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Multiscale network for 20 stock markets using DCCA

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HIGHLIGHTS

- We analyze the stock exchanges for 20 countries.
- We build a multiscale network identifying the linkages between markets.
- Results show the central role of European stock markets.

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ABSTRACT

The aim of this paper is to analyze the stock exchanges for a large set of countries (20 in total) before and after the subprime crisis, identifying which markets are the most central and if the linkage pattern changed after the crisis. We started by calculating the correlations between stock markets' returns, using the ρDCCA, in order to identify if there is some variation in the scale between the links in the different stock markets of the network, in both periods. Additionally, a cross-correlation filtering process will be performed with the intention of identifying which countries have stronger relationships according to the used time scales. The results show the central role of European markets among the world's main financial markets, mainly France, Germany and the United Kingdom. Moreover, after the subprime crisis we find the formation of two large communities, one of European and American countries and the other formed by Asian countries plus Australia, while in the pre-crisis period three communities could be identified. It is possible to conclude that after the 2008 crisis the connectivity and integration of the network for the whole set of analyzed timescales increased.

1. Introduction

Financial markets move trillions of USD annually, and understanding their dynamics is of vital importance to the world economy, for several types of economic agents: actual or potential investors, managers of firms and of mutual funds, for economic authorities and also for policy makers. The fact that any information coming from financial markets could be

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used, for example, to prevent financial crises or to improve the financial system underlines the importance of continuing to study these markets. In the context of financial markets, stock market integration is a much studied topic in the financial literature and also a very broad one, not only with a vast amount of literature but also using different methodologies to assess the evolution of stock market integration. So, it is firstly important to identify a general overview about integration, as well as its advantages and disadvantages.

Stock market integration is a particular aspect of the broader issue of financial integration. As a whole, if markets are more integrated, this is expected to boost countries' growth, allowing citizens to increase their well-being. This is due, for example, to the fact that more integrated markets could cause better savings allocation (see, amongst many others, [1] or [2]). However, authors also recognize that, despite these potential advantages, increased market integration could have a negative effect because this potentiates greater financial instability and financial contagion (see, for example, [3]). The fact that economies increase their interdependence could heighten these effects [4]. Authors such as Bekaert et al. [5] identify a constant increase in international trade, including in financial assets, besides causing instability in macroeconomic variables such as exchange rates, national income or employment, and also affecting governments' capacity in their policy decisions.

Stock market integration could be studied using several approaches, with the use of correlations and cointegration tests probably being the most common. The evolution of methodologies and data availability has led to multiple types of studies, with linear and non-linear methodologies but also in different countries and regions. The use of so many different approaches is seen, for example, in [6] and [7], who report strong evidence of integration over time, mainly in developed markets.

In this paper, to analyze stock market integration, we will use a network of financial indices corresponding to twenty stock exchanges worldwide. We study the periods before and after the subprime crisis to verify how these markets behaved after this important economic event. The subprime crisis began with the real estate bubble in the US in 2006, with the culmination of the crisis being the collapse of the Lehman Brothers Bank in 2008. Subprime loans are high-risk bank loans to clients with a poor or unproven track record. Most of these credits were granted to buy real estate and with a fixed interest rate. With increased interest rates in the United States, many clients became defaulters. Many banks lending to subprime clients automatically went through a difficult situation, some of them becoming bankrupt and others having to go through financial restructuring. This crisis has affected many countries around the world, causing recession in several. Investor mistrust has increased, reducing investment in financial assets and causing instabilities in the financial sector.

Financial markets in general and stock markets in particular are seen as complex systems, due to the large amount of interactions between agents. The use of complex systems in economics has been termed econophysics by Stanley et al. [8] and Mantegna and Stanley [9]. According to Pereira et al. [10], in the beginning econophysics was used to study only the format of the distribution of financial assets' returns (stocks, exchange rates, commodities and stock indexes). Later it adapted other tools originating in statistical physics, such as the Hurst exponent, correlation cross-modeling, agent-based models and complex networks. Complex networks have been established as important analytical tools in several areas, providing a new vision in the study of several problems. The different methods and techniques can be found in classic studies like Barabási and Albert [11], Albert and Barabási [12], Newman [13], Boccaletti et al. [14] or Jackson [15].

The use of complex networks, which allows much information about financial series to be captured, according to Mantegna [16], is a type of approach useful to analyze market integration. Additionally, complex networks allow us to measure characteristics such as centrality, medium degree, network hub and others. Kwapień and Drozdz [17] demonstrate the importance of the application of complex systems in several phenomena, including with the use of econophysics.

Mantegna [16] applied the Minimum Spanning Tree (MST) method between July 1989 and October 1995, using companies listed on the New York Stock Exchange (NYSE) detecting a hierarchical behavior in stock markets. Bonanno et al. [18] used high-frequency data for the major stocks traded in the United States stock markets demonstrating that the degree of cross-correlation varied according to the time horizon used to compute them. Onnela et al. [19] also analyzed the New York Stock Exchange to build hierarchical structures corresponding to the networks. In this context, the use of MST on the stock exchange to demonstrate the hierarchical structure of several financial markets has grown: see, for example, [20–23]. Another application of MST was made by Kristoufek et al. [24], when studying the correlation between biofuels and related commodities before and after the food crisis, finding that correlations are considerably higher in the post-crisis period than in the pre-crisis one. In another study, Kristoufek et al. [24] also use MST and demonstrate there are correlations between food and fuel commodity prices in the United States and the European Union between 2003 and 2008, the interaction dynamics varying according to the weekly, monthly and quarterly data.

