 to 100, and can be thought of as percentages. The charts are estimated from a VAR(1) model with a two-year rolling window and a one week prediction horizon.

in the spillover index are observed. In particular, the volatility spillover series show increases at three distinct points:

1. Prior to the onset of the global financial crisis in 2007.

2. Prior to the onset of the European sovereign debt crisis in 2010.

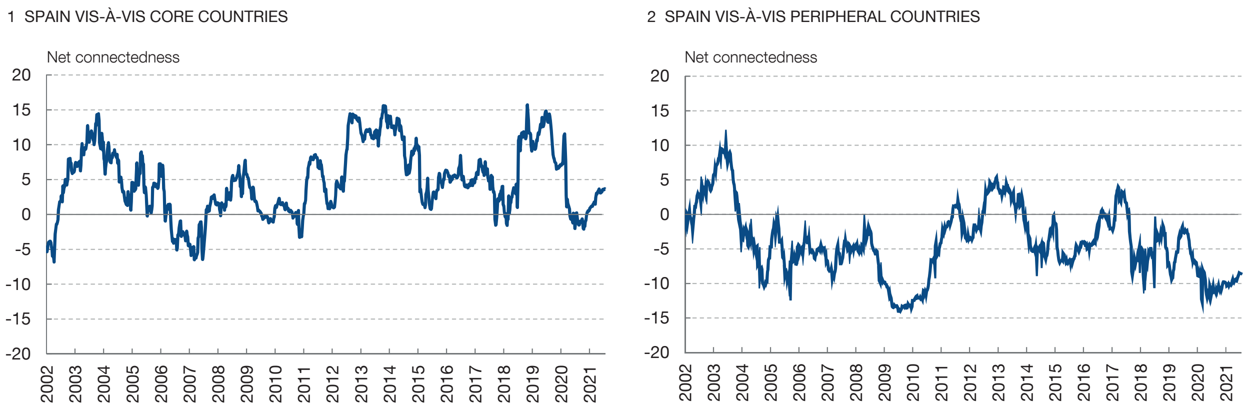
3. The stock market crash as a result of the lockdown measures at the onset of the 2020 COVID-19 pandemic.

The fact that there is much movement in volatility spillovers but not in return spillovers is consistent with the results in Diebold and Yilmaz (2009), who find similar results, but for global asset markets. As noted by Diebold and Yilmaz (2009), this result for equity markets can be largely associated with a high level of financial integration across several economies, hence the relatively stable plot for equity returns.[11] Meanwhile, the movements in volatilities are due to responses to economic and political events.

Pairwise net connectedness between Spain and the core and periphery equity markets, respectively, are examined and shown in Chart 5 for equity market volatilities. The chart indicates that, for the most part, Spain is a net receiver of

11 Given that the spillover index is a measure of system-wide interconnectedness, the fact that around 70%-90% of forecast error variance decompositions can be attributed to spillovers from one equity market to another underscores the increasing financial integration across the euro area.

Chart 5
NET CONTRIBUTION OF IBEX 35 REALIZED VOLATILITY TO CORE AND PERIPHERAL EQUITY MARKET VOLATILITIES



SOURCES: Datastream and own elaboration.
NOTE: The charts above shows the net pairwise connectedness of the IBEX 35 return volatility with respect to core (see Chart 5.1) and peripheral (see Chart 5.2) equity market volatilities. The charts are estimated from a VAR(1) model with a two-year rolling window and a one week prediction horizon. A positive value of the measure indicates that Spain is a net absorber of contagion, while a negative value of the measure indicates that Spain is a net transmitter of contagion.

shocks from core equity markets, while it is a net transmitter of shocks to peripheral equity markets.[12]

