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Network dynamic and stability on European Union

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ABSTRACT

This paper proposes an analysis of the financial market of 14 countries of the European Union, under the vision of the dynamic networks using the motif-synchronization method. It is found that the countries of Central Europe (France, the Netherlands, Germany, and the UK) are the most influential in the remaining exchanges of the European Union countries. They were also found as hubs during and after the subprime crisis in Ireland and Greece. The network formed between the indices of the countries in the European Union increased its connectivity constantly from 1988 up to 2008 and 2009, years in which the subprime crisis occurred, and after 2008–2009 the connection gradually decreased until the year 2017, revealing behavior before and after the crisis. The results corroborate the thesis that strongly connected financial networks are more susceptible to exogenous shocks than sparse networks.

1. Introduction

Since its creation, the European Economic Community, now the European Union (EU), had the objective of increasing economic integration between countries. Initially, it was created with the objective of fostering international trade, but it always had the expectation of increasing the level of integration. Thus, the integration of a number of new countries into the EU was not unexpected, neither was the deepening of the integration, with the creation of the single market, which expanded the free circulation not only of products but also services, citizens, and capital. Later, the establishment of a common currency for the majority of EU countries followed the objective of increased integration.

In particular, the free flow of capital and the creation of a common currency should have a major impact on the integration of financial markets, namely the stock markets. Because integration in general and stock market integration in particular could have important effects on economies, studying this feature continues to be important. In fact, it is expected that a deeper market integration could promote economic growth, because it would improve savings allocation

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and investments. However, it could also have negative impacts, such as the possibility of increasing risks and a faster spread of negative shocks.

In this context, it was found that as a result, there is a strong connection between EU stock markets, both before and after the 2008–2009 crisis, as well as a change in the connectivity pattern of the network once it turned sparser after the subprime crisis (see, for example, Ferreira et al. [1]). This result reinforces the idea that connected networks are more sensitive to exogenous shocks than sparse networks, mainly in the EU, where historically strong financial integration exists.

Thus, we focused our analysis on the study of stock market integration in the EU, based on a network formed by stock market indices before and after the crisis using the theory of time-varying graphs (TVG) and the motif-synchronization method. We create dynamic networks that will allow us to identify those markets that are more influenced by and have more influence on other markets. Our proposal has two main advantages: (i) as we use a network, we can investigate which are the most important stock markets in that network; (ii) as our methodology can be studied dynamically, we can study the evolution of the network over time showing that when a network tends towards stability, this can be indicative of financial crisis.

Owing to data availability, our sample starts in 1988. Because we are interested in studying how the network developed, we split our sample into several subsamples, all of them with a two-year dimension. This will allow us to study the evolution of the network over time.

The remainder of this paper is organized as follows. In the second section, we present a review of the literature on stock market integration, first identifying some advantages and disadvantages and, second, centered on the analysis of how the stock market evolved in the EU. In the third section, we present the data and the methodologies used in this paper. In the fourth section, we present the results and discuss on them, and, in the fifth section, we present our conclusions.

2. Literature review

Amount of literature on stock market integration is huge, which makes a complete analysis difficult. Furthermore, as we also have to make some reference to the use of networks in previous works, we provide only a brief review of this topic, but make a distinction between several important issues in the theoretical aspects of our approach. Thus, we first present a general overview of stock market integration, identifying expected advantages and disadvantages, and, second, we identify different methodologies to measure stock market integration that were applied to the EU. Finally, we present some studies applying networks.

Stock markets are very important markets that are used not only for financing firms but also for investment (both by persons and firms), thus maintaining the interest in analysis. One motive is the rapid increase of international trade, not only of goods and services but also for financial assets. Another motive is that markets are now much more inter-related than in previous years, which could have benefits but also possible contagion effects (see, for example, Bekaert et al. [2]). This increase in stock market integration makes markets more interdependent and could also have effects on how governments design their policies, because that integration has direct impacts on variables such as exchange rates, national income, or even in employment (see, for example, Kearney and Lucey [3]).

Theoretically, it is expected that more integrated markets will have a positive impact on the welfare and growth of countries, because it promotes a certain investment specialization that as consequence will have a better allocation of savings (see, among others, Obstfeld [4] and Bekaert et al. [5]). In the case of the EU, this was the expectation of all countries when they pursued their initiatives of increasing economic integration (remember that stock market integration is just a part of the whole process of integration). In addition to the advantages for the countries, it could also be of benefit for potential investors because more integrated stock markets would increase returns and reduce costs. This important factor was raised, for example, by Lemmen [6] and was empirically confirmed by Hardouvelis et al. [7]. Although these positive effects, it is also recognized that an increase in market integration (mainly in the case of the financial market) could have a negative effect on financial stability, mainly if capital inflows are not used efficiently. In addition, the risks of the existence of financial contagion increase, in particular when economies are more interdependent, i.e., when they are more integrated (see, for example, Beine et al. [8]).