Tumminello et al. [25] introduced the concept of the Planar Maximally Filtered Graph (PMFG) as an alternative to MST. Another relationship involving networks and financial markets is the possibility of network theory measuring systemic risk in the banking payment system: see [26–28]. It is also possible to analyze the dynamics of a financial network's connectivity, as a predictor of possible financial crises [29–31]. Other relevant studies involving networks and financial markets are those by Boginski et al. [32], Billio et al. [33], Hautsch et al. [34], Diebold and Yılmaz [35], Wang et al. [36,37].

Rather than using the Pearson's correlation, which is a linear measure of correlation amongst two series, considering a given data sample, an alternative way of calculating the correlation between the nodes of a network is by using multiscale methods. Multiscale methods allow the analysis of different networks for different time scales, allowing the identification of different behavior for each scale. They could be used, for example, to differentiate between the behavior of networks in the short or long-term (considering, for example, lower or higher time scales). A pioneering study was that of Kenett et al. [38], which studied the New York Stock Exchange (NYSE) from 2000 to 2003, using the 300 largest companies and Partial Correlation Network (PCN), and with a dynamic window. The authors checked the persistence of financial sector actions both for a window of one month and for a four-month trading window. Another study was that of Wang et al. [39], which combined ρ DCCA (detrended cross correlation analysis) with MST (Minimum Spanning Tree) obtaining a multiscale network from calculation of the cross correlation, applying 44 different currencies from 2007 to 2012. Following this idea, Wang et al. [40] applied the MST and ρDCCA to analyze the network based on the exchange rate of several countries from 2007 to 2012, finding that the cross-correlation coefficient of the foreign exchange market has a long tailed distribution, and identifying that USD and the euro are the predominant currencies.

Wang et al. [41] analyzed 57 stock markets using the MST Pearson and the MST Partial methods, finding different results in relation to betweenness centrality and closeness centrality. Wang et al. [42] calculated the cross correlation using wavelet cross correlation and Pearson correlation by analyzing 457 shares quoted in the SP 500 during the period 2005 to 2012, finding fat tail distribution with wavelet with clusters formed by the following sectors: Financial, Material and Industrial. Kwapien et al. [43] generalized the Minimum Spanning Tree (MST) concept by introducing the q-dependent minimum spanning tree family. This method allowed them to work with data ranging from one minute to one month, in addition to using the value of the coefficient $q = 2$ and $q \neq 2$, the latter value being more satisfactory. Battiston et al. [28] and Battiston et al. [44] use Debt Rank's concept of centrality, emphasizing that there are "too many core markets not to fall", so the use of centralities in financial networks makes it possible to identify which exchanges or banks are central to a financial network.

In this paper we propose to build a network based on Zebende's [45] method, calculating the correlation coefficient for multiple scales. Zebende [45] developed a method to investigate the cross-correlation power laws between two simultaneous time series, called Detrended Cross Correlation Analysis (DCCA). According to Pereira et al. [10], the analysis of cross-correlations between time series has been a new frontier in economics since the study by Podobnik and Stanley [46] when they created the DCCA, extending the methods to analysis of cross-correlations between different variables, including economic assets, such as the correlations between trade volume and share prices. Podobnik et al. [47] and Gvozdanovic et al. [48] applied the DCCA between the Dow Jones index and 30 constituent companies.

Some variations of DCCA can be found in the literature, with Horvatic et al. [49] proposing the DCCA-ℓ (n) or Duan et al. [50] using the random matrix theory of modified time lag to study time-delay cross correlations in several time series in several countries. Another variation was proposed by Kristoufek [51]. Duan and Stanley [52] combined DCCA with support vector machines (SVM) to predict returns from financial series. Podobnik et al. [53] introduced a new test to quantify the long-range cross-correlations, observing the effects of trends in the series, and Podobnik et al. [54] used time lag cross correlation in several phenomena.

Thus, this article has the following objectives: (i) to develop a model of financial networks with the calculation of correlations from Zebende [45], since this is an established method in the literature allowing the use of different time scales; (ii) analyze the behavior of the main stock exchanges in the world ten years after the subprime crisis with the purpose of identifying which markets are the hubs, i.e., have the most central markets according to the indicated time scale; (iii) identify the main communities formed among the stock markets of the countries studied; and (iv) analyze the hypothesis that after the subprime crisis the market became strongly connected. Therefore, this article is divided as follows: in the next section we present the data (Section 2), followed by the methodology (Section 3). Section 4 presents the results and Section 5 concludes.

2. Data

The data was retrieved from the ADVFN and yahoo finance platforms and correspond to the period from 2nd February 2001 to 18th January 2017. We split the sample in two subsamples, considering the pre and post-subprime crisis periods. The division was made in January 2009, with this date corresponding to the moment in which the Dow Jones index (index of the American stock market) comes out of a downtrend and moves on to a bullish sequence and the period after the subprime crisis. The period under analysis includes the Eurodebt crisis and the political crisis caused by the Brexit referendum, which could give us interesting results. The 20 stock markets used are those included in Table 1. It considers 19 of the most relevant stock markets, according to data availability, as well as the Eurostoxx50, representing the Eurozone as a whole.

The descriptive statistics of the return rates are presented in Table 2. A brief reading reveals that 6 of the 20 indices had negative means in the period considered. Curiously, 4 of those countries are European and the Eurozone is also in this situation. Remember that in the European Union, after the subprime crisis, countries faced the Eurodebt crisis, which also affected stock markets generally. The other country with a negative mean was Brazil, which also experienced a severe economic crisis as well as a political one.

From the remaining indicators, the negative skewness for almost all indices stands out, meaning that for most of them, higher losses are more frequent than higher gains (the exception is the Indian index). Furthermore, and regarding kurtosis, all the indices but Taiwan show levels higher than the normal distribution benchmark, meaning that return rates should suffer from fat tails, which is a well-known stylized fