Master in Actuarial and Financial Sciences

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Title:

EVOLUTION OF CONNECTEDNESS LEVEL OF EUROPEAN CREDIT AND INSURANCE FIRMS.

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ABSTRACT: In this paper it's proposed an analytical study of the economical European environment, focusing into credit and insurance sectors. Measuring the volatility connectedness of a sample composed by insurance and credit firms, using the variance decomposition approach, it's pretended to, in first term, analyse if the economic and political grade of integration in the European Union has been implemented into this sectors, and also study the evolution of these measures as a historical series, in aim to understand better how the economic cycle and different extraordinary or significant events affects to the connectedness levels.

Key words:

Connectedness ***Economy*** ***Risk*** ***Transmission*** ***Volatility***

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1. INTRODUCTION

The interconnection between banks and insurance companies has intensified at the same time. Since the outbreak of the financial crisis, which began with the collapse of Lehman Brothers on 15 September 2008, traditional banking activity (project finance, consumer loans, etc.) has suffered as a result of the slowdown in the economy and an increase in risk arising from the construction of investment portfolios and customer defaults. Faced with this situation of contraction of the traditional banking business and losses derived from it, the profitability of these activities was considerably reduced. Moreover, in view of the decisions taken by the main institutions (European Central Bank, Federal Reserve) to adopt policies based on ensuring the liquidity of the economy, keeping legal interest rates very low (at times negative), the potential profit to be made from traditional banking business was further reduced. To alleviate this unfavourable economic environment, banks began to explore new sectors which have been consolidated over the last decade, expanding their lines of business in different areas, such as the sale of products and the provision of different services. The insurance sector is particularly noteworthy due to its current importance and the profound transformation of the sector brought about by the massive entry of credit institutions. Since the financial crisis of 2008, the growth in the insurance sector by entities with their original/main banking business has been exponential, and some of the most important insurance entities in Europe (in terms of volume of premiums collected) are currently banking entities. The introduction of these entities has been experienced through different formulas, either in association with traditional insurance companies, as marketing channels or by integrating the business itself through subsidiaries. Whichever formula is chosen, the presence of banks, as opposed to traditional insurance companies, is increasing. Based on this consolidated reality, the proposal of this paper is to analyse the connectivity in risk between different European entities encompassed in these two lines of business: banking and insurance. To analyse connectivity, the methodology proposed by Diebold and Yilmaz (2009, 2014)[1] will be used to study connectivity between the different institutions, not only from a static perspective, but with a dynamic depth over a selected sample period, based on the variance decomposition obtained through the estimation of a p-order vector autoregressive model (VAR). The data to be used will be the daily stock market prices of a sample of banking and insurance companies comprising the largest companies in these sectors, measured by their size based on their level of bank capitalisation. The geographical framework to be studied is Europe. Adjusted close prices will be used. In the particular case that a company's securities are listed on more than one stock market and/or in different currencies, as a data selection criterion it is established that the securities listed on the market of the company's nationality, as well as in the national currency of this state, will be used. In order to study the volatility of these time series, of each of the share price series of each of the companies, it is proposed to work not directly with the values of the share prices of the time series, but with a transformation of the variables consisting of calculating the differences between a value and its immediately preceding value, to construct a series that includes the gains or losses of the securities of each of the firms, thus defining the profitability of the shares of each of these companies, which can also be studied from the perspective of the volatility/risk of the company, which will be the approach proposed in this article.

[1] Referenced article is, in fact, Diebold, F.X. and K. Yilmaz (2014), "On the Network Topology of Variance Decompositions: Measuring the Connectedness of Financial Firms". Principally it would be followed the methodology implemented on this article, thus other articles and studies will be consulted, particularly such as Diebold and Yilmaz (2009).

2. DATA

In order to achieve the objectives proposed in this work, it is essential firstly to select a database that can meet all the necessary requirements. In line with the nature of the market to be studied, the sample chosen for this analysis is made up of information from 21 European banking and insurance companies. In order to obtain a broad sample of the different countries and realities in the European Union (EU)[2], the dispersion in the choice of the different entities fulfils the objective of representing the main economies of the European economic environment in a fairly equitable manner. The selection of entities has been based on criteria of their relevance in the current market, based on criteria of greater market capitalisation, for bank firms, and major volume of premiums, for insurance entities[3].

Dataset it's composed by the stock's prices of each 21 companies selected. The source of the data is Yahoo Finance. Stock prices are freely available information, and the availability of historical observations, for large samples such as the one required for this analysis, make these time series a very useful tool for the analysis of the volatility connectedness of these firms. Specifically, we have selected the time series corresponding to share prices at the close of trading on their reference markets, with a daily frequency of data collection. The sample period covered corresponds to the time interval from 01/01/2002 to 31/03/2022, both dates included. In total, this period includes up to 5152 observations for each of the companies. The large sample size is desirable for different reasons: Firstly, from a purely methodological perspective, time series with a high absolute frequency of data guarantee greater efficiency in the prediction stage of the results, which is a substantial advantage in the robustness of the results that will be obtained throughout this analysis. Furthermore, the overextension of the sample period makes it possible to reduce the margin of error in the selection of a relatively significant number of strange values and outliers that could distort the results obtained and the derived conclusions that could be drawn. Apart from these arguments of a formal nature, the main conceptual reason for the selection of such a rich sample of observations is based on the broad time spectrum that such a long time series allows us to study the evolution of connectivity between companies over an extended period. Not only the length of the period, but also the varying socio-economic context during the first two decades of the 21st century, with successive periods of growth cycles and stages of economic recession, immersed in a period of instability but also of opportunities, with a technological revolution associated with office technology and artificial intelligence, where we observe a growing trend of business concentration in the sectors studied, both in terms of vertical and horizontal integration of products and services, reduction in the number of institutions and integration of the different national markets, as well as of supervisory bodies and regulatory bodies, with clear examples such as the implementation of the common European currency and the standardisation of the banking and insurance regulations of each EU member state to the directives approved by the European Commission (Solvency II for insurance institutions and Basel III for credit institutions).

The list of the institutions selected, the stock market tag available for each of them, as well as the country of origin of each one and the currency used, are shown in Table 1:

[2] The represented countries are, alphabetically ordered: Belgium, France, Germany, Italy, Netherlands, Spain and United Kingdom.

[3] Insurance firms selected from MAPFRE Economics article (2021) "2020 Ranking of the largest European Insurance Groups", consult bibliography for more details.

COMPANY	TAG	COUNTRY	CURRENCY
Crédit Agricole S.A.	ACA.PA	France	Euro
Aegon N.V.	AGN.AS	Netherlands	Euro
Allianz SE	ALV.DE	Germany	Euro
Aviva plc	AV.L	UK	Pound Sterling
Barclays PLC	BARC.L	UK	Pound Sterling
Banco Bilbao Vizcaya Argentaria, S.A.	BBVA.MC	Spain	Euro
BNP Paribas SA	BNP.PA	France	Euro
Commerzbank AG	CBK.DE	Germany	Euro
CNP Assurances SA	CNP.PA	France	Euro
AXA SA	CS.PA	France	Euro
Deutsche Bank Aktiengesellschaft	DBK.DE	Germany	Euro
Assicuarazioni Generali S.p.A.	G.MI	Italy	Euro
Société Générale Société anonyme	GLE.PA	France	Euro
HSBC holdings plc	HSBA.L	UK	Pound Sterling
ING Groep N.V.	INGA.AS	Netherlands	Euro
Intesa Sanpaolo S.p.A	ISP.MI	Italy	Euro
KBC group NV	KBC.BR	Belgium	Euro
MAPFRE, S.A.	MAP.MC	Spain	Euro
Prudential plc	PRU.L	UK	Pound Sterling
Banco Santander, S.A.	SAN.MC	Spain	Euro
UniCredit S.p.A	UCG.MI	Italy	Euro

Table 1: List of selected entities. Source: own elaboration

In the case of companies listed on more than one stock market, which due to the characteristics of the selected entities are in the majority, the choice of the time series of daily share prices has been made by selecting the securities listed on the national markets of the original nationality of each of the companies.

2.1. Data Analysis

The number of time series chosen and the number of observations that make up each of these translates into a wide range of values obtained in the different statistical measures that we have obtained. From the observation of these descriptive values, we can perform a preliminary analysis of the time series. Table 2 below shows the values obtained for each of the time series, identified by their representative stock market code, for some of the main descriptive statistics: minimum, median and maximum values, the mean value, the standard deviation, and the skewness and kurtosis coefficients.

	Minimum	Mean	Median	Maximum	St. Dev	Skewness	Kurtosis
ACA.PA	2.775258	13.3625	12.0455	31.54646	5.929815	0.939852	0.511247
AGN.AS	1.67	7.434657	5.383	30.4	4.681681	1.823879	4.217397
ALV.DE	45.4	134.6	127.8	286.7999	48.79635	0.512129	-0.540492
AV.L	163.3	481.9073	456.5	873	138.0442	0.741252	0.069111
BARC.L	47.2957	306.609	255.325	728.7584	155.9196	0.830741	-0.444079
BBVA.MC	2.16	8.896431	8.246	19.29173	3.727521	0.766431	-0.022239
BNP.PA	21.38	52.45579	51.95674	94.3	12.99875	0.538165	0.512032
CNP.PA	5.415	15.02932	14.63382	24.98749	3.975679	0.18666	-0.881191
CBK.DE	2.883	65.38259	16.9	300.7549	77.63612	1.246024	0.357675
CS.PA	5.743263	19.3773	19.19957	34.19772	5.407375	0.163311	-0.578458
DBK.DE	4.871	32.84044	29.17647	91.62565	20.58877	0.673261	-0.384527
G.MI	8.215	18.03382	16.76499	33.43999	5.16815	0.965907	0.237622
GLE.PA	10.904	48.34423	42.9825	141.5376	26.15081	1.287635	1.279311
HSBA.L	283.35	640.3375	655.05	895.8371	121.443	-0.545295	-0.208149
INGA.AS	1.919695	12.61656	11.311	27.6129	5.657908	0.755006	-0.150988
ISP.MI	0.868	2.628483	2.414	5.851561	1.016016	1.009963	0.685532
KBC.BR	5.5	51.28208	50.61	106.231	22.09129	0.198227	-0.681928
MAP.MC	1.111635	2.468458	2.515	4.079306	0.58608	-0.071703	-0.549415
PRU.L	171.4591	823.8432	616.6729	1640.872	417.8448	0.320353	-1.462464
SAN.MC	1.473533	6.543077	6.067162	12.98252	2.644928	0.443473	-0.522522
UCG.MI	6.213	61.28679	31.55254	204.7992	54.01049	0.783711	-0.689707

Table 2: Descriptive statistics. Source: own elaboration.

The main conclusion drawn from the observation of these different descriptive statistics is the wide range of values obtained for each of them. As the respective time series are stock market share prices, there is a wide range of different prices quoted for the shares of the different companies, not always due to financial reasons that allow us to compare directly, such as the number of shares of each of the companies. Therefore, direct comparison of prices is not intrinsically meaningful for drawing conclusions about possible connections between companies. Furthermore, this dispersion in the values of the observations of each of the series also translates into dispersion in the values of the relative standard deviation between the companies. Generalising, we can observe that the wide range between the maximum and minimum observations could be an example of high volatility, as well as the significant levels of the standard deviation. However, given the number of observations included in the sample, the statistics corresponding to the position of the securities in the time series are very sensitive to the existence of outliers, so their significance is relative. In contrast, similar behaviour is observed for the vast majority of variables studied, with positive skewness coefficients for all companies except for HSBC holdings plc (HSBL.L) and MAPFRE, S.A. (MAP.MC).