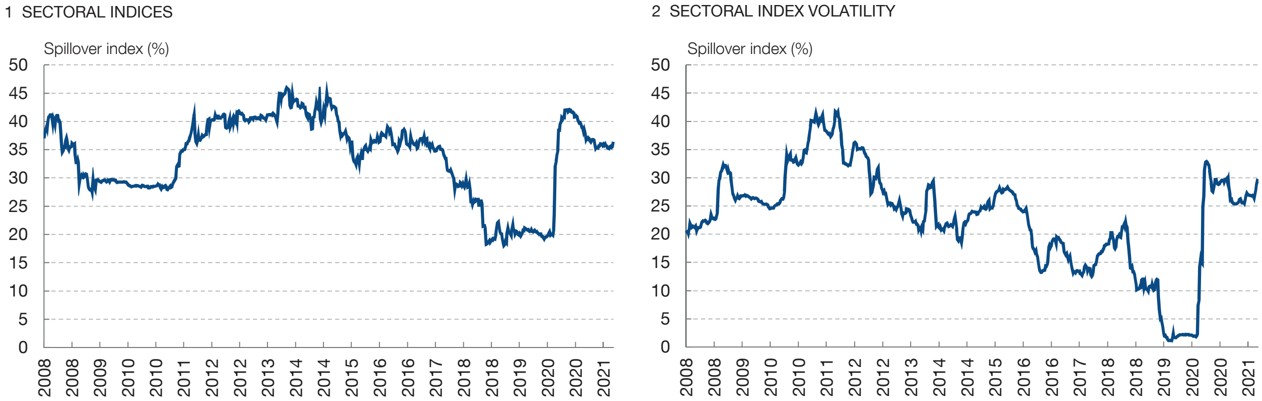
4.2.3 Sectoral indices

Having established how the Spanish sovereign and the Spanish equity markets influence and are influenced by other economies, the analysis turns to the interconnections between sectoral indices within the Spanish economy.[13] The corresponding spillover indices both for returns and volatilities are shown in Chart 6. The spillover indices for different sectors indicate spikes around the 2010-2014 European sovereign debt crisis, and at the onset of the COVID-19 pandemic in March 2020, the spillover index reached levels close to historical highs. The volatility spillovers in Chart 6.2 show a similar spike around March 2020, though not at the same levels as in sectoral indices.

12 In order to verify whether the results in relation to the spillover index are due to other advanced economies such as the UK and the US, an alternative model is estimated where the S&P 500 and the FTSE are considered as additional variables in the VAR system. The results obtained show that the spillover index retains the same dynamics as that showed in the main text, and that Spain still is a net transmitter of risk to peripheral countries, and a net receiver from core countries. Results are available upon request.

13 In contrast to the earlier estimations, a VARX(1) model is estimated for the purpose of computing the spillover index and the net connectedness measures. The exogenous variables used for estimation are the EURO STOXX 600, and an index of European sovereign bond yields ex-Spain. An alternative estimation is considered, which is to net out the exogenous variables via OLS estimation, following Boeckelmann and Stalla-Bourdillon (2021). Results obtained are quite similar.

Chart 6
SPILLOVER INDEX FOR SPANISH SECTORAL INDEX RETURNS AND RETURN VOLATILITIES



SOURCES: Datastream and own elaboration.
NOTE: The charts above show the total spillover index for sectoral indices (see Chart 6.1) and for sectoral index volatilities (see Chart 6.2) for the Spanish economy. The spillover indices are defined as the sum of all variance decomposition "contributions to others". The values of the index are from 0 to 100, and can be thought of as percentages. The charts are estimated from a VAR(1) model with a two-year rolling window and a one week prediction horizon.

The analysis studies how contagion spreads across different sectors of the Spanish economy, with a particular focus on the recent COVID-19 pandemic, given that spillovers were near the maximum levels reached in the historical data. Chart 7 shows the net connectedness of each of the sectors considered. In the case of Chart 7.1, a positive net connectedness value implies a stronger contagion from the non-financial sector to the financial sector than in the other direction, and vice-versa for negative values. The chart shows that during the onset of the COVID-19 lockdowns, there was an increase in net contagion from the non-financial sector to financial sector. This increase possibly reflects the rise in risks and vulnerabilities of non-financial firms as a result of the COVID-19 pandemic [Banco de España (2021)], thus spilling over to the financial sector due to is exposure to non-financial firms, which moreover increased during this episode as a result of increased lending to such firms.