In addition, it is possible to find studies that identify that increased integration in financial markets could reduce the possibility of gains due to the increase of correlation among assets, as stated by Famá and Pereira [9]. Similarly, it is possible to find that strategies using models of portfolio optimization in countries with low levels of financial integration could minimize risks and maximize returns (see, for example, Coroa et al. [10]).

Furthermore, in the context of the EU, the increase in this interdependence when financial integration is not complete (not only stock market integration, but other issues of financial integration, such as money markets, banking or bond market integration) could have very nefarious effects. In fact, the increased exposure to risk and the possibility of emergence of a global crisis are among the possible risks that could not be solved in each country due to the impossibility of implementing some types of economic policies to combat possible asymmetry (see, for example, Lemmen [6]).

There are plenty of studies using several methodologies and countries, but, as stated previously, we focus on studies including EU countries. Owing to data restrictions, it is difficult to find many studies including only EU countries before the 1990s. Normally, they also include other non-EU countries (mainly Canada, Japan, and the USA) and most of these studies do not provide a direct analysis of EU-only countries. Although, for example, Ayuso and Blanco [11] concluded that there has been an increase in the degree of integration in the large EU countries (and also with Japan). However, even at that time the authors were warning that the situation could be problematic if there was a continued lack of supervision, because the political capacity to intervene when problems in the financial markets appear may be lost in the context of the EU.

Rangvid [12] analyzed data for France, Germany, and the United Kingdom, with a long sample (from 1960 to 1999), searching for common trends. Their results showed evidence of an increase in stock market integration, especially after 1982. Rangvid concluded that periods with greater integration are those immediately following the lifting of restrictions. Yang et al. [13] used data before and after the creation of the Euro and found evidence of a general increase in stock market integration after the establishment of the single currency, which could be a result of the faster transmission of information, technological advances, and the existence of mergers of stock indexes. Cerný [14] also showed that the transmission of information is a cause of the increase in integration, but also concluded that it is more evident in more developed markets. Yang et al. [13] identified that the levels of integration are different if they analyzed the largest Eurozone markets (Germany, France, Italy, and the Netherlands) or smaller markets (including Portugal, Spain, and Ireland) that are more isolated.

Although most studies found evidence of an increase in stock market integration, it is also possible to find some studies pointing to some contrasting evidence, mainly when smaller markets are investigated, as stated previously. For example, Rouwenhorst [15] identified that the integration levels are lower than the expected, which could be explained by the existence of home bias (a higher weight of domestic assets in investors' portfolios). The fact that countries have different answers in the case of asymmetric shocks is presented as another possible explanation of the results.

With the increase of in the number of countries in the EU and with the increase of available data, it is possible to find more studies, inclusively with newer EU countries.[1] Scheicher [16] found that Hungary, Poland, and the Czech Republic (countries which entered in the EU in 2004) had increased integration levels between themselves and also with other EU countries. Fratzscher [17] also found an increase in market integration in Europe and, in addition, showed that the EU gained importance in relation to the American markets. In studies that also included countries that entered in the EU in 2004, Pungulescu [18] and Voronkova [19] showed an increase in stock market integration, even controlling for structural changes. Regarding the Euro, it is also possible to find several studies studying the direct impact of the creation of the common currency in the increase of stock market integration; examples include those of Baele et al. [20], Kim et al. [21], Hardouvelis et al. [7], Cappiello et al. [22], Bartram et al. [23], and Bley [24].

However, both the subprime crisis and mainly the Eurodebt crisis altered how stock market integration was viewed. First, it increased the debate about the fact that deep integration could have a negative impact, mainly with contagion effects, even in smaller countries such as Greece (see, for example, Beirne and Fratzscher [25] and Samitas and Tsakalos [26]). Second, it drew attention to the necessity of a more homogeneous EU and greater supervision (as stated previously). Thus, to measure the effects of integration during the subprime crisis, we use the theory of networks.

The use of networks in financial markets could actually be considered as one of the main topics of research in finance. According to Schweitzer et al. [27], the networks allow the analysis of two or more interconnected assets in a system. Battiston et al. [28] stated that networks can measure the likelihood of systemic risk arising from interconnections and interdependence between agents of a system or market in which insolvency or bankruptcy of a single entity or group of entities can lead to bankruptcy of the whole network.

Mantegna [29] in one of the first studies involving networks and financial markets applying the minimum spanning tree (MST) method between the periods from July 1989 to October 1995 using companies listed on the New York Stock Exchange (NYSE). Mantegna detected that time series could pass on valuable information to the financial markets. Mantegna's study has practically revolutionized the way in which financial relationships between financial assets can be perceived, ranging from the network of shares in a given stock exchange to the financial relationship between stock exchanges in different countries.

Onnela et al. [30] also analyzed the NYSE to build hierarchical structures corresponding to the networks. Bonanno et al. [31] used high-frequency data for the major stocks traded in US stock markets and found that the degree of cross-correlation varied according to the time horizon used to compute them.