A characteristic of financial time series, which is the nature of the series we work with in this analysis, is that they usually present trends, deterministic and/or stochastic, , throughout the sample period. In order to test the stationarity of the series chosen, various unit root tests have been carried out to test the hypothesis of non-stationarity. Specifically, the statistical tests proposed and carried out in this paper are the Augmented Dickey-Fuller, ADF (Dickey and Fuller, 1979) and Phillips-Perron contrast, on both versions, with a short and large number of lags, PP (Phillips and Perron, 1988). The results obtained for this statistics are shown into table 3:

	PRICES			RETURNS		
FIRM	ADF	Short	Long	ADF	Short	Long
ACA.PA	-0.8067	-1.7067	-1.7572	-50.5005	-70.0014	-69.9884
AGN.AS	-3.9917	-5.2513	-5.3292	-49.5462	-71.1347	-71.2944
ALV.DE	-1.2121	-2.6109	-2.6332	-50.3599	-69.4479	-69.45
AV.L	-1.4267	-3.1521	-3.0897	-50.756	-70.5725	-71.1706
BARC.L	-1.4606	-1.6705	-1.6752	-48.6106	-68.8704	-68.8704
BBVA.MC	-1.2668	-1.7347	-1.7165	-49.9522	-68.5726	-68.5797
BNP.PA	-0.5562	-2.7845	-2.818	-49.628	-70.3023	-70.3405
CBK.DE	-1.4231	-1.1197	-1.198	-49.2408	-66.3123	-66.4761
CNP.PA	-0.0686	-2.5472	-2.5252	-48.1637	-70.0014	-69.9884
CS.PA	-0.6411	-2.5675	-2.5533	-52.6973	-73.3933	-73.884
DBK.DE	-1.5864	-1.4247	-1.4899	-50.7652	-69.0291	-69.0271
G.MI	-1.2537	-2.4503	-2.4214	-48.5187	-70.2016	-70.1699
GLE.PA	-1.0179	-1.446	-1.4815	-49.8404	-67.9287	-67.9269
HSBA.L	-0.7632	-2.4893	-2.4256	-52.6551	-74.9098	-75.1565
INGA.AS	-1.2322	-2.1573	-2.1818	-49.0918	-69.0337	-69.035
ISP.MI	-0.8324	-1.8448	-1.881	-51.4129	-71.1833	-71.1606
KBC.BR	-0.1538	-1.4921	-1.5037	-49.3808	-65.2369	-65.248
MAP.MC	-0.5216	-2.9666	-2.9807	-52.886	-73.859	-73.8594
PRU.L	-0.3324	-1.4458	-1.2562	-54.4006	-72.8296	-74.4949
SAN.MC	-1.0982	-1.5688	-1.607	-50.8689	-70.8601	-70.8683
UCG.MI	-1.4373	-1.0135	-0.9934	-50.0083	-73.6556	-73.7222

Table: 3: Results obtained by the alternative unitary root tests. Source: own elaboration.[4]

The results obtained for the share price series are consistent with their presumed non-stationarity. Of the 21 series analysed, only one series, that corresponds to the company AEGON N.V. (AGN.AS), the results of the various tests indicate that it is stationary. For the rest of the institutions, the results of the unit root tests coincide in determining their non-stationary nature. These values are those corresponding to the "Price" columns in Table 3. Applying a differentiation in the series, and calculating the series of financial returns of each company, the application of the same tests obtains results that clearly indicate the stationarity of these returns series, as would be expected from a stochastic series corresponding to financial returns. These values are represented in the columns corresponding to "Returns" in table 3.

[4] Critical Values for unitary root tests.

	99%	95%	90%
Critical Value	-3.434666	-2.862632	-2.567379

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3. METHODOLOGICAL APPROACH

The main methodological basis of this analysis is based on the methodology proposed and subsequently developed by Diebold and Yilmaz (2009, 2014), consisting of the decomposition of the variance obtained from a vector autoregressive model (VAR) as an index for analysing the degree of connectivity of the variance obtained in the estimation of the aforementioned VAR model. The main advantage of using a VAR model in this context is that it allows us to correctly characterise the interactions between the different variables that make it up, such as the time series used in this paper. Another of the advantages of using these models is their usefulness derived from the unrestricted nature of the system of equations that comprise it, as it is not necessary to (correctly) identify the exogenous and endogenous variables of the model; furthermore, in this context of this analysis, where it is desired to analyse the simultaneous interactions of all the variables with each other, the fact that no endogenous variables are specified is an additional advantage.

For the necessary construction of the VAR model, estimates of the volatility obtained for each of the time series used, corresponding to the different companies selected for the proposed sample will be used. This volatility, following the methodology proposed by the reference authors, will be obtained by means of the proposed estimation of a Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model, proposed by Bollerslev (1986), as a generalisation of the Autoregressive Conditional Heteroscedasticity (ARCH) model originally proposed by Engle (1982).

3.1. Conditional Variance. GARCH Models

GARCH models, as we have already mentioned, are models built to model and predict the variance of time series. As their name suggests, the main characteristics of these models are as follows:

- Generalised: This model includes both recent and historical observations.
- Autoregressive: All of the variables analysed by the model (temporal series of stock prices returns) depend on their respective previous values. There exists a linear dependence between the contemporaneous value of the variable and their *p* last values.
- Conditional: The expected value of the variance depends on the value of his historical variance estimated.
- Heteroscedasticity: The variance of ε_t , the error of an observation *t*, is the same as its own observation "*t*".

The mathematical definition of any GARCH (p, q) model is embodied in the following equation:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i * \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i * \sigma_{t-i}^2 \qquad [1]$$

Where each predicted value of the variance, for each observation t, σ_t^2, depends linearly on the estimated values of the variance for the p immediately preceding observations and the q last squared errors. This modelling results in the projection of a model with p + q + 1 parameters. Parameter 0 is a constant value, while the parameters of vectors i and i are the values associated with the weighting of each of their corresponding observations. Considering the nature and properties of the variance, the intrinsic conditions in the estimation of α_0, α_i and β_i parameters that must be fulfilled are the following:

- Positivity Condition: variance being a measure of dispersion defined in a strictly non-negative range of values ($\sigma_t^2 \geq 0$); the same condition is imposed for all the parameters to be estimated:

$$\alpha_0 \geq 0,\ \alpha_i \geq 0,\ \beta_i \geq 0 \qquad [3]$$

- Stationarity Condition: $\sum_{i=1}^{q} \alpha_i + \sum_{i=1}^{p} \beta_i < 1$ [4]

With these considerations, the determination of the number of parameters to be estimated is the responsibility of the observer performing each analysis. For this work, with the aim of simplifying this secondary modelling stage, the model with the smallest number of parameters to estimate has been selected, selecting the values p = 1 and q = 1, the GARCH (1,1) proposed model also it's the most common in the estimation of conditional variances.

The generic structure of a GARCH (1,1) model such as the one estimated in this work, for each of the time series, is as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 * \varepsilon_{t-1}^2 + \beta_1 * \sigma_{t-2}^2 \qquad [5]$$

Estimating the corresponding GARCH (1,1) model for each of the 21 variables considered in the sample, we will obtain an estimate of the series corresponding to the values of the conditional variance, which we will use for the construction of the VAR model.

3.2 Vector Autoregressive Models (VAR)

A vector Autoregressive model (VAR) is a statistical model, first proposed by Sims (1980), used to identify and model the possible relationship between different stochastic variables. Therefore, a VAR model is constituted as a reduced and sequenced system of equations in matrix form, made up of as many variables as desired. With this methodology, the aim is to model each of the variables (in this case, the volatility estimates obtained with the respective GARCH models, for each of the time series of the stock returns of the companies in the sample), as a linear relationship with the other time series. In this model, the different estimated parameters represent the component of the value of a variable that corresponds to the interaction with another variable.

Since this is an autoregressive model, like GARCH models, it is up to the observer to decide on the choice of the number p of past observations to use for the estimation of the model. In the simplest case, using a model with p = 1, VAR(1); and the minimum number of variables necessary for its construction, 2, the specification of a generic VAR model with these characteristics would be as follows:

$$\begin{cases} x_t = c_{11} + a_{11}x_{t-1} + a_{12}y_{t-1} + \varepsilon_{x_t} \\ y_t = c_{22} + a_{21}x_{t-1} + a_{22}y_{t-1} + \varepsilon_{y_t} \end{cases} \qquad [6]$$

An alternative representation of a Vector Moving Average (VMA) model to the above is as follows:

$$z_t = \sum_{i=1}^{\infty} A_i \cdot \varepsilon_{t-i} \qquad [7]$$

Where i = 1,2, … , N; $\varepsilon_{t-i} \sim N(0, \sigma^2)$ and A_i is a matrix of order NxN, formed by the different estimated coefficients.

This representation of a VAR(p) model allows us to simplify the identification of each of the variance components. Matrix $[A_i]_{NxN}$ indicates the proportion attributable to each of the variables that make up the autoregressive vector of the variance of the prediction error of each of the variables. The elements of the main diagonal of this matrix correspond to those of the variable itself, while the elements outside this correspond to the effects of the other variables.

3.3. Connectedness. Variance Decomposition

For the actual analysis of the connectivity between all variables, once the respective conditional variance values have been obtained by estimating GARCH (1,1) models, and the corresponding VAR model has been modelled, it is first necessary to specify a number of different assumptions or hypotheses to work within a defined framework. Following the benchmark methodology proposed by Diebold and Yilmaz (2014), the choice of methodology for variance decomposition will be based on methods of the family of Cholesky-factor decomposition vector autoregression (Sims, 1980) and, complementary for some special measures, we propose to use the Generalised Variance Decomposition (GVD) framework, elaborated by Koop et al. (1996), and Pesaran and Shin (1998). One of the principal differences between Cholesky and GDV is that Cholesky decomposition results may be sensible to the variables chosen order, otherwise GVD don't have this issue. As Diebold and Yilmaz (2014) mentioned, "*total connectedness is robust to Cholesky ... Directional connectedness, however, is* *sometimes more sensitive to Cholesky ordering*". Taking into consideration that the number of time series used is 21, the possible different combinations in the ordering of these is a very high number, being the exercise of finding the most efficient combination a superfluous effort, considering the use of GVD, which assures us that the selected order of the variables has no significance whatsoever..

The matrix $D^{gH} = [d_{ij}^{gH}]$ is noted by Diebold and Yilmaz (2014) as "*The H-step generalised variance decomposition matrix*" and each element d_{ij}^{gH} is defined in the next equation:

$$d_{ij}^{gH} = \frac{\sigma_{jj}^{-1} \cdot \sum_{h=0}^{H-1}(e_i'\theta_h\Sigma e_j)^2}{\sum_{h=0}^{H-1}(e_i'\theta_h\Sigma\theta_h' e_i)}, \qquad [8]$$

Where:

- e_j is a vector of j^{th} elements and zeros elsewhere.
- θ_h is a matrix of coefficients multiplying the h-lagged shock vector of the moving-average matrix of the non-orthogonal VAR model estimated.
- Σ corresponds to the covariance matrix of shocked vector in the non-orthogonalized vector.
- σ_{jj} corresponds to the element j^{th} of the principal diagonal of matrix Σ.