The increase in contagion was steady until November 2020, which coincides with announcements of the effectivity of some vaccines to fight the COVID-19 virus, and the extension of programs to provide support to non-financial firms. In particular, these programs included the public guarantee facilities managed by the Official Credit Institute (ICO, in its Spanish acronym). While there was another round of increase in net spillovers from non-financial to financial firms earlier in 2021, these dissipated later on. During the pandemic crisis, net spillovers from the non-financial sector to the financial sector have been above the historical mean (marked by the dashed red line in the chart).

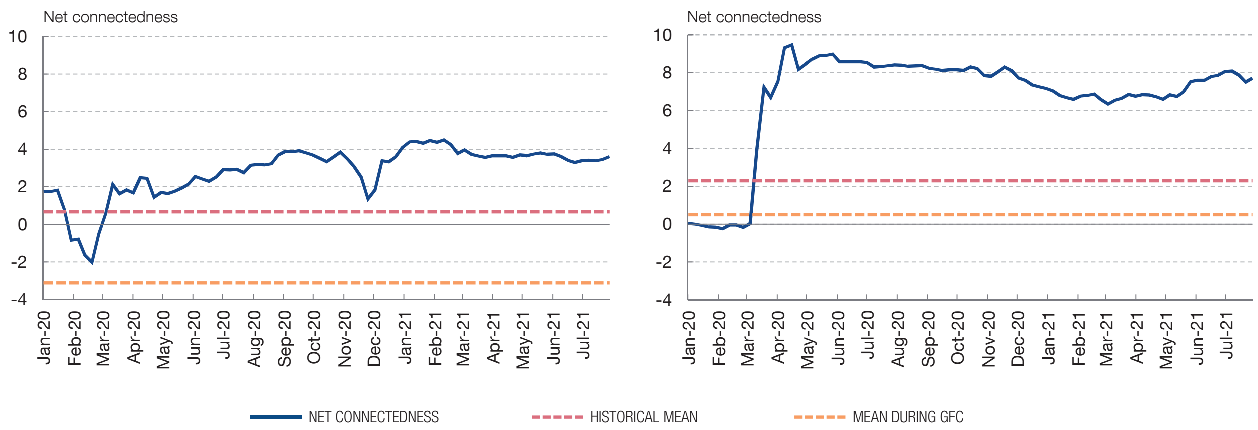
Chart 7.2 shows net spillovers between the non-financial sector and the Spanish sovereign bond market. As in Chart 7.1, a positive net connectedness measure implies that the contagion from the non-financial sector to the sovereign is higher

Chart 7

NET CONTRIBUTION OF NON-FINANCIAL SECTORS VIS-À-VIS FINANCIAL AND SOVEREIGN SECTORS

1 NON-FINANCIAL VIS-À-VIS FINANCIALS

2 NON-FINANCIALS VIS-À-VIS SOVEREIGN



SOURCES: Datastream and own elaboration.

NOTE: The charts show the net connectedness between non-financial and financial sectors (see Chart 7.1) and the non-financial vis-à-vis the sovereign (see Chart 7.2) in Spain. The charts are estimated from a VARX(1) model with a two-year rolling window. The blue line is the net connectedness measure, the red line is the historical mean, while the orange line is the mean of the series during the global financial crisis. A negative value of the measure indicates that the non-financial sector is a net absorber of contagion, while a positive value of the measure indicates that the non-financial sector is a net transmitter of contagion.