Sandoval-Junior and França [32] used random matrix theory (RMT) to analyze the correlation of the returns of various country indices to demonstrate that periods of strong volatility are associated with strong correlations between the world financial indices. Sandoval-Junior [33] set up the complex network of companies comprising BM & F-Bovespa (São Paulo Stock Exchange, Futures and Commodities Exchange) using MST, concluding that they were clustered by sector. Huang et al. [34] analyzed the return of companies forming Hong Kong's financial market between November 2011 and February 2015 and found a distribution in the power law format for the network formed by the correlation between them. Liu and Tse [35] analyzed the complex network of 32 market indices for several countries finding a strong correlation between volatilities with the exception of developing countries. Matesanz et al. [36] applied complex networks in the commodities

[1] Recall that 10 extra countries joined the EU in 2004, followed by three more countries in 2007 and 2013, but the UK is currently in the process of leaving.

market and found a similar dynamic between commodities of the same sector (metals, oils, and grains) but did not observe an increase in the co-movements between them over time with the exception of the years of 2008 and 2009. There are also applications of financial networks in the foreign exchange market, e.g. Wang and Xie [37], Wang et al. [38] and Wang et al. [39]; biofuels, e.g. Kristoufek et al. [40] and Filip et al. [41]; and commodities Tabak et al. [42].

An important link has been found between the connectivity of a financial network and a crisis in the stock market. Some authors have found this relationship can be used in predicting crises or as a sign of financial market instability. In general, before a crisis the network for stock exchanges tends to become more connected or tends to a small world topology, however after the crisis the network becomes less connected. A pioneering study in this area was presented by Minoiu and Reyes [43] analyzed the properties of networks formed by banks from 184 countries between 1978 and 2009 and found that connectivity tends to fall during and after a financial crisis. They also found that 2009 had a strong impact on the network.

Tabak et al. [44], Minoiu et al. [45], and Bardoscia et al. [46] found a relationship between banking system connectivity and systemic risk. Acemoglu et al. [47] found a financial network such as a highly connected banking network has contributed to spreading an exogenous shock (such as a crisis) making the system more unstable than a sparse network. For them, sparser financial networks are less prone to systemic risk than highly connected networks.

Regarding the relation between the connectivity of stock exchanges and financial crises, we mention the study of Yan et al. [48] who analyzed 710 companies from the Chinese stock market from 2005 to 2011, dividing the period analyzed into three parts: before the subprime crisis, during the subprime crisis, and after the subprime crisis. They presented some robustness tests to verify whether the network topology changed during the analyzed period, concluding that the network is sensitive to the failure of the nodes being unstable and that before the crisis the financial market had a strong robustness against intentional attacks. According to Yellen [49], complex interactions between market actors can serve to amplify the frictions in the market, information asymmetries, or other externalities, generating more instability than stability.

3. Materials and methods

We describe how we use TVG and motif synchronization to build dynamic networks in this section. The proposed method is summarized in a framework presented in Fig. 1, which consists of eleven processes: (1) Obtaining data; (2) Translation into new series; (3) Property calculation; (4) Building the networks; (5) Parameter definition; (6) Application of the motif-synchronization method; (7) Randomization process; (8) Building Aggregated Static Network (ASN); (9) Network analysis; (10) Results and discussion; and (11) Conclusion. The method flow and its processes are described as follows.

The EU is formed by 28 countries (including the UK at the time of writing), 19 of which share the Euro as their common currency. Our objective is to provide a deep analysis, including as many countries and as long a sample as possible. However, not all countries have a long sample of data available: some of them only joined the EU recently, others are relatively new countries, and some simply do not have data available. Thus, with these objectives, we retrieved data for 14 EU countries, from January 1988 to June 23, 2017. The database includes a total of 7404 observations for each country. The countries used are Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Spain (with the Euro as their currency), Denmark, Sweden, and the UK (non-Eurozone countries). For each country, we retrieved prices for the Morgan Stanley Capital International (MSCI) indexes. In addition to the availability criteria (some of the national indexes were not available at the same time), this allowed us to have comparable indexes. Data was retrieved from Datastream.

Because our objective is to analyze the evolution of the network, we split the whole sample into subperiods of 2 years. This allowed us to have a good sample size in each subperiod (of about 1000 observations). Thus, the first period is from the beginning of 1988 to the end of 1989, the second period from 1990 to 1991, and so forth.

Considering the price level P_t, we calculated return rates using the difference of consecutive logarithms, i.e., $r_t = \ln(P_t) - \ln(P_{t-1})$.

3.1. TVG and dynamic networks

When networks refer to real systems, it is difficult to find relationships between elements of the system that are persistent over time. In many cases, a static interpretation of these relations is just a simplifying approach, so we use a dynamic one, evaluating how the synchronization patterns among the MSCI indexes evolve over time. In this case, the theory of time-varying graphs (TVG) added to the motif synchronization method, seemed to us the most appropriate approach. The notion of TVG is a common method to represent such dynamic networks (Holme and Saramäki [50]).

The simplest way to describe a TVG is as an ordered sequence of static graphs $G = \{G_t\}$, $t = 1, 2, \ldots, T$, where each G_t represents the configuration of the network edges at a given time t, with T the total observations of time of the system under analysis.

Formally, according to Casteigts et al. [51], a TVG can be defined as a quintuple function $G = (V, A, T, \rho, \zeta)$, where:

- V represents the set of vertices of G;
- A represents the set of edges of G;

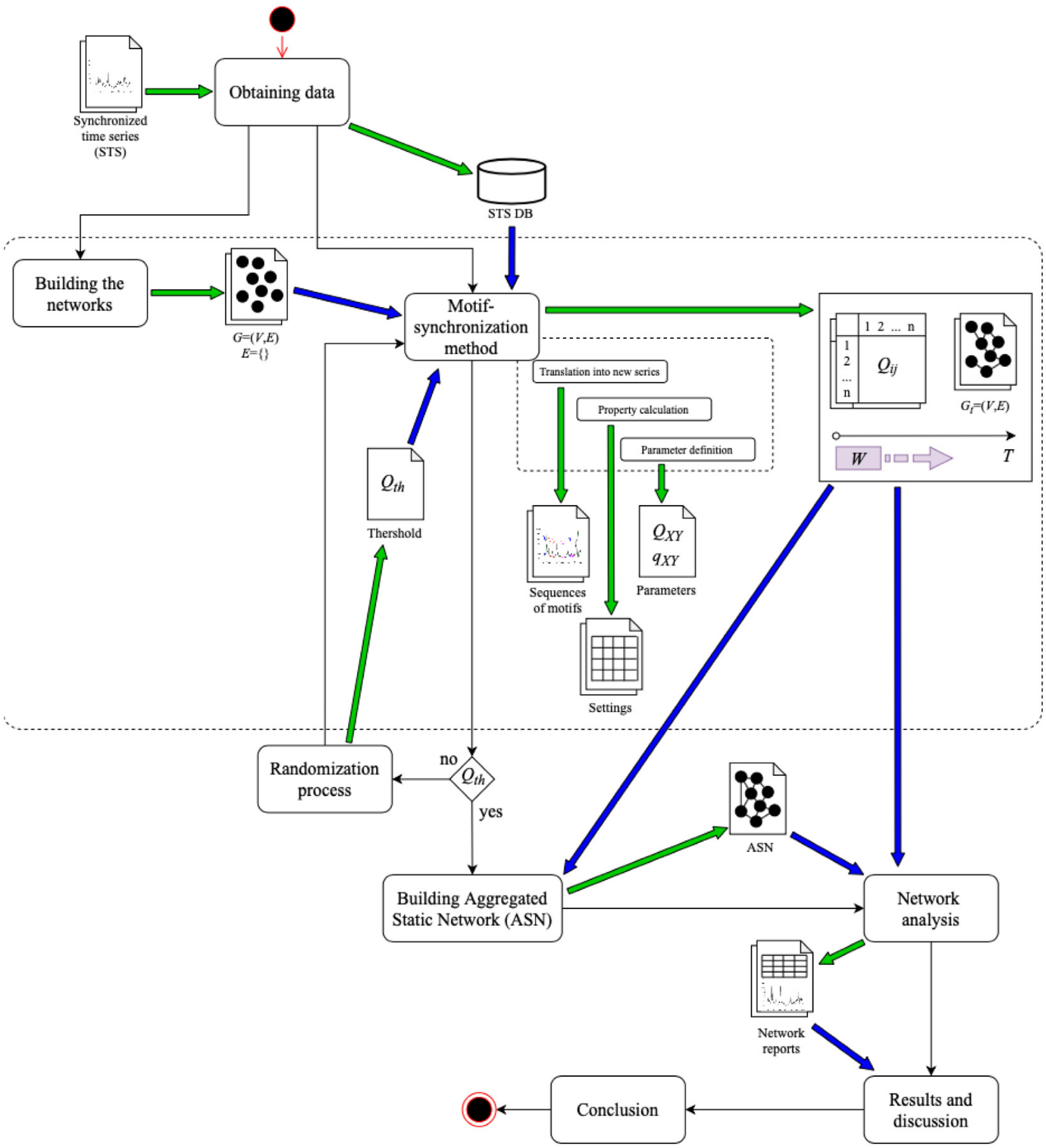

Fig. 1. Framework of the proposed method for building and analyzing the financial market of 14 countries of the European Union as time-varying and motif-synchronous networks.

- T is the lifetime of the system;
- $\rho(A, T)$ is a function that indicates the existence of a given edge at a given time;
- $\zeta(A, T)$ is a latency function that indicates the lifetime of a given edge.

3.2. Motif synchronization

Motif synchronization is a method of association proposed by Rosário et al. [52], as a more efficient method to build dynamic brain networks. A more in-depth discussion of the efficiency of the method can be found in (Rosário et al. [52]).