As it's indicated, the framework of the GVD is not necessarily orthogonal; the aggregate of all contributions of the forecasting error variances mustn't need to be unity

Hence, the connectedness indexes are constructed on $\widetilde{D}^g = [\tilde{d}_{ij}^g]$ [9], we can extend this matrix to represent their values as a connectedness table:

	x_1	x_2	...	x_N	**From Others**
x_1	$\tilde{d}_{11}^g$	$\tilde{d}_{12}^g$	...	$\tilde{d}_{1N}^g$	$\sum_{j=1}^{N} \tilde{d}_{1j}^g, j \neq 1$
x_2	$\tilde{d}_{21}^g$	$\tilde{d}_{22}^g$	...	$\tilde{d}_{2N}^g$	$\sum_{j=1}^{N} \tilde{d}_{2j}^g, j \neq 2$
⋮	⋮	⋮		⋮	⋮
x_N	$\tilde{d}_{N1}^g$	$\tilde{d}_{N2}^g$	...	$\tilde{d}_{NN}^g$	$\sum_{j=1}^{N} \tilde{d}_{Nj}^g, j \neq N$
To Others	$\sum_{i=1}^{N} \tilde{d}_{i1}^g$ $i \neq 1$	$\sum_{i=1}^{N} \tilde{d}_{i2}^g$ $i \neq 2$	...	$\sum_{i=1}^{N} \tilde{d}_{iN}^g,$ $i \neq N$	$\frac{1}{N}\sum_{i,j=1}^{N} \tilde{d}_1^g$ $i \neq j$

Table 4: Connectedness table. Source: own elaboration.

Where $\tilde{d}^g_{ij} = \frac{d^g_{ij}}{\sum_{j=1}^{N} d^g_{ij}}$. With this definition of $\tilde{d}^g_{ij}$, by construction we obtain that $\sum_{j=1}^{N} \tilde{d}^g_{ij} = 1$, and also $\sum_{i,j=1}^{N} \tilde{d}^g_{ij} = N$. From these definitions, we can directly proceed to calculate the generalised connectedness measures.

3.3.1. Connectedness measures

From the components exposed from the connectedness table, we can obtain the different measures that we will use for the analysis of static or unconditional connectedness, in the following section.

The connectedness table, with respect to "variance decomposition matrix", differs in the addition of a rightmost column, and a row on the bottom. The rightmost column contains the aggregate results of sums of each row values, and the bottom row it's the result of summing all the values, for each column values. Also, additionally, the element from the bottom-right corner represents the total connectedness[4] (for all values if $i \neq j$).

The principal diagonal elements of the matrix $\widetilde{D}^g$ corresponds to what could be defined as the "own connectedness" (Diebold and Yilmaz, 2014). These values represent the intrinsic percentage of the total variance for each variable. This is the argument why both, rightmost column ("From Others") and bottom row ("To Others"), on the connectedness table, these diagonal values are not included on the aggregation. The off-diagonal elements, otherwise, are the components of the forecast-error decomposition of the variance that are relevant to study and understand the connectedness between the different elements. These elements, following always the nomenclature presented by Diebold and Yilmaz, are defined as *pairwise directional connectedness* from j to i, with these nomenclature:

$$\tilde{C}^g_{i \leftarrow j} = \tilde{d}^g_{ij} \qquad [10]$$

Coincidence between the values of $\tilde{C}^g_{i \leftarrow j}$ and $\tilde{C}^g_{j \leftarrow i}$it's not systematic, quite the opposite; generally$\tilde{C}^g_{i \leftarrow j} \neq \tilde{C}^g_{j \leftarrow i}$, so the total number of existing pairwise connectedness values are equal to N^2 - N, that for 21 variables, it's 420. These values correspond to the connectedness that a variable i receives from a variable j, in percent terms of the total variance of the element i.

This element $\tilde{C}^g_{i \leftarrow j}$, as it has been defined, it can be interpreted also as the gross connectedness received from one company from another. The next logical measure to define is the *net pairwise directional connectedness*, mathematical represented as;

$$\tilde{C}^g_{ij} = \tilde{C}^g_{i \leftarrow j} - \tilde{C}^g_{j \leftarrow i} \qquad [11]$$

In these case, the number of net pairwise directional connectedness values obtained are just half of pairwise directional connectedness values, $\frac{N^2-N}{2}$. The number of these elements, for our sample is, thus, equal to 210.

The aggregation of the elements in each column outside the main diagonal of the matrix$\widetilde{D}^g$, represented in the column "From to", represents the total (in percentage terms) of the variance prediction error of a particular company that is transmitted to it from shocks affecting any of the other entities (the aggregation of all, from each of the other 20 entities). This measure is defined as *total directional connectedness from other to i*:

$$\tilde{C}^g_{i\leftarrow\cdot} = \sum_{j=1,j\neq i}^{N} \tilde{d}^g_{ij} \qquad [12]$$

At the same time, by inverting the terms of this definition, we can obtain the complementary measure, i.e. the value that indicates (also in percentage terms, respect to the total variance), the total volume of variance that company j transmits to the set formed by the rest of the companies in the sample. We define this measure as total directional connectedness to others from j, formalised by the following notation:

$$\tilde{C}^g_{\cdot\leftarrow j} = \sum_{i=1,i\neq j}^{N} \tilde{d}^g_{ij} \qquad [13]$$

For each company series, there exists one value of both measures, so the total number of connectedness measures is 42, 21 of each.

At least, the average connectedness value, represented on the right-bottom element of the connectedness table, could be calculated as the average value of the elements of the "From Others" column, and also with the values of "To Others" row, with identical results. Mathematically, this value is represented by:

$$\tilde{C}^g = \frac{1}{N} \sum_{i,j=1,i\neq j}^{N} \tilde{d}^g_{ij} \qquad [14]$$

[5] The total connectedness value it's obtained as the mean of column "from" values, or equivalently, mean of "to" elements.

4. EMPIRICAL APLICATION OF THE CONNECTEDNESS

Having described up to this point the different tools to determine the connectivity between the companies chosen for this work, the next section is to apply the aforementioned tools to analyse the possible relationships in the estimated volatilities. To do this, we use the information obtained from the share prices of 21 of the most important companies in the European banking and insurance sectors. The main objective is to carry out a comprehensive study to establish the structural behaviour of the risk transmission relationships, in order to be able to draw reliable conclusions about how the different entities coexist and whether and to what degree there are dependency relationships between their risk profiles. With the aforementioned aim of establishing a structural framework for these relationships, a broad temporal scope has been selected for this work, corresponding to almost the entire period corresponding to the last 21 years. In order for this analysis to give a true picture of these companies in particular, and of the insurance and banking sector in general, the choice of a time frame up to the present day is doubly recommended. The large sample size means that the results obtained are less sensitive to a specific economic moment, or to a single phase of the economic cycle, but rather that there is an overlapping of different stages of the economic cycle, as well as the vast majority of the most important socio-economic events that have taken place so far in the 21st century.

In order to meet these two proposed objectives, two complementary approaches will be used to analyse the connectivity between the different entities proposed. Firstly, we will study static connectivity (full-sample), in which we will determine the degree of average (or unconditional) connectivity throughout the sample period. This still image is a useful tool to determine the existing relationships, and to what degree or intensity they exist, both in modulus and in direction. Thanks to the methodology implemented by Diebold & Yilmaz (2014), we can determine and analyse both the aggregate volatility that a firm transmits (and is transmitted to it) by the remaining set of its peers, as well as the singular effects between all possible pairs of firms resulting from the different dual combinations that we can form between all of them. The empirical implementation of the described methodology and the interpretation of the results are supported by the use of software *R,* package "*frequencyConnectedness*" (Krehlik, 2018), as accompanies of the implementation exposed in a paper of Barunik and Krehlik (2018).

To study the effects in line with the sample moment of connectivity, determining its evolution over the sample period, we will carry out a dynamic study (rolling-sample) of conditional connectivity, conditioned, as we are dealing with time series, to the equivalent date of the different estimated observations. This dynamic analysis will allow us to understand how the interrelationship between all the companies, aggregate and singular, has varied, allowing us to deepen our knowledge of how the different stages of the economic cycle influence the risk of owning a portfolio of securities representative of these securities. Furthermore, it will allow us to fulfil the proposed objective of being able to relate moments and remarkable temporary events and try to correlate them with remarkable values or trends in the results obtained.

4.1 Static Analysis. Fixed Window of the Connectedness

As mentioned above, the selection of companies chosen for the development of this article consists of a compendium of 21 banking and insurance companies, including some of the largest companies in their respective sectors, in terms of market capitalisation. The selection of these entities, as well as the number selected, has been based on the overriding criterion of obtaining the most reliable picture possible of the sector. In order to meet this primary objective of fidelity, as a complementary criterion, a proportional distribution has been considered, as far as possible, in the representation of the main economies of the European Union. Specifically, companies from the following countries are represented: Germany, Belgium, Spain, France, Italy, the Netherlands and the United Kingdom (the latter country ceased to be a member of the community club effectively on 31/01/2020, as a result of the result obtained in the referendum on the United Kingdom's membership of the European Union on 23/06/2016).

The broad sample period chosen has two main advantages: The first of these, is the availability of a substantial number of observations (more than 5000 per time series), with the corresponding benefits in terms of efficiency in the estimation of the proposed models and in the use of the tools already described. The second advantage, derived from the chosen sample size, is the conjunction of different and varied events and different time series, with the corresponding benefits in terms of efficiency in the estimation of the proposed models and in the use of the tools already described.

Table 7 shows the results obtained in the estimation of the full-sample connectedness. First, we study the elements located on the main diagonal of the results matrix. These values correspond to what Diebold & Yilmaz (2014) define as "own connectedness", i.e. the proportion of the variance that it’s explained by it’s own shocks, the endogenous connectivity that generates the volatility of the values of each company. It is to be expected, or rather it would be expected, that the greatest value of connectivity for an entity is provided by the effect of its own values. Observing the results present in the main diagonal of the static connectivity matrix, we find different values within a range located at a lower limit of only 2.92% of "own connectedness", up to 64.27%, the highest value.

1	MAP.MC	**2.92**	8	BARC.L	**9.28**	15	SAN.MC	**14.46**
2	CNP.PA	**3.55**	9	ACA.PA	**11.25**	16	GLE.PA	**14.49**
3	ISP.MI	**3.73**	10	ALV.DE	**12.13**	17	PRU.L	**15.74**
4	BNP.PA	**4.85**	11	G.MI	**12.54**	18	INGA.AS	**29.19**
5	CS.PA	**7.04**	12	HSBA.L	**12.57**	19	AGN.AS	**31.27**
6	AV.L	**7.24**	13	KBC.BR	**13.57**	20	BBVA.MC	**34.64**
7	DBK.DE	**7.26**	14	CBK.DE	**13.66**	21	UCG.MI	**64.27**

Table 5: “Own Connectedness” Values, per each firm. Source: own elaboration.