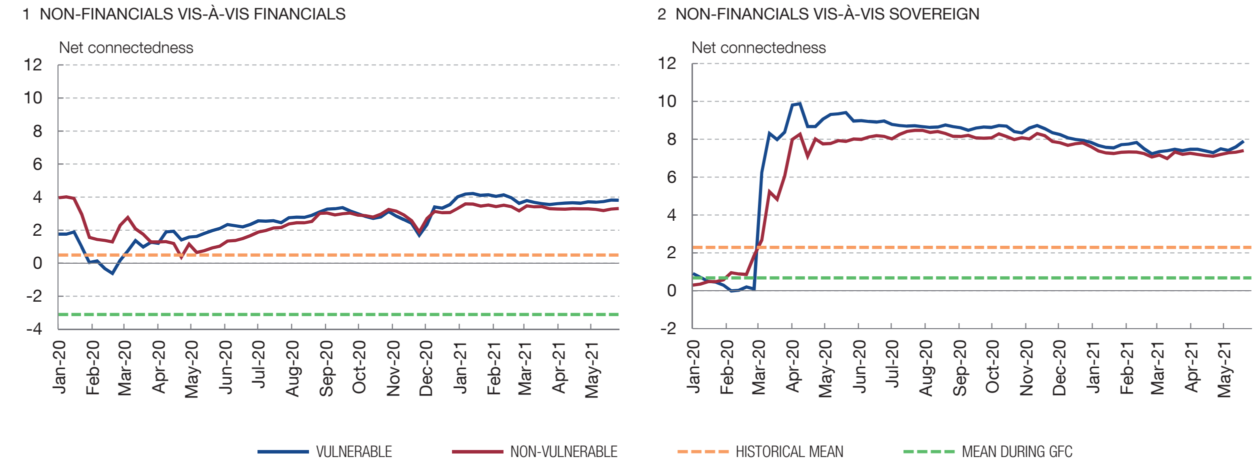
than in the other direction. A sharp increase in contagion from non-financial sectors to the sovereign is found, which continued throughout most of 2020, and then stabilized. This rise in net spillovers from the non-financial sectors can also possibly be associated to the overall fiscal policy response in support of the nonfinancial corporate sector, including public guaranteed loan programs which increased the contingent exposures of the government to the non-financial sector.

Digging deeper into the transmission from the non-financial to the financial sector and conduct a more elaborate analysis is conducted wherein the non-financial sector is divided into vulnerable and non-vulnerable sectors. The results, which are shown in Chart 8, show that during the COVID-19 pandemic, indicate that there was an increase in the transmission of shocks from vulnerable non-financial sectors to the financial sector, while there was a decrease in the transmission of shocks from the non-vulnerable non-financial sectors to the financial sector. From June 2020 onwards, however, both vulnerable and non-vulnerable sectors move together. With respect to the linkages with the sovereign, meanwhile, the results are quite similar in direction.

All in all, these results emphasize the different nature of the COVID-19 crisis from the European sovereign debt crisis. In particular, in the COVID-19 crisis, it was the non-financial sector that affected the other sectors of the economy. This is as opposed to the sovereign debt crisis, wherein we can observe (from the orange line that depicts the mean net spillover during the period) that the non-financial sector was a net receiver of contagion from the financial sector.

Chart 8

COMPARISON BETWEEN VULNERABLE AND NON-VULNERABLE SECTORS



SOURCES: Datastream and own elaboration.

NOTE: The charts show the net connectedness between non-financial and financial sectors (see Chart 8.1) and the non-financial vis-à-vis the sovereign (see Chart 8.2) in Spain. The charts are estimated from a VARX(1) model with a two-year rolling window. The blue line is the net connectedness measure for vulnerable sectors, the red line is the net connectedness measure for non-vulnerable sectors, the orange line is the historical mean, while the green line is the mean of the series during the global financial crisis. A negative value of the measure indicates that the non-financial sector is a net absorber of contagion, while a positive value of the measure indicates that the non-financial sector is a net transmitter of contagion.