The MSCI time series can be described as a sequence of micro patterns such as slopes, peaks, and ditches in a given order of occurrence. These patterns are called motifs. In general, motif synchronization consists of counting the quasi-simultaneous occurrence of those motifs. The motifs are defined according to their 'lag' λ and 'order' n. The order n is the number of data points/sections that are included in each motif and the lag λ is the number of sample points spanned by each section of the motif (Olofsen et al. [53]. In this work, motifs of lag $\lambda = 1$ and degree $n = 3$ were used, thus obtaining a total of $n! = 3! = 6$ types of motifs defined as

$$X_{Mi} = \begin{cases} 1, & \text{if } X_i > X_{i+\lambda}, X_{i+\lambda} > X_{i+2\lambda}, X_i > X_{i+2\lambda} \\ 2, & \text{if } X_i > X_{i+\lambda}, X_{i+\lambda} < X_{i+2\lambda}, X_i > X_{i+2\lambda} \\ 3, & \text{if } X_i < X_{i+\lambda}, X_{i+\lambda} > X_{i+2\lambda}, X_i > X_{i+2\lambda} \\ 4, & \text{if } X_i > X_{i+\lambda}, X_{i+\lambda} < X_{i+2\lambda}, X_i < X_{i+2\lambda} \\ 5, & \text{if } X_i < X_{i+\lambda}, X_{i+\lambda} < X_{i+2\lambda}, X_i < X_{i+2\lambda} \\ 6, & \text{if } X_i < X_{i+\lambda}, X_{i+\lambda} > X_{i+2\lambda}, X_i < X_{i+2\lambda} \end{cases} \quad (1)$$

For the description of the method, let us assume two time series X and Y, recorded simultaneously from different countries. The first step is the translation of these time series into two new series X_M and Y_M, sequences of motifs. We then define $c(X_M; Y_M)$ as the largest number of times that the same motif was found in Y_M shortly after being found in X_M, within a delay τ, that is,

$$c(X_M; Y_M) = c_{XY}$$
$$c_{XY} = \max\left(\sum_{i=1}^{L_m} J_i^{\tau_0}, \sum_{i=1}^{L_m} J_i^{\tau_1}, \ldots, \sum_{i=1}^{L_m} J_i^{\tau_n}\right) \quad (2)$$

being

$$J_i^{\tau} = \begin{cases} 1 & , \text{ if } M\#_{x_i} = M\#_{y_{i+\tau}} \quad \text{or} \\ 0 & , \text{ otherwise} \end{cases} \quad (3)$$

where $\#_{x_i}$ is the motif of the country x at time i and L_m the total size of the motifs series. The time delay τ varies between τ_0 = 0 and τ_n, where τ_n is the maximum value considered. In an analogous manner, we define c_{XY}. Finally, we define the degree of synchronization Q_{XY} and the direction of synchronization q_{XY}, given by

$$Q_{XY} = \frac{\max(c_{XY}, c_{YX})}{L_m} \quad (4)$$

and

$$q_{XY} = \begin{cases} 0 & , \text{ if } c_{XY} = c_{YX} \quad \text{or} \\ signal(c_{XY} - c_{YX}) & , \text{ otherwise} \end{cases} \quad (5)$$

The degree of synchronization Q_{XY} would be between 0 and 1 and the index q_{XY} assumes a value of 0 for a synchronization with no preferred direction between X and Y, assumes a value of 1 when X precedes Y, and assumes a value of -1 when Y precedes X.

3.3. Building a network

In this work we use as nodes, for the dynamic networks, the 14 EU countries mentioned previously. For each node, a time series of MSCI indices is associated, $f(t)$, $t \in [0; T]$, where T is the total time of the period considered.

We apply the motif-synchronization method to the time series of each pair of nodes, and the connectivity index generated for each edge is subjected to a significance test. The significance test consists of comparing the synchronization generated with a threshold value Q_{th}. For example, if the degree of synchronization Q_{XY} between countries X and Y is equal or greater than the Q_{th}, this edge will be considered, that is, $a_{xy} \equiv 1$; otherwise, $a_{xy} \equiv 0$. At the end of this process, we obtain the adjacency matrix of the network.

This process is performed for a mobile time window W. When moving the window over the signal period the process repeats itself by generating new networks, thereby building the time-varying networks. Fig. 2 illustrates the process.

As stated earlier, the nearly 30-year MSCI indices have been divided into subperiods of 2 years. The subperiod of 2 years corresponds to the total period of each TVG. Thus, each graph of the dynamic network is built from the synchronizations between the 7 days of the time window. This time window is then shifted over the subperiod of 2 years, thus generating TVG networks.

3.4. Hub distribution

Hubs are the nodes that present their degree higher than the average of the network $\langle k \rangle$ by twice the standard deviation σ, or more precisely,

$$x^{hub}, \text{ if } k_x \geq \langle k \rangle + 2 \times \sigma \quad (6)$$

In financial networks, hubs can represent countries with the greatest influence in the whole financial market. In directed networks, hubs can also represent two important characteristics: the receiving and generating countries. Fostering countries are those that, during the dynamics of the system, receive more information flows and consequently are highly influenced by the market. Generating countries, on the other hand, have the flow of information in the opposite direction, thus exerting more influence on the global network. As the TVG method generates several networks over time, it becomes possible to check the number of times a node was a hub and thus generate the hub distribution.