Although this range is certainly not very narrow, a closer look at the values of this set clearly identifies that the vast majority of values fall within a much more limited range, between 2.92% and 15.74%. Only the results for 4 entities, corresponding to the tickets INGA.PA, AGN.AS, BNP.PA and UCG.MI obtain a value above this given range. Of these last four observations, the proximity between the values obtained for INGA.PA, AGN.AS and BNP.PA results in the value obtained for UCG.MI being an outlier with respect to the rest of the sample.

Based on the definition of the elements of the main diagonal of the matrix, the remaining elements *Cij-th*, where *i* is not = *j*, represent the possible pairs of directional connectivity, i.e. the proportion of connectivity that element *i* = *k* receives from each element *j* =1,2, ..., *k*, ..., *n*. With this definition, the sum of the values defined above, for each element i of the portfolio, is the totality of connectivity that this element receives, both from its own volatility and that generated by the other elements. By construction of this percentage index, as each *ij-th* value is the 12-day-ahead forecast error variance of the ticket i, due to impacts derived from ticket j, the result of this aggregation is 100. Therefore, if their own connectedness is subtracted from the total possible connectedness, the result is the aggregate value of connectedness received from all of the pairwise possible for an element i. This aggregation, collects the information on the total percentage of connectivity that each element receives from its congeners, being the measure to study how much impact the aggregate has on each individual company. All these values, for each of the companies, are collected on the rightmost column of table 8, tagged as "FROM".

1	UCG.MI	**35.73**	8	CBK.DE	**86.35**	15	AV.L	**92.74**
2	BBVA.MC	**65.37**	9	KBC.BR	**86.42**	16	DBK.DE	**92.75**
3	AGN.AS	**68.75**	10	HSBA.L	**87.43**	17	CS.PA	**92.96**
4	INGA.AS	**70.82**	11	G.MI	**87.46**	18	BNP.PA	**95.14**
5	PRU.L	**84.27**	12	ALV.DE	**87.86**	19	ISP.MI	**96.28**
6	GLE.PA	**85.52**	13	ACA.PA	**88.74**	20	CNP.PA	**96.44**
7	SAN.MC	**85.56**	14	BARC.L	**90.74**	21	MAP.MC	**97.08**

Table 6: Total Connectedness values, per each firm. Source: own elaboration.

As we can see, the value obtained is complementary to the previously mentioned own connectedness. We observe that, for most entities, the connectivity they receive from the rest of their peers turns out to be very important, with the same particularities as those mentioned above: The cluster formed by INGA.AS, AGN.AS and BNP.PA, and the extreme value of UCG.MI. Just as the aggregation of all the pairs of directional connectivity received by company *i* allows us to establish the amount of volatility transmitted to it by the other elements of the set; if instead we add up the *ij* elements of each of the columns, we obtain a complementary value that represents the total directional connectivity of company *k* towards all the others. In this case, the results obtained are not limited to a range less than or equal to 100 (in percentage), since it is the level of volatility that a company contributes to the whole, with respect to the total of its own volatility measure. These values are shown in the last column of Table 9, "TO".

1	AGN.AS	**403.08**	8	CBK.DE	**67.65**	15	AV.L	**17.69**
2	INGA.AS	**315.51**	9	ACA.PA	**59.76**	16	GLE.PA	**16.31**
3	UCG.MI	**218.1**	10	PRU.L	**42.6**	17	HSBA.L	**16.07**
4	BBVA.MC	**166.37**	11	KBC.BR	**35.73**	18	DBK.DE	**14.16**
5	CS.PA	**143.48**	12	BNP.PA	**32.09**	19	ISP.MI	**13.15**
6	G.MI	**82.78**	13	ALV.DE	**27.37**	20	SAN.MC	**12.42**
7	BARC.L	**68.91**	14	MAP.MC	**26.74**	21	CNP.PA	**8.61**

Table 7: Total Directional Connectedness (to) values. Source: own elaboration.

With this relaxation of the upper limit of the range of possible heats, we observe that the range of results obtained is much larger, ranging from 8,61% value, corresponding to CNP.PA, to a 403,08% of AGN.AS. However, we observe that similar clusters are formed around the same companies, such as the one formed by INGA.PA, AGN.AS and BNP.PA; however, on this occasion we observe that it is precisely these tickets (together with the one corresponding to UGI.MI) that present a greater transmission of volatility towards the totality of their peers. We observe that the five entities that transmit a volatility higher than 100% of their own (AGN.AS, INGA.AS, UCG.MI, BBVA.MC, CS.PA); this list is made up of 3 banking entities and 2 insurance entities. If we extend this selection to include the 10 entities that transmit the most risk, the ratio of insurers to banks is 6 banks and 4 insurance companies.

Taking into account the structure of the selected portfolio, this distribution of total directional connectivity, according to the highest degree of vulnerability, is consistent with the proportion of institutions from each sector in the sample. If we perform the same measure for total directional connectivity received by each of the entities from the other entities, we observe that the distribution for the 5 entities receiving the least volatility is also 3 banks and 2 insurance entities. If we extend the selection to the top 10 firms, this distribution is 7 banks and 3 insurance companies.

10-th fewer "TO" connectedness						10-th larger "FROM" connectedness					
1	CNP.PA	**8.61**	6	GLE.PA	**16.31**	1	MAP.MC	**97.08**	6	DBK.DE	**92.75**
2	SAN.MC	**12.42**	7	AV.L	**17.69**	2	CNP.PA	**96.44**	7	AV.L	**92.74**
3	ISP.MI	**13.15**	8	MAP.MC	**26.74**	3	ISP.MI	**96.28**	8	BARC.L	**90.74**
4	DBK.DE	**14.16**	9	ALV.DE	**27.37**	4	BNP.PA	**95.14**	9	ACA.PA	**88.74**
5	HSBA.L	**16.07**	10	BNP.PA	**32.09**	5	CS.PA	**92.96**	10	ALV.DE	**87.86**

Table 8: Fewer "To" Connectedness and larger "From" connectedness firms, ordered by their respective values. Source: own elaboration.

If we also check which entities make up both lists, we observe that the coincidence between elements present in the two lists is up to 5 entities out of a total of 10. Restricting this selection to only the first 5, the coincidence between their members

	ACA.PA	AGN.AS	ALV.DE	AV.L	BARC.L	BBVA.MC	BNP.PA	CBK.DE	CNP.PA	CS.PA	DBK.DE	G.MI	GLE.PA	HSBA.L	INGA.AS	ISP.MI	KBC.BR	MAP.MC	PRU.L	SAN.MC	UCG.MI	**FROM**
ACA.PA	11.25	23.56	0.42	0.6	3.97	8.62	1.55	7.44	0.85	5.16	0.38	4.15	0.45	0.9	15.34	0.41	1.39	2.44	3.28	0.33	7.5	**88.74**
AGN.AS	2.28	31.27	0.79	0.44	4.32	9.21	2.4	1.17	0.29	12.53	0.68	9.68	1.7	0.13	11.26	0.1	2.27	0.67	0.8	0.2	7.83	**68.75**
ALV.DE	1.11	26.04	12.13	1.72	4.3	4.55	0.66	2.32	0.31	12.89	2.3	7.35	0.22	0.77	16.24	1.01	2.25	0.18	1.33	0.26	2.05	**87.86**
AV.L	1.93	26.76	4.5	7.24	4.14	4.55	1.43	4.97	0.55	7.29	1.68	6.71	1.07	2.2	10.1	0.88	1.86	1.17	1.96	0.31	8.68	**92.74**
BARC.L	3.56	25.32	1.59	0.33	9.28	8.55	1.9	3.25	0.39	11.05	0.91	5.06	0.34	0.23	17.3	0.48	2.81	1.28	0.93	0.7	4.76	**90.74**
BBVA.MC	1.67	23.83	0.32	1	1.91	34.64	3.96	0.33	0.76	0.39	0.14	0.34	2.25	0.67	14.72	0.5	1.49	2.4	2.35	0.19	6.15	**65.37**
BNP.PA	3.05	21.84	1.33	0.4	3.85	10.62	4.85	1.31	0.6	11.24	0.31	4.41	2.13	0.82	21.68	0.26	1.99	0.4	1.07	0.14	7.69	**95.14**
CBK.DE	4.11	21.1	0.53	0.12	3.08	6.36	0.68	13.66	0.16	7.56	0.26	3.63	0.29	0.5	18.67	0.83	1.99	0.66	4.9	0.45	10.47	**86.35**
CNP.PA	1.25	22.65	2.07	0.07	2.62	8.56	0.45	1.9	3.55	8.13	0.54	3.38	1.4	0.33	18.74	0.39	1.98	0.56	1.68	0.36	19.38	**96.44**
CS.PA	9.24	20.62	0.34	1.22	2.31	8.35	0.84	13.14	1.12	7.04	1.26	2.09	0.35	1.47	14.12	0.86	0.45	3.22	3.96	0.51	7.49	**92.96**
DBK.DE	2.17	22.96	2.38	0.11	5.95	4.57	1.26	4.07	0.1	12.72	7.26	12.92	0.58	0.07	12.68	0.64	2.13	0.3	2.05	0.33	4.76	**92.75**
G.MI	2.76	22.06	1.18	0.06	5.91	9.88	1.44	2.3	0.18	11.7	0.75	12.54	0.35	0.43	17.74	0.43	2.5	1.09	1.19	0.27	5.24	**87.46**
GLE.PA	5.12	13.73	1.75	0.52	4.78	7.85	5.15	1.11	0.25	11.06	1.24	3.82	14.49	2.47	17.02	0.2	2.11	0.52	2.55	0.58	3.69	**85.52**
HSBA.L	0.56	10.36	5.17	1.5	1.13	6.92	0.16	1.86	0.94	3.96	0.78	0.22	1.38	12.57	16.21	0.1	0.9	0.38	2.37	1.24	31.29	**87.43**
INGA.AS	3.33	19.98	0.33	0.27	3.38	12.06	2.43	1.03	0.15	8.61	0.06	2.79	1.24	0.06	29.19	0.02	1.69	0.46	1.38	0.3	11.25	**70.82**
ISP.MI	4.37	22.79	0.56	0.99	6.06	10.48	0.87	4.64	0.27	2.8	0.29	1.14	0.1	0.9	17.13	3.73	2.86	1.88	1.66	0.76	15.73	**96.28**
KBC.BR	1.6	17.06	1.22	0.38	2.99	10.41	0.42	2.28	0.21	1.15	0.56	1.03	1.25	0.64	19.34	0.9	13.57	3.52	0.9	0.82	19.74	**86.42**
MAP.MC	2.9	19.87	1.26	0.12	3.77	9.13	0.26	3.09	0.19	6.98	0.34	1.15	0.28	1.01	19.3	0.62	2.73	2.92	2.81	0.74	20.53	**97.08**
PRU.L	3.21	21.41	1.39	0.23	3.26	7.26	0.97	7.03	0.41	6.51	1	5.04	0.36	0.34	15.05	0.35	1.22	0.64	15.74	1.05	7.54	**84.27**
SAN.MC	4.84	17.04	0.09	0.61	0.92	11.92	0.76	2.81	0.65	0.46	0.08	5.16	0.32	1.26	13.48	1.26	0.42	4.91	2.24	14.46	16.33	**85.56**
UCG.MI	0.7	4.1	0.15	0.09	0.26	6.52	0.1	1.6	0.23	1.29	0.6	2.71	0.25	0.87	9.39	0.05	0.69	0.06	3.19	2.88	64.27	**35.73**
TO	**59.76**	**403.08**	**27.37**	**17.69**	**68.91**	**166.37**	**32.09**	**67.65**	**8.61**	**143.48**	**14.16**	**82.78**	**16.31**	**16.07**	**315.51**	**13.15**	**35.73**	**26.74**	**42.6**	**12.42**	**218.1**	

Table 9: Full-sample table. Sample length starts January 1, 2002 through March 31, 2022. Source: own elaboration.

grows to represent 4 entities in common, these four entities being those previously mentioned, the first 4 in each of the lists.