4.2.4 Robustness

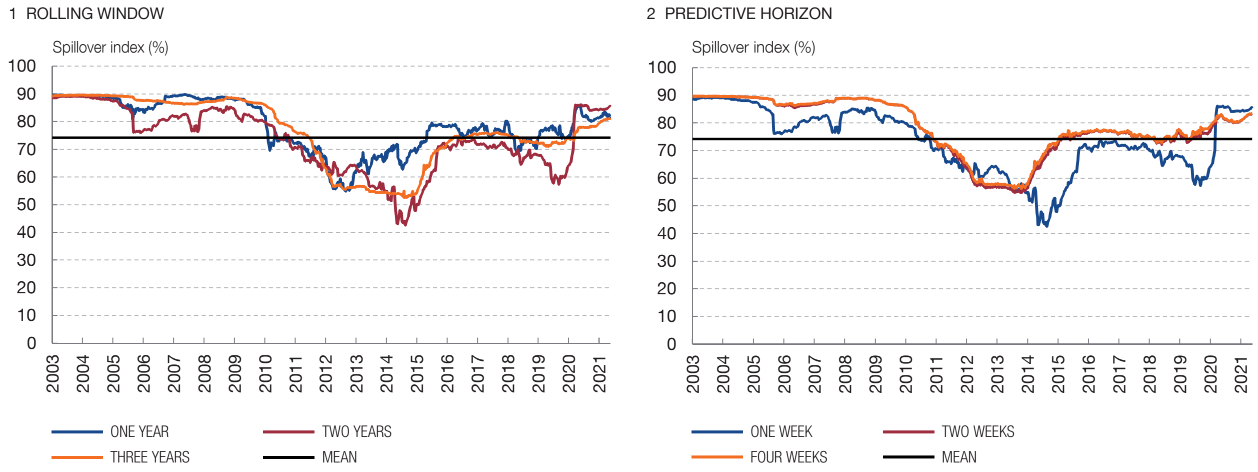
Finally, the analysis looks at the robustness of the spillover indices to differences in the predictive horizon or to differences in the length of the rolling windows. For brevity in the presentation, the focus is on the results with respect to the sovereign debt markets. Results are presented in Chart 9, which shows the spillover indices for sovereign bond yields.

Chart 9.1 shows the estimation results when the size of the rolling window is changed to a smaller size (1 year), or to a wider size (3 years).[14] The finding is that, in general, the spillover index retains the same dynamics. However, another finding is that the smaller window size yields to a higher degree of spikes from 2012 to 2014, which smoothen out the window length increases. Meanwhile, Chart 9.2 shows the estimation results when the predictive horizon changes from one week to four weeks.[15] As the chart indicates, the general pattern remains the same.

14 As explained by Diebold and Yilmaz (2009), the trade-off between sizes of the rolling window is either one can have a more stable estimation (larger rolling window), or one can capture dynamics better (smaller rolling window).

15 Diebold and Yilmaz (2009) choose the smaller prediction horizon as it corresponds to the Basel II regulations, and work with the larger prediction horizon because it can capture long-term dynamics more precisely.

Chart 9
ROBUSTNESS OF THE DIEBOLD AND YILMAZ (2009) SPILLOVER INDICES FOR SOVEREIGN BOND YIELDS



SOURCES: Datastream and own elaboration.
NOTE: The charts show the robustness of the spillover measures of Diebold and Yilmaz (2009) when I change the size of the rolling window (see Chart 9.1), or when I change the prediction horizon for the variance decompositions (see Chart 9.2). The spillover indices are defined as the sum of all variance decomposition "contributions to others". The values of the index are from 0 to 100, and can be thought of as percentages. I estimate this model for soveriegn bond yields, with a VAR(1) model.

5 Conclusion

This article studies the interconnectedness of different financial markets using the Diebold and Yilmaz connectedness methodology. The spillover indices that result from this estimation show a high degree of connectedness across sovereign debt markets in Europe prior to the 2010-2014 sovereign debt crisis, followed by a decoupling between peripheral and core sovereign bond yields during such crisis, and a partial reintegration afterwards. With respect to equity markets, the estimation shows wide movements in equity market volatility spillovers, which coincide with critical events in financial markets. Finally, estimating sector-wide models for Spain, it is found that there is a net contagion from non-financials to both the financial sector and the Spanish sovereign bond market since the outbreak of the COVID-19 pandemic.