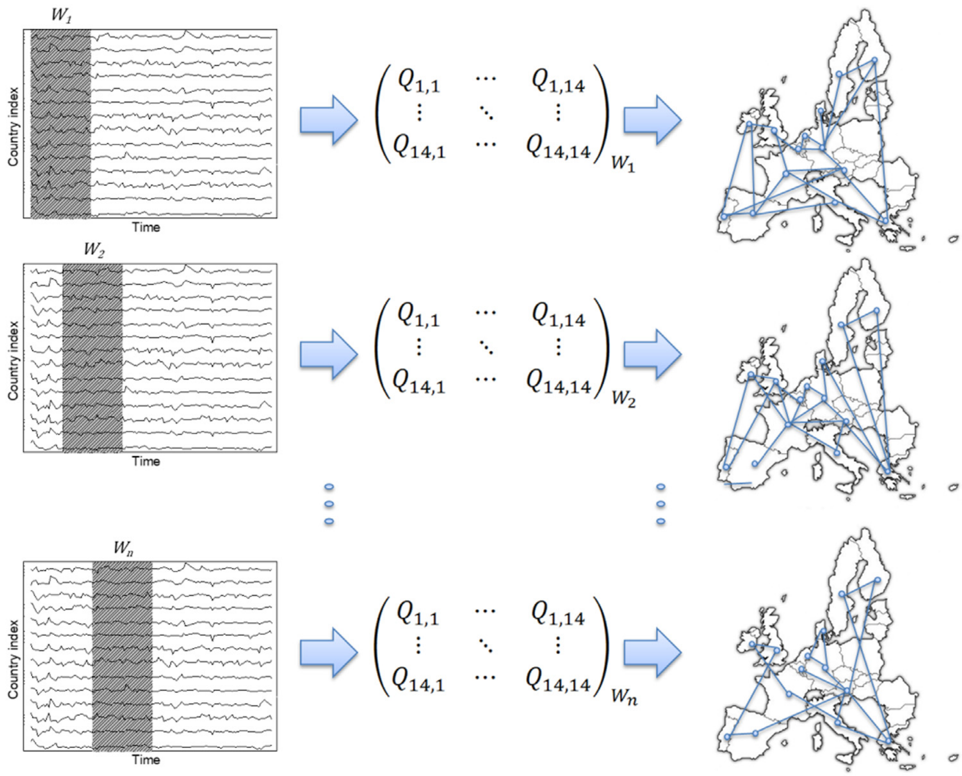

Fig. 2. Application of the motif-synchronization method. For each window W_i, the method is applied, building a network for a given instant of time. By moving the window along the time series, the process repeats itself, thus generating the TVG.

3.5. Aggregated static network

Dynamic networks generate a huge amount of data from which we can extract information about the dynamics of the studied system. To extract the main characteristics and to optimize the statistical analysis of these data, some methods from the theory of TVG and complex networks are necessary. One of the most important and efficient approaches is the aggregated static network (ASN).

Let $G = \{G_t\}$ where $t = 1, 2, \ldots, T$ be a TVG and $A_G = \{A_t\}$ for $t = 1, 2, \ldots, T$ is the set of adjacency matrices of each graph G_t. The ASN of G is given by

$$A_G^{ASN} = \sum_{t=1}^{T} A_t \tag{7}$$

That is, the ASN is the network resulting from the sum of all adjacency matrices generated by the TVG method. Thus, A^{ASN} represents a weighted network whose edge weights w_{xy} denote the number of times the countries x and y were significantly synchronized along the TVG period T.

4. Results

We recall that for each subperiod of 2 years, the dynamic networks were built for a temporal window W of fixed size equal to 7 days and with a threshold of $Q_t h = 0.90$. In the motif-synchronization method, we adopted motifs of degree $n = 3$, lag $\lambda = 1$, and the delay time used was $\tau_n = 7$ days.

Three types of analyses were performed. First, we attempted to study the distributions of hubs to evaluate the countries that presented the greatest structural importance exercised in the dynamically constructed networks. Second, we compared the weighted degrees (level of temporal connectivity of each country) of the ASNs constructed. Finally, we used the indices, average degree, average clustering coefficient, average minimal path length, density, efficiencies, and their respective coefficients of variation to characterize the temporal evolution of the system throughout the evaluated period.

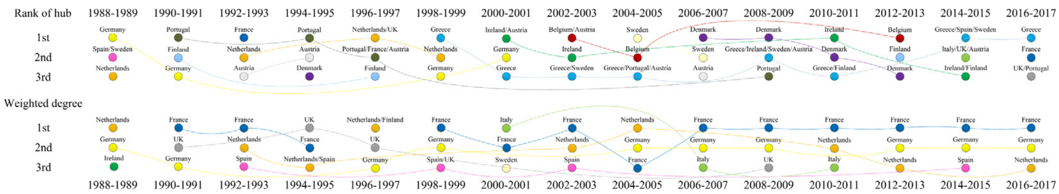

Fig. 3. Hub and weighted degree in descending order.