It seems that it could be deduced, at least for this set of entities, that there is an inversely proportional relationship between the risk they receive from the other entities and the risk they transmit to their peers. In other words, the entities that receive the least risk from the set are the same entities that transmit the most risk. In the reverse lists, i.e. considering the ten firms that transmit the least connectivity and the ten that receive the most connectivity, the coincidence is 6 entities in common. Under these circumstances, with such remarkable differences between the connectivity received and transmitted by the companies, the net connectivity of each of them, which we will define below, will be high.

The difference between the values of the total directional connectivity that a company transmits towards the others (column "TO") and the total directional connectivity that it receives (column "FROM"), is the net total directional connectivity of a company towards the others. This value will allow us to define which companies, in net terms, discounting the total directional connectivity that each of them transmits to its peers, these others transmit to it, to know if it transmits more risk than it receives. As pointed out above, the disparity between the total directional connectivity received and transmitted, by verifying a more than possible existence of an inversely proportional relationship for some of the entities in the sample, leads us to think that for some companies it will be positive, and for others, negative. AGN.AS leads the ranking of entities with the highest total net positive directional connectivity (334.33%), followed by INGA.AS (244.69%), UCG.MI (182.37%), BBVA.MC (101.00%) and CS.PA (50.52%). It should be noted that of these five companies, these are the five companies that complete the list of entities with the highest volatility transmitted to the market. These five listed companies are the only ones that have a positive total net directional connectivity balance, i.e. they contribute more volatility to the other companies than they receive from them. Only these 5 companies out of the total of 21 entities in the sample. The remaining 16 entities in the sample are net receivers of connectivity, so that, in terms of total net directional connectivity, a few companies transmit a lot of volatility to the whole.

1	AGN.AS	**334.33**	8	BARC.L	**-21.83**	15	MAP.MC	-70.34
2	INGA.AS	**244.69**	9	ACA.PA	**-28.98**	16	HSBA.L	-71.36
3	UCG.MI	**182.37**	10	PRU.L	**-41.67**	17	SAN.MC	-73.14
4	BBVA.MC	**101**	11	KBC.BR	**-50.69**	18	AV.L	-75.05
5	CS.PA	**50.52**	12	ALV.DE	**-60.49**	19	DBK.DE	-78.59
6	G.MI	**-4.68**	13	BNP.PA	**-63.05**	20	ISP.MI	-83.13
7	CBK.DE	**-18.7**	14	GLE.PA	**-69.21**	21	CNP.PA	-87.83

Table 10: Total Net Directional Connectedness values. Source: own elaboration.

On average, the total directional connectivity value received by each of the 21 securities represented in the sample is 84.5%. This value indicates the existence of a degree of connectivity in the banking and insurance sector as a whole, of which the selected sample is a reliable representation. This result is similar to that obtained by Diebold and Yilmaz (2014), who estimated an average total directional connectivity value of 78.3% for a sample of thirteen financial institutions[6]. No particular differences were found in the segmentation between banks and insurance companies, as it can be seen that both banks and insurance companies are among those that transmit more volatility and those that also receive more connectivity. The high degree of connectivity can be explained to some extent by the high degree of integration of these sectors, especially in the case of the banking sector, a sector in which the weight of insurance activity, either by the banks themselves or through subsidiaries dedicated to insurance activity, or through the creation of economic associations or joint ventures such as the one between AEGON (AGN.AS) and Banco Bilbao Vizcaya Argentaria (BBVA.MC). Another important factor is the integration of all companies into the common European economic area, and with the exception of the British companies (AV.L, BARC.L, HSBA.L and PRU.L), they operate in the same currency, the euro (€). Integration into the European Union, and monetary union, entails supervision by the European Central Bank (ECB) for banks of a significant size, including all the banks in the sample[7]. The integration of the sector, together with the financial nature of the banks themselves, entails a high degree of total connectivity. Although the total connectivity received is relatively homogeneous across all banks, the total connectivity generated presents a much wider range, being mostly transmitted by a few banks, while some others make a rather small contribution.

4.1.1. Bounds

In an exercise of analysing how volatility shocks are distributed, we can decompose the measure on desired frequencies and get the frequency dependent measures. The objective of implementing this methodology at this point is to identify whether there are significant differences in the connectivity matrix for two segments: The volatility, on each given date, corresponding to a period from 1 to 4 days, and the corresponding volatility for a period from those 4 days onwards. The objective of this connectivity segmentation is to observe, firstly, whether the connectivity generated in the immediately preceding period is significant with respect to the total connectivity generated by each possible pair, and also to analyse whether for this specific segment the previously described distribution of entities changes in terms of the total directional connectivity they generate towards others and receive from others.

As can be seen in table 13, the directional connectivity originating in the indicated interval is only a very small fraction of the total directional connectivity. These results clearly indicates that the connectivity results are almost entirely dependent on the information immediately prior to the predicted observation, while the weight of the information coming from the oldest observations has almost no significant relevance in the transmission of volatility between the different companies. In the corresponding table, moreover, we can observe that the main component of connectivity for this interval (above the 4 days immediately prior to each predicted observation), the main component is the own connectedness, unlike the behaviour observed for the observations as a whole, as we have discussed in this section. These results indicate that the ability to transmit volatility across firms is much smaller with older information, in relative terms. The impact of risk transmission is different if we take into account closer or more distant information, from the perspective of the time instant of the observation, with a greater impact of the own connectedness itself, and as the relative importance of this decreases if we also take into account the immediately preceding information.

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[5] The large number of series used to construct the sample is directly related to the large degree of connectivity calculated. The percentage of "own connectedness" of each variable (firms) it's inversely related to the number of variables, as larger is the sample, the each variable's intrinsically connectedness is fewer.

[6] All of credit firms displayed are considered "significant supervised entities which are directly supervised by the ECB". The list of supervised entities could be consulted in the last report of the List of supervised entities (as of 1 April 2022), publicized by ECB.

Table 11: Segmented full-sample connectedness table, by intervals. Lower interval. Source: own elaboration.

	ACA.PA	AGN.AS	ALV.DE	AV.L	BARC.L	BBVA.MC	BNP.PA	CBK.DE	CNP.PA	CS.PA	DBK.DE	G.MI	GLE.PA	HSBA.L	INGA.AS	ISP.MI	KBC.BR	MAP.MC	PRU.L	SAN.MC	UCG.MI	**FROM**
ACA.PA	0.15	0	0	0	0.01	0	0	0	0	0.01	0	0.01	0	0	0	0	0.01	0	0.01	0	0.01	**0.06**
AGN.AS	0	0.14	0	0	0.01	0.05	0	0.01	0	0.01	0	0.01	0	0	0.05	0	0	0	0.01	0	0.07	**0.22**
ALV.DE	0	0.01	0.08	0.03	0	0	0	0	0	0.02	0	0.01	0	0.01	0	0	0.01	0	0	0	0	**0.09**
AV.L	0.01	0	0.04	0.15	0.01	0	0	0	0	0.01	0	0.01	0	0.04	0	0	0	0	0.01	0	0.02	**0.15**
BARC.L	0.01	0.01	0	0	0.09	0	0	0	0	0.01	0	0.01	0	0	0	0	0.04	0	0.01	0	0	**0.09**
BBVA.MC	0	0.04	0	0	0	0.19	0	0	0	0	0	0	0	0	0.05	0	0	0	0	0	0.06	**0.15**
BNP.PA	0.01	0	0	0	0.01	0	0.07	0	0.01	0.01	0	0	0.03	0	0	0	0	0	0	0	0	**0.07**
CBK.DE	0	0	0	0	0	0	0	0.15	0	0.01	0	0.01	0	0	0	0	0	0	0.06	0	0	**0.08**
CNP.PA	0	0	0	0	0	0	0	0	0.1	0.01	0	0	0	0	0	0	0	0	0	0	0	**0.01**
CS.PA	0.16	0	0	0	0.02	0	0	0	0	0.08	0	0	0	0	0	0	0	0	0	0	0.01	**0.19**
DBK.DE	0	0.01	0	0	0	0	0	0.03	0	0.02	0.18	0.01	0	0	0	0	0	0	0.03	0	0.01	**0.11**
G.MI	0.01	0	0	0	0.06	0	0	0	0	0.02	0	0.03	0	0	0	0.01	0.03	0	0	0	0	**0.13**
GLE.PA	0.01	0	0	0.01	0.01	0	0.05	0	0.01	0.01	0	0	0.13	0.01	0	0	0	0	0.01	0	0.01	**0.13**
HSBA.L	0	0	0.01	0.04	0.01	0	0	0.01	0	0	0	0	0.01	0.11	0	0	0	0	0.01	0	0.01	**0.1**
INGA.AS	0.01	0.04	0	0	0.01	0.04	0	0.01	0	0.01	0	0	0	0	0.17	0	0	0	0.01	0	0.06	**0.19**
ISP.MI	0.02	0	0	0	0.12	0	0	0	0	0.01	0	0	0	0	0	0.09	0.06	0.01	0	0	0	**0.22**
KBC.BR	0	0	0	0	0.02	0	0	0	0	0	0	0	0	0	0	0	0.17	0	0	0	0	**0.02**
MAP.MC	0.02	0	0	0	0.08	0	0	0	0	0.01	0	0	0	0	0	0.01	0.06	0.13	0	0	0	**0.18**
PRU.L	0	0	0	0	0	0	0	0.07	0	0.01	0	0.01	0	0	0	0	0	0	0.17	0	0	**0.09**
SAN.MC	0.07	0.01	0	0	0	0	0.01	0	0	0.01	0	0	0	0	0	0	0	0	0	0.14	0	**0.1**
UCG.MI	0	0.03	0	0	0	0.04	0	0	0	0	0	0	0	0	0.04	0	0	0	0	0	0.08	**0.11**
TO	**0.33**	**0.15**	**0.05**	**0.08**	**0.37**	**0.13**	**0.06**	**0.13**	**0.02**	**0.19**	**0**	**0.08**	**0.04**	**0.06**	**0.14**	**0.02**	**0.21**	**0.01**	**0.16**	**0**	**0.26**	**0.12**

Table 12: Segmented full-sample connectedness table, by intervals. Lower interval. Source: own elaboration.