The analysis conducted in this paper suggests several extensions for future work. For instance, while measures of contagion are obtained from market prices, there is no clear identification of structural shocks. Moving in this direction might provide further guidance on the understanding of the movements in the financial market spillovers.

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The main text describes in words the Diebold and Yilmaz (2009) approach to study interconnectedness. This annex, meanwhile, provides a more formal description of the approach. Suppose that one observes a vector of financial returns $x_t = (x_{1t}, x_{2t}, x_{3t}, \cdots, x_{Nt})'$. A vector autoregressive model of order p for these variables can be written as the following equation:

$$x_t = A_1 x_{t-1} + A_2 x_{t-2} + \cdots + A_p x_{t-p} + w_t$$

In this equation, the A_p 's are matrixes of the coefficients, p is the lag order, and w_t is a vector of innovations that is normally distributed: $w_t \sim N(0, \Sigma)$. The Wold decomposition of the equation above can be written as $x_t = \sum_{i=1}^{\infty} \Phi_i w_{t-i}$, where the $N \times N$ coefficient matrixes Φ_i obey the following recursion: $\Phi_i = A_1 \Phi_{i-1} + A_2 \Phi_{i-2} + \cdots + A_p \Phi_{i-p}$. The moving average coefficients (or transformations of these, such as impulse responses and variance decompositions), are important for understanding the dynamics of the variables.

The DY methodology focuses on the uHse of variance decompositions to describe the interconnectedness between several variables. Crucially, variance decompositions allow one to assess the fraction of the H step ahead error variance in forecasting x_i that is due to shocks in x_j, $\forall i \neq j$, for each variable i. The main upper left block of the connectedness table presented in the main text contains the variance decomposition matrix $D^H = \left[d_{ij}^H \right]$. To obtain this, we rewrite the VAR system to its moving average representation, and compute H step ahead forecasts. We then compute the corresponding forecast errors and calculate the covariance matrix.

The discussion above assumes orthogonality of the shocks, which permits a relatively easy calculation of the variance decompositions. In general, however, the innovations from a VAR are generally correlated. The usual identification schemes, such as the Cholesky decomposition, however, depend on the ordering of the variables. As such, DY propose to circumvent this problem by relying on generalized variance decompositions (GVD) as proposed by Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998). Specifically, in this framework, the entries of the H step generalized variance decomposition matrix are:

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

where e_j is a selection vector with its j-th element equal to one and zeros elsewhere, A_h is the coefficient matrix multiplying the h lagged shock vector in the infinite sum moving-average representation of the non-orthogonalized VAR, and σ_{jj} is the j-th diagonal element of Σ. Because shocks are not necessarily orthogonal in the GVD environment, sums of the forecast error variance decompositions are not necessarily unity. Hence, the measures of connectedness are normalized and based on the following decomposition matrix: $\widetilde{D^g} = \left[\widetilde{d^g_{ij}}\right]$, wherein $\widetilde{d^g_{ij}} = \frac{d^g_{ij}}{\sum_{j=1}^{N} d^g_{ij}}$. Using this decomposition, generalized connectedness measures can be computed, as reported in this article.

As DY note, the variance decompositions have a tight link to the network literature. Specifically, the variance decomposition matrix D^H is the adjacency matrix of a weighted, directed network. In this regard, the connectedness measures described earlier have analogous counterparts in the network literature. Specifically, $C^H_{i\leftarrow\cdot}$ and $C^H_{\cdot\leftarrow j}$ are from- and to-degree measures, respectively, while C^H is simply the mean degree.[1]

1 A network is an object that consists of N nodes and L links between the nodes. A node's degree is its link to other nodes. From-degrees correspond to out-degrees, which is the number of outgoing connections a node has to other nodes. To-degrees correspond to in-degrees, which is the number of incoming connections a node has to other nodes. The mean degree is, simply put, the average degree.