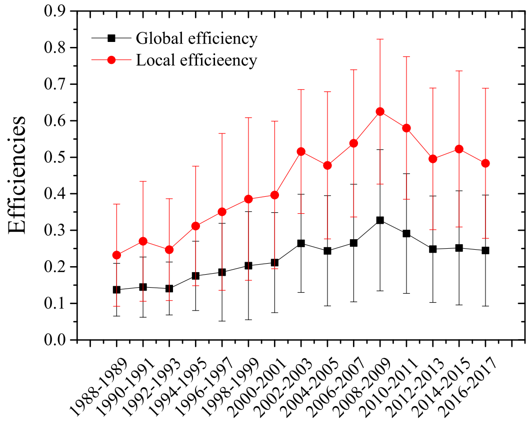

Fig. 4. Global efficiency (black) and local efficiency (red) throughout each analyzed period. The error bars represent the standard deviation of the index.

4.1. ASN results

We built an ASN for each analyzed period and we calculated the weighted degree of all the nodes of the network. Fig. 3 shows the hub and weighted degree of each country for the different periods.

In Fig. 3, we can observe that, according to the hub, before 2006–2007, although no particular pattern could be found, most of the predominance in the network is from Central and North European countries. Interestingly, during the 1990s, Portugal appeared several times in the top ranking, probably because of its recognized good economic performance. Greece also appears in the end of the 1990s and the beginning of the new century, after its acceptance on the Eurozone. Since 2008–2009, the Greek stock market is the one which appears most times in the top of the hub, and in this case accompanied by other countries which were most affected by both crisis: Ireland and Portugal with major problems and Spain with minor ones. In relation to the weighted degree, the predominant stock markets are mostly Central European countries, like France, the Netherlands, and Germany.

These results are certainly related to the economic and financial situation of the EU in recent years, in particular the sovereign debt crisis that mostly affected the Eurozone. After the creation of the single currency, countries that are generally small will begin to have a greater presence in the remaining vertices of the network; see, for example, the continuous rise in weight, as an influencer, of the Greek and Portuguese stock markets. The sovereign debt crisis had a major impact on the way that stock markets networked, with Greece and Portugal clearly emerging.

4.2. Network general indices

For the characterization of the dynamic networks throughout the considered periods, we calculated the time averages of the global and local efficiency, the average degree, the clustering coefficient, and the minimum mean path. Fig. 4 shows the temporal evolution of global and local efficiency.

Fig. 5 shows the temporal evolution of the clustering coefficient and the average path length. Fig. 6 shows the temporal evolution of the average degree.

As can be observed, both global and local efficiency, the clustering coefficient, and the average degree showed a very similar behavior, demonstrating an increase in the network connectivity up to a peak in the period 2008–2009, declining in the following periods. Comparing this increase in connectivity with the evolution of the average minimal path length in Fig. 5, we can observe a network trend to a small-world topology, that is, a typical community network of high robustness and transitivity. To better analyze this effect, we can observe the phase space between the average clustering coefficient (C) and the average minimal path length (L) in Fig. 7.

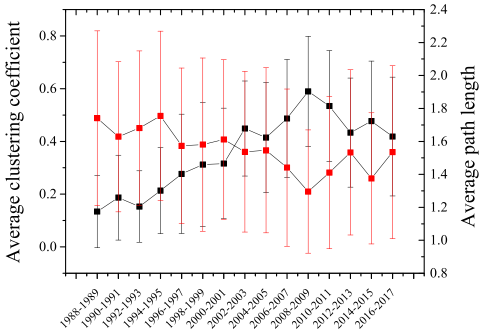

Fig. 5. Average clustering coefficient (black) and average minimal path length (red) throughout each analyzed period. The error bars represent the standard deviation of the index.

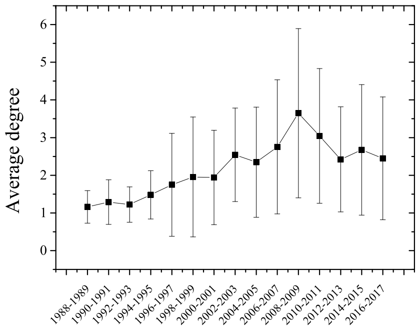

Fig. 6. Average degree over each analyzed period. The error bars represent the standard deviation of the index.

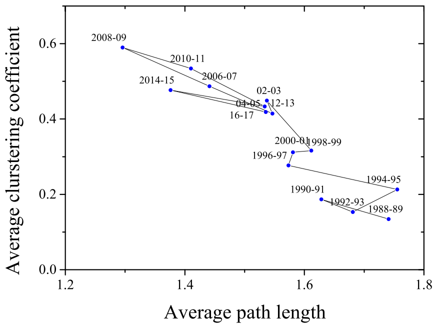

Fig. 7. Evolution of the system from the perspective of the average clustering coefficient and the average minimal path length.