	ACA.PA	AGN.AS	ALV.DE	AV.L	BARC.L	BBVA.MC	BNP.PA	CBK.DE	CNP.PA	CS.PA	DBK.DE	G.MI	GLE.PA	HSBA.L	INGA.AS	ISP.MI	KBC.BR	MAP.MC	PRU.L	SAN.MC	UCG.MI	**FROM**
ACA.PA	11.1	23.55	0.42	0.6	3.96	8.62	1.55	7.44	0.85	5.15	0.38	4.14	0.44	0.9	15.34	0.41	1.38	2.44	3.27	0.33	7.49	**88.66**
AGN.AS	2.27	31.13	0.79	0.43	4.31	9.16	2.4	1.17	0.28	12.52	0.68	9.67	1.7	0.13	11.21	0.1	2.27	0.67	0.79	0.2	7.76	**68.51**
ALV.DE	1.11	26.04	12.05	1.69	4.29	4.55	0.66	2.32	0.31	12.88	2.3	7.34	0.22	0.76	16.23	1.01	2.24	0.18	1.33	0.26	2.05	**87.77**
AV.L	1.92	26.76	4.46	7.09	4.13	4.55	1.43	4.97	0.55	7.28	1.68	6.7	1.07	2.15	10.1	0.88	1.86	1.17	1.96	0.31	8.66	**92.59**
BARC.L	3.56	25.32	1.59	0.33	9.19	8.55	1.9	3.25	0.39	11.03	0.91	5.05	0.33	0.23	17.3	0.48	2.77	1.28	0.92	0.7	4.76	**90.65**
BBVA.MC	1.66	23.78	0.32	1	1.9	34.45	3.96	0.32	0.76	0.39	0.14	0.34	2.25	0.67	14.67	0.5	1.49	2.4	2.34	0.19	6.09	**65.17**
BNP.PA	3.04	21.84	1.33	0.4	3.84	10.62	4.79	1.31	0.59	11.23	0.31	4.4	2.1	0.82	21.68	0.26	1.99	0.4	1.07	0.14	7.69	**95.06**
CBK.DE	4.11	21.1	0.53	0.12	3.08	6.35	0.68	13.51	0.16	7.54	0.26	3.63	0.28	0.5	18.67	0.83	1.99	0.66	4.84	0.45	10.47	**86.25**
CNP.PA	1.25	22.65	2.07	0.07	2.62	8.56	0.45	1.9	3.45	8.12	0.54	3.37	1.4	0.33	18.74	0.39	1.98	0.56	1.68	0.36	19.37	**96.41**
CS.PA	9.07	20.62	0.34	1.22	2.29	8.35	0.84	13.13	1.12	6.96	1.26	2.08	0.35	1.46	14.12	0.86	0.45	3.22	3.96	0.5	7.48	**92.72**
DBK.DE	2.17	22.95	2.38	0.11	5.95	4.57	1.26	4.04	0.1	12.69	7.08	12.91	0.58	0.07	12.67	0.64	2.13	0.3	2.03	0.33	4.75	**92.63**
G.MI	2.75	22.06	1.18	0.06	5.85	9.88	1.44	2.3	0.18	11.69	0.75	12.51	0.35	0.43	17.74	0.42	2.47	1.08	1.19	0.27	5.24	**87.33**
GLE.PA	5.1	13.73	1.75	0.51	4.77	7.84	5.1	1.11	0.24	11.05	1.24	3.82	14.36	2.46	17.02	0.2	2.11	0.51	2.53	0.58	3.68	**85.35**
HSBA.L	0.55	10.36	5.16	1.46	1.13	6.92	0.16	1.86	0.94	3.95	0.78	0.22	1.37	12.46	16.21	0.1	0.9	0.38	2.35	1.24	31.28	**87.32**
INGA.AS	3.33	19.93	0.33	0.26	3.37	12.02	2.43	1.03	0.15	8.61	0.06	2.79	1.24	0.06	29.02	0.02	1.69	0.46	1.37	0.29	11.18	**70.62**
ISP.MI	4.35	22.79	0.56	0.99	5.93	10.48	0.87	4.64	0.27	2.79	0.29	1.14	0.1	0.9	17.13	3.64	2.8	1.87	1.65	0.76	15.73	**96.04**
KBC.BR	1.6	17.06	1.22	0.38	2.97	10.41	0.42	2.28	0.21	1.15	0.56	1.03	1.25	0.64	19.33	0.9	13.4	3.52	0.9	0.82	19.74	**86.39**
MAP.MC	2.88	19.87	1.26	0.12	3.69	9.13	0.26	3.09	0.19	6.97	0.34	1.14	0.27	1.01	19.3	0.61	2.67	2.79	2.8	0.73	20.53	**96.86**
PRU.L	3.2	21.41	1.39	0.23	3.26	7.26	0.97	6.97	0.41	6.5	1	5.03	0.36	0.34	15.05	0.35	1.21	0.64	15.57	1.05	7.54	**84.17**
SAN.MC	4.77	17.04	0.09	0.61	0.91	11.91	0.75	2.81	0.65	0.44	0.08	5.16	0.32	1.26	13.48	1.26	0.41	4.9	2.24	14.32	16.33	**85.42**
UCG.MI	0.7	4.07	0.15	0.09	0.26	6.48	0.1	1.6	0.23	1.29	0.6	2.71	0.25	0.87	9.35	0.05	0.69	0.06	3.19	2.88	64.19	**35.62**
TO	**59.39**	**402.93**	**27.32**	**10.68**	**68.51**	**166.21**	**27.63**	**67.54**	**8.58**	**143.27**	**14.16**	**82.67**	**16.23**	15.99	315.34	10.27	35.5	26.7	42.41	12.39	217.82	**84.36**

4.2. Dynamic Connectedness. Rolling-window approach to Connectedness.

The analysis in the section on static or unconditional connectivity has provided a complete picture of the average connectivity over the entire sample period, which corresponds to a time period of 21 years and 3 months. Intrinsic to the nature of averaging, it encompasses periods of higher connectivity with periods of lower connectivity, especially since the sample size of the data used is so large. In order to really study connectivity in relation to time, to analyse its evolution over the sample period, this section proposes a dynamic analysis using an estimation of connectivity values based on the moving window method, where past information is used to calculate each of the successive values. For this analysis, as for the static connectivity, we use the same data.

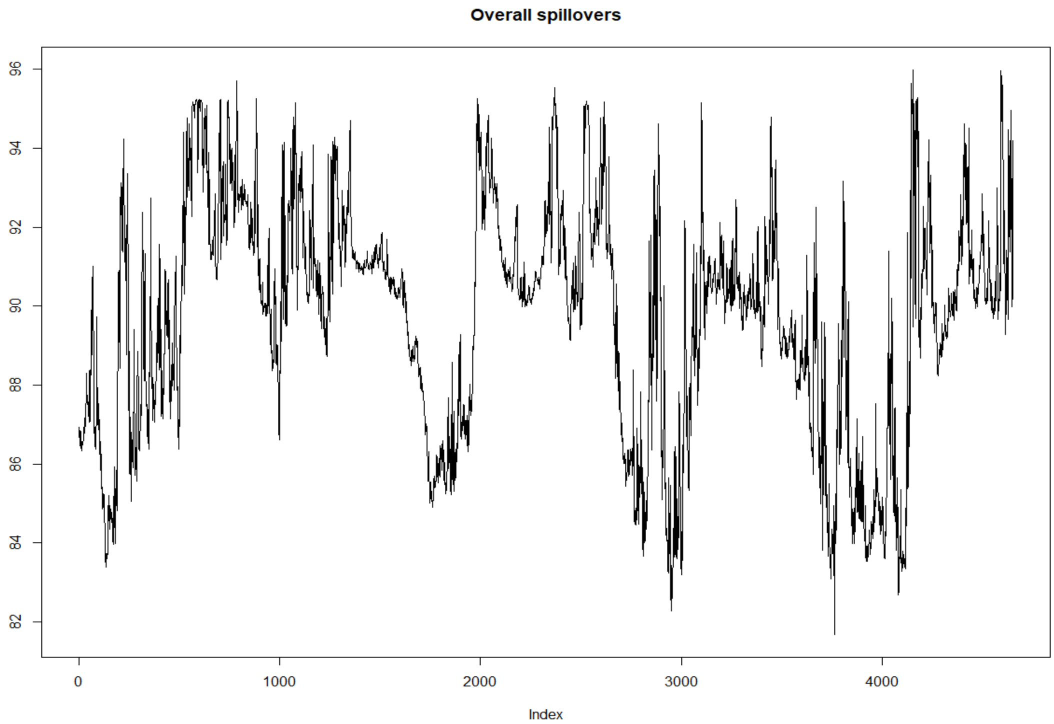


Figure 1: Rolling-window-estimation of total connectedness. The predictive horizon for the variance decomposition (H) is 12 days, and the rolling estimation window width (w) is 500 days. Source: own elaboration.

4.2.1. Total Dynamic Connectedness

For the estimation, we use a rolling estimation window of 500 days width. For the elaboration of figure 1, the use of 500 observations for the volatility estimation implies that the first value represented corresponds to observation 501. Our period starts with the first observation corresponding to 01/01/2022. Based on an approximation of the number of observations per calendar year, which we define as 250 observations per year, the first value of the estimate would correspond to the beginning of 2004. With this consideration, looking at figure 1, we can identify different stages and patterns along the time frame. In the first years (corresponding to the period immediately prior to the onset of the 2008 financial crisis), we observe an upward trend in connectivity, from a level similar to the average calculated in the previous section, to a level close to 96%. In this first cycle, corresponding to one of the most buoyant periods of the European economy, we observe a fairly homogeneous upward trend in connectivity throughout the period, only being affected by occasional decreases that could be attributable to major socio-political events that affected several states, such as the terrorist attacks on the train network in Madrid (Spain) on 11 March 2004 (coinciding with the first sharp drop in the level of total connectivity represented in the figure 1) and also with the terrorist attack on the London Underground (UK) on 7 July 2005. This upward cycle in the level of connectivity between all the entities in the sample was first halted by the financial crisis of 2007, derived from the bursting of the subprime mortgage bubble in the United States, and complemented by the subsequent financial crisis, which was widely considered to have started with the collapse of Lehman Brothers on 15 September 2008.

These events, although they had a negative impact on the level of total connectivity, were not permanent over a very long period, recovering in a short time to a level similar to the peak reached years earlier. During this period, the level of total connectivity showed certain stagnation, fluctuating around a value of 92%. It was not until 2009-2010 that a second trend began, in this case a negative one, with a significant and lasting reduction in the level of connectivity, with a drop to values close to 85%. This period corresponds to the beginning and most severe stage of the economic recession derived from the aforementioned financial crises, in the first instance. The recovery of the level of connectivity after this period with a downward trend, again leads to a period of high volatility in the level of connectivity with a trend again around 92%, just the level prior to the great economic recession of 2009. In this case, the period elapsed during this period, which includes approximately the years between 2011 and 2013, both inclusive, is characterised by a series of successive increases and decreases, in line with the climate of economic uncertainty of the time, with periods of economic growth, stagnation and correlative recession, marked by events as relevant as the sovereign debt crisis of different states of the European Union, the bailout of the Spanish banking sector in July 2012, among others.

This period of high volatility around a relatively constant trend is preceded by an abrupt decrease in the level of total connectivity in 2014, with events that generated so much uncertainty and political and economic instability, such as the Crimean crisis in February 2014, which led to a political and economic confrontation between the main economies of the developed countries (including the member states of the European Union and the United Kingdom) and Russia, and the referendum on Scottish independence from the United Kingdom on 18 September 2014. The resulting increase in the level of connectivity turns out to be transitory, with a subsequent sharp drop to return to a previous level of less than 84%. Since then, and up to the present day, the volatility in the estimated connectivity levels has been very high, a true reflection of the instability in all areas in which the European (and, in general, global) economy and society have been immersed over the last decade: the referendum on the United Kingdom's permanence in the European Union on 23 June 2016, the victory in the United States of the candidate Donald J. Trump in November 2016, with a legislature marked by tensions and tensions both internally and in international politics, the economic war between China and the United States (with indirect effects for European countries), the effective exit of the United Kingdom from the European Union on 31

January 2020, the economic crisis derived from the Covid-19 epidemic and the war in Ukraine this year, 2022, are among the most notable.

The upheaval suffered in the European geographical environment, and globally in general, has also translated into the upheaval observed in figure 1. of the total connectivity values estimated for this representative set of companies in the insurance and banking sectors, with successive and pronounced rises and falls, with few intervals of low volatility, and no significant interval with a clear trend. The instability of the period clearly translates into the volatility of the estimated total connectivity values, increasing in magnitude in periods of uncertainty, and decreasing in calmer periods.

4.2.2. Total Directional Dynamic Connectedness

The dynamic analysis of total connectivity allows us to identify how the different economic cycles and the main socio-political events of the 21st century have had a significant impact on the price of the securities represented in the selected sample. In order to identify and study the singular effects for each of the entities analysed, we will now perform the same analysis for dynamic directional connectivity.

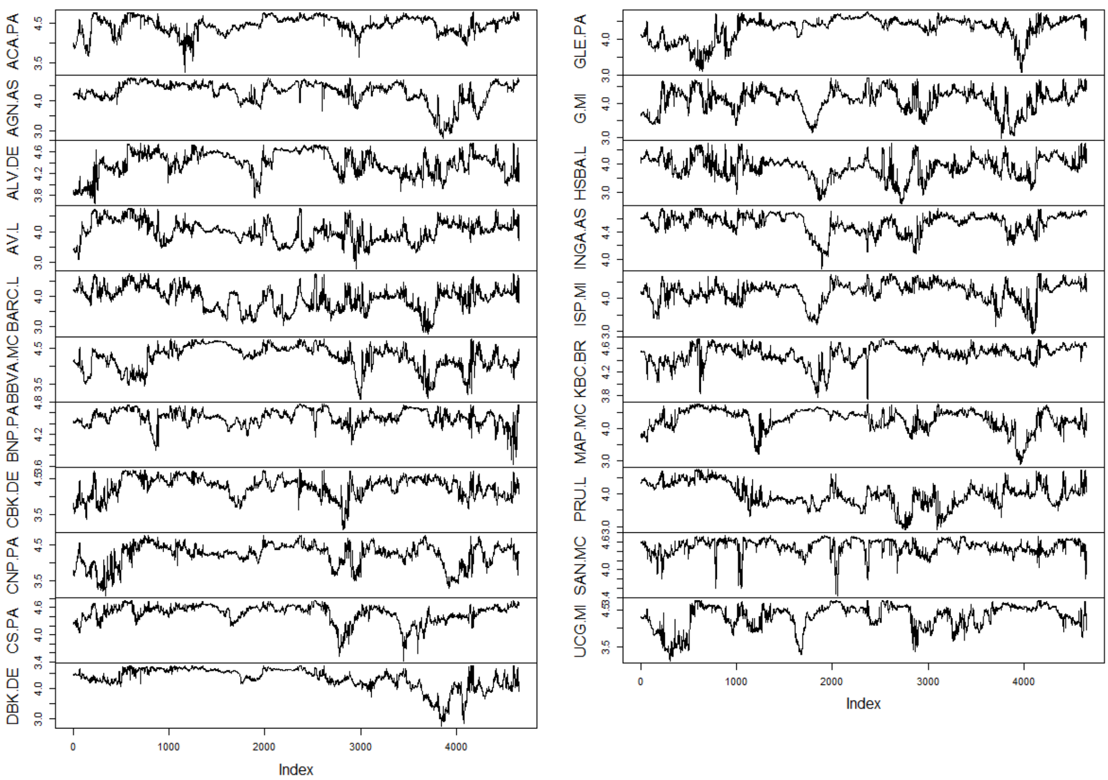
To study the dynamic directional connectivity, the following page shows the figure 2, which includes both the results of the estimation of the total directional connectivity that the entity itself receives ("from"), in the upper panels; and the results of the estimation of the directional connectivity that it transmits to the other entities that make up the set studied ("to"), in the lower panels.

Firstly, we can observe that the range of estimated values of dynamic directional connectivity estimated for "to" is wider than "from", in line with the values obtained during the static connectivity estimation phase. It is also found, as expected, that the degree of connectivity is high for all the entities, in line with all the results obtained and with the idiosyncrasies of the political and economic environment, with a high degree of integration in these areas, and also because these are some of the most representative and important companies in the insurance and banking sectors.

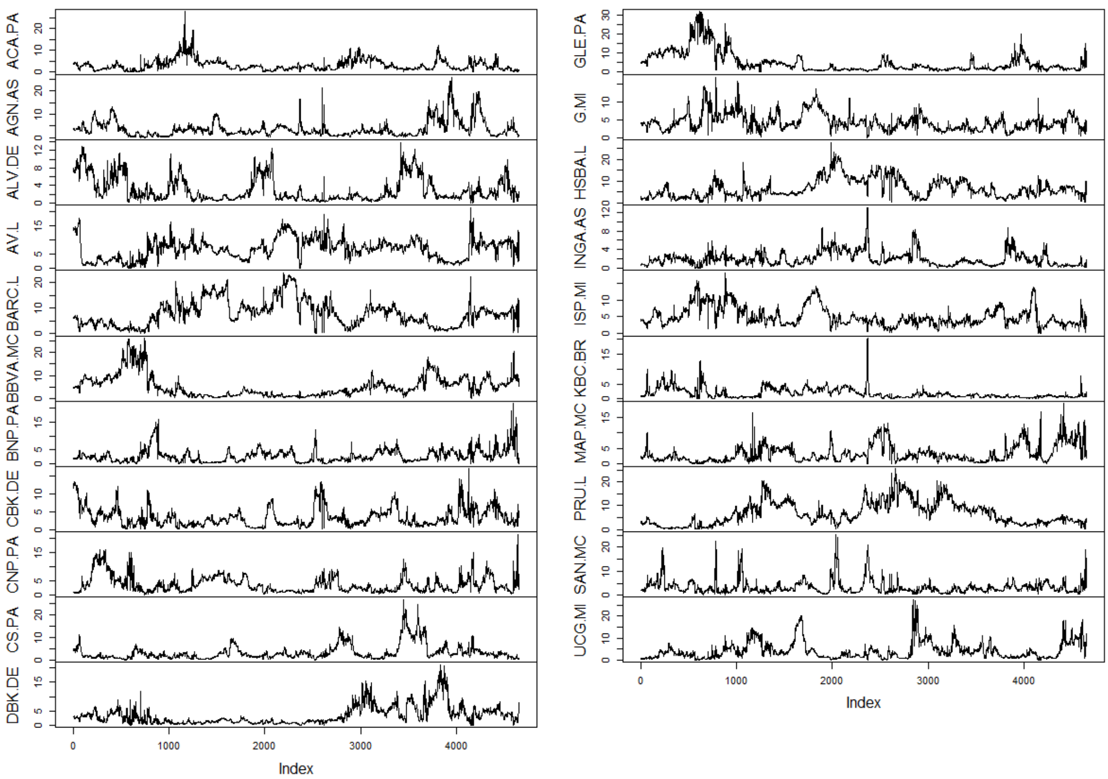
It can also be clearly observed that there is no significant trend for the entire analysed interval, and it is also difficult to determine clear segments, in all the analysed series, that can be observed as common to all the series.

Looking at the figures corresponding to the total directional connectivity towards the other companies, ("to"), does not indicate the existence of any common trend for all the time series, yet it seems that there could be distinct clusters or groups with consistent connectivity transmission profiles over most of the time period. The number of series used in this work has allowed us to obtain a very rich sample of different observations and time series.

From spillovers



To spillovers



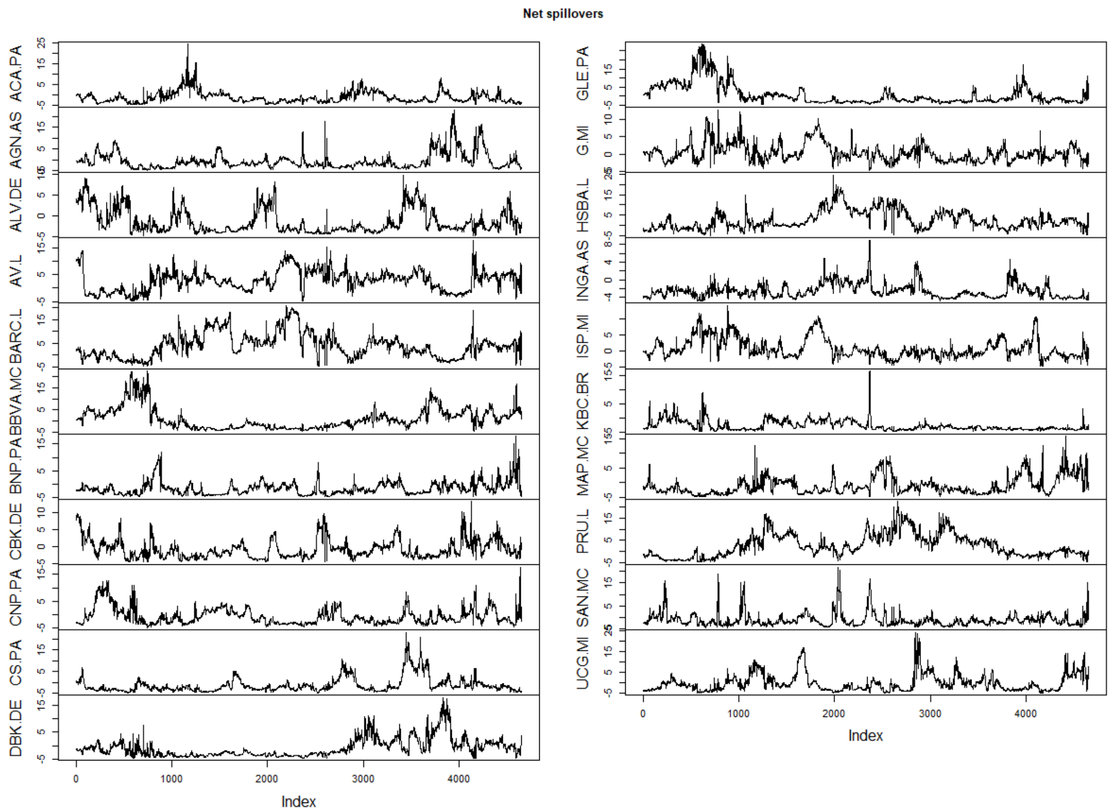


Figure 2: Total directional pairwise rolling-window connectedness estimations, per each firm. Source: own elaboration

4.2.3. Robustness Analysis

The model parameters considered for the estimation of the above predictions, as indicated in the previous section, are a predictive horizon for the variance decomposition of 12 days (*H* = 12 days), and a sample window width equal to 500 observations (*w* = 500 days). To analyse the robustness of the results obtained with these parameters, we will now present graphically the results obtained for total connectivity obtained by modifying the hypotheses used for these two parameters. Specifically, we consider an alternative for the number of days of the productive horizon, modifying this value to *H* = 9 days; and we also proceed to the prediction of the results using two alternative sample window widths (*w* = 250 and *w* = 750). The original parameters, and their respective alternatives tested, are represented in the next table:

	Proposed	**Alternatives**	
Predictive Horizon (*H*)	12 days	9 days	
Window Width (*w*)	500 observations	250 observations	750 observations

Table 13: Selected values, and their respective possible alternatives, for parameters *H* and *w*. Source: own elaboration.