Fig. 7 shows that with the growth of C, in general, L decreases. Although small, there is a tendency against this effect in the periods 1992–1995 and 2000–2003, which may represent a qualitative influence of some important historical facts on the evolution of the network. Historically, the first period is related to the signing of Maastricht Treaty in 1993 and thus the formation of the single market in the EU, which has made Europe a market with free movement of capital with a direct influence on stock markets. On the other hand, the following time period coincides with the moments immediately following the creation of the single currency in 1999.

To analyze the stability of the network, under different issues, we calculated the coefficient of variation of each index for all periods, which can be observed in Fig. 8.

The coefficient of variation of the degree (K_{cv}) and the global efficiency (GE_{cv}) presented a similar behavior, with a peak in the period 1996–1999 and values, in periods from 2000, higher than the average from 1988 to 1995. It is important to note that even though the behavior of K_{cv} and GE_{cv} varies, the coefficient of variation of local efficiency (LE_{cv}) also shows a visible peak of instability in the period 1996–1999, which may be associated with the period before the creation of the Euro. The coefficient of variation of the average minimal path length (L_{cv}) does not show large changes, being approximately constant over time. A reduction of the average clustering coefficient (C_{cv}) and the local efficiency variation

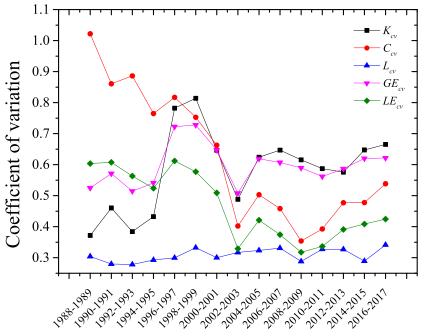

Fig. 8. Coefficients of variation by period of the indices evaluated: K_{cv}, average degree; C_{cv}, average clustering coefficient; L_{cv}, average minimal path length; GE_{cv}, global efficiency; and LE_{cv}, local efficiency.

(LE_{cv}) can be observed until the period 2008–2009 and then an increase of both, demonstrating that the network was in a tendency to increase connectivity and change after the crisis of 2008–2009, reducing its connectivity later.

5. Conclusions

This paper has proposed an approach to analyze EU stock markets using dynamic networks. The application of TVG, jointly with motif synchronization, has enabled the characterization of the level of connectivity of each index of the network. We found that France, the Netherlands, Germany, and the UK were the countries that presented the highest weighted degree in the majority of the ASN, that is, they remained synchronized with the remaining vertices (i.e. countries) of the network most of the time.

In particular, the results allow us to conclude that the countries of Central Europe (France, the Netherlands, Germany, and the UK) have the highest weighted degree of the network. Regarding countries that have become hubs, it is worth mentioning the change pattern in the hubs, passed mainly from Central European countries before the crisis to countries which are in the most affected ones after the subprime crisis and those which are in the origin of the Eurodebt crisis. In fact, since 2008–2009 Greece dominates the rank of hub, with some relevance for Ireland and Portugal.

Another result is that the network formed between the indices of the countries in the EU increased its connectivity constantly from 1988 up to 2008 and 2009, years in which the subprime crisis occurred and, following this, the connection diminished, indicative of contagion as there was a change in properties (clustering coefficient, path length, and local efficiency). This result is in line with that found by Tabak et al. [44] and Yan et al. [48], demonstrating that an exogenous shock tends to make the network less dense, and with that of Acemoglu et al. [47], who found that a connected financial network is more susceptible to exogenous shocks than a sparse network.

Therefore, this paper intends to collaborate with the study of financial interconnections in the EU from 1988 to 2017, observing its dynamics and stability. We can see that the EU stock markets increased their integration over time, with the possible benefits from that increase of integration but also the risks that possible non-asymmetric shocks could occur. In fact, this was what happened during the subprime crisis, when some EU countries faced different problems related to their debt, causing high turmoil in the markets but also changes in the network design. In this sense, the stability of the financial network of the main exchanges in this region can help in macroprudential policies, as there is a monitoring of the financial interconnections between the different markets that make up the EU by the agents that make up the financial system. This area is an essential region for the solvency and liquidity of financial markets and any instability that may occur in it can have a major effect on international finances.

CRediT authorship contribution statement

Hernane Borges de Barros Pereira: Conceptualization, Methodology, Writing – original draft, Supervision, Visualization, Writing – review & editing. **Raphael Silva do Rosário:** Methodology, Writing – original draft, Validation, Writing – review & editing. **Eder Johnson de Area Leão Pereira:** Conceptualization, Methodology, Data curation. **Davidson Martins Moreira:** Conceptualization. **Paulo Ferreira:** Conceptualization, Methodology, Data curation, Writing – original draft, Validation, Writing – review & editing. **José Garcia Vivas Miranda:** Methodology, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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