The results of the different combinations of predicted horizons (*H*) and different sample window widths (*w*), for the total connectivity, are plotted in figure 3:

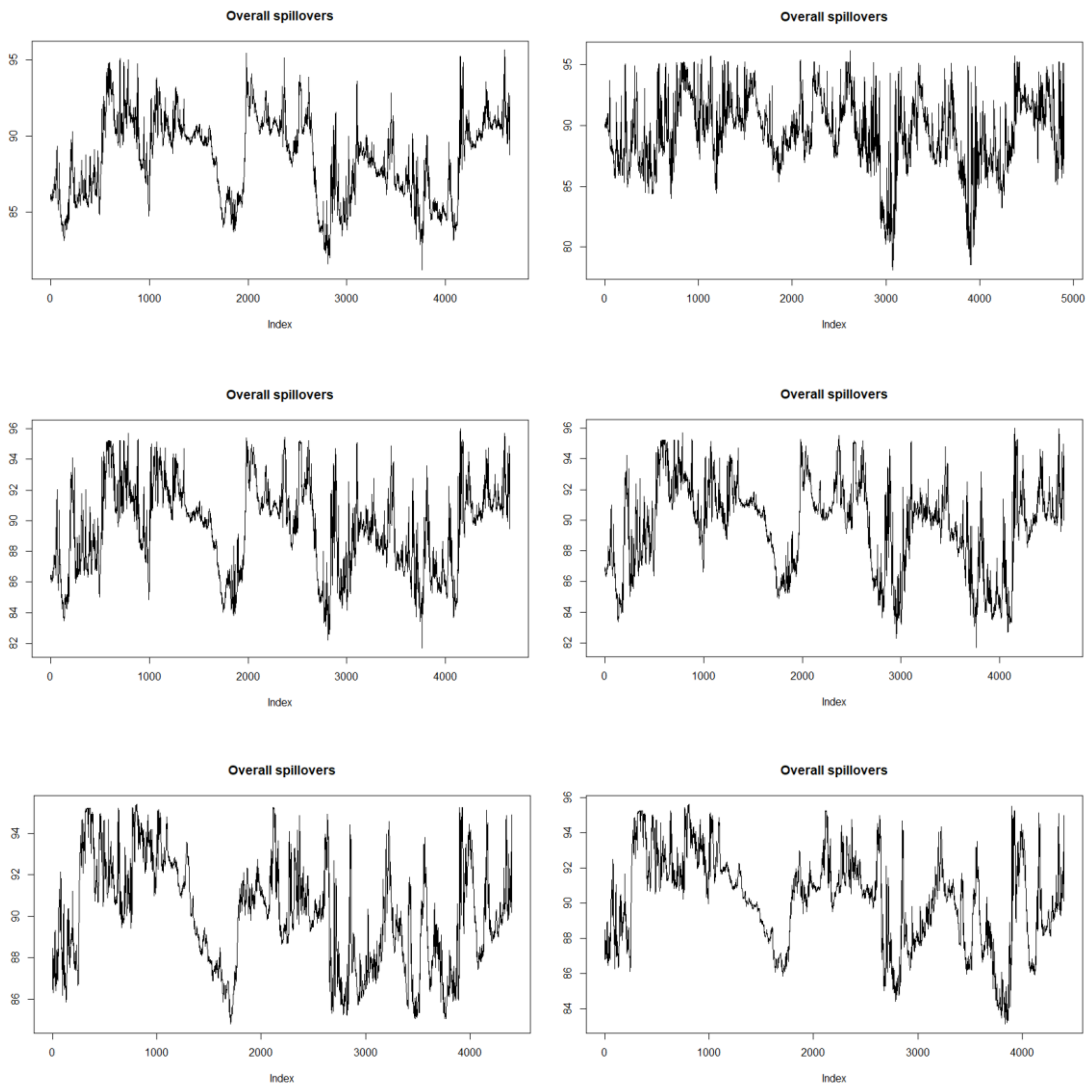


Figure 3: *Rolling-window-estimation of total connectedness. Different alternatives are modelled. The left column of figures represents the predictions, starting for the top, for scenarios H = 9, w = 250; H = 9 w = 500; and H = 9, w = 750; respectively. Rightmost figures represented, in the same order, the results for scenarios H = 12, w = 250; H = 12 w = 500; and H = 12, w = 750. Source: own elaboration.*

It can be seen in the different graphs that there are no very significant differences between the respective results, with different predictive horizons and prediction window sizes. The results obtained, represented in the respective figures, show similar trends to those discussed in section 4.2.1, and the range of connectivity values is basically the same in the different alternatives.

Observing the different elements that make up figure 3, we can establish that the increase in the size of the moving window, *w*, implies an increase in the "sensitivity" of the predicted values, in line with the greater number of previous observations used to make the prediction. The same expected behaviour, but in the opposite direction, is observed for predictions made with a decrease in the size of the aforementioned moving window, with the corresponding loss of precision in the values resulting from the prediction, and the "flattening" of the time series. This last aspect is clearly identifiable for the alternative prediction corresponding to a predictive horizon H = 12 days and a moving window w = 250 observations; the loss in the number of observations used implies a substantial decrease in the quality of the predictions, disseminating to a substantial extent the different trends/characteristics observed in the series with a larger size of w, while maintaining the amplitude of the time series within a range of values similar to those obtained in its counterparts. With reference to the results obtained with the modification of the predictive horizon, H, no substantial differences are observed in the different predicted series, comparatively speaking.

Summarising, it can be concluded that the robustness of the total dynamic connectivity results is significant, using alternatively different sizes of moving windows (w), and predictive horizons (H), obtaining similar time series. Decreasing the observations of the moving average may lead to a decrease in the accuracy of the prediction results, being advisable to use a substantial size.

5. CONCLUSIONS AND RESULTS

During the first two decades of the 21st century, the process of economic, political and social integration reflected in the European Union project has been consolidated and has continued to develop, to a greater or lesser extent, depending on the area, albeit with some setbacks and difficulties. Since the euro came into circulation in 2002, the economic integration of the different economies of the European Union, especially the countries that make up the euro area, has experienced very significant growth, with a homogenisation of regulations, institutions and markets. This homogenisation has also been reflected in the insurance and banking sectors. The main hypothesis formulated about the degree of integration in the aforementioned sectors, measured by the proposal to analyse and interpret the existing connectivity in the share prices of representative companies, has been fully accepted and validated by the results obtained. The results obtained in the determination of the value corresponding to the total static connectivity of the sample as a whole indicate that up to 85.5% of the total volatility of the set of 21 entities that make up the sample corresponds to volatility mutually transmitted between the values of all the entities among themselves. This value is very high compared with that obtained in other studies carried out for assets of a similar nature. However, although the total connectivity of the whole group is very high, we have been able to see that it is not uniform for all the institutions, with very different behaviour between institutions. In terms of the singular percentage of variation received from the other institutions, we observe that this is a majority percentage for 20 of the institutions (in line with the overall value), with only one institution having a higher intrinsic component in the composition of its total volatility. This relative uniformity in terms of the connectivity received disappears when analysing its inverse behaviour, in percentage terms of the connectivity transmitted to the rest of the institutions. The range of results obtained for this measure is very uneven, with some institutions obtaining values much higher than the estimated total volatility, while for some others the amount of risk transmitted is, in percentage terms, very low. It is worth noting that, of the total of 21 companies analysed, only 5 of them transmit a higher volume of volatility than their own. In terms of net volatility connectivity, this figure of 5 companies remains the number of net transmitters of connectivity, with the remaining 16 companies being net receivers. Of this number of companies, up to a total of 11 companies have net connectivity values equal to or higher (in absolute value) than -50.0%, i.e. these companies receive 50% or more risk from the rest of the set than they transmit to it.

These results clearly indicate that the risk, with respect to the elements that make up the sample, is not transmitted uniformly among all the entities, the distribution of transmitted risk is very disparate from the values established for the degree of total connectivity received; we observe that although the level of connectivity received is relatively similar for all the elements of the group studied, its counterpart, in terms of transmission, its values are totally disparate, highlighting the main idea that only a few elements are the net transmitters of volatility to the group, while the majority are recipients of it, also being terms of the absolute majority of the entities that are significant net receivers of connectivity, in the terms indicated above, it can be seen that the transmission of connectivity is not homogeneous in the set, with a specific and reduced set of entities being the net transmitters (in percentage terms) of risk to the set, although the structure of the different possible combinations of pairs of firms, in terms of net connectivity, did converge, in their entirety, to similar values, in line with the fact that, in overall terms, the total connectivity received from all the firms is in a relatively small range, with marked exceptions, and their mode and median coincide in values close to those of the mean.

In terms of the dynamic behaviour of these risk measures, we have found, firstly, that the high level of connectivity existing in the elements of the sample and, by extension, in the economic sectors represented by it, is historically high throughout the entire period analysed, with this high value of connectivity being consistently high. In terms of the historical evolution of connectivity, one of the hypotheses formulated, about the increase in the degree of connectivity over the sample period, could not be verified or refuted with clear results, as no consistent trend could be identified for the entire predicted historical series. The results of the conditional prediction of the connectivity values have shown that connectivity, as has been mentioned, has been very important throughout the period, with values in a range around the value obtained for the unconditional analyses. However, even without being able to identify a trend for the whole period, different cycles / singular trends have been observed, corresponding, in different periods, to different stages or events in the economic cycle. It has been possible to analyse and identify which, chronologically, expansive stages of the economic cycle were correlated with positive trends in the growth of the degree of connectivity existing in these sectors, while in recessive stages this identified behaviour was of an inverse nature. Even so, these trends have turned out to comprise a limited number of observations/periods, with the majority of observations corresponding to cycles without a clear trend, with very pronounced and repeated oscillations, especially being more frequent in the values corresponding to the predictions closest to the current date, in the second half of the time series. This stage would coincide with greater political, economic and social uncertainty and instability, characteristic of the second decade of the 21st century. The results obtained from the analysis of dynamic connectivity lead to the conclusion that instability, in terms of uncertainty and pronounced changes in the macroeconomic environment, translates into instability in the transmission of volatility in the affected sectors.

6. BIBLIOGRAPHY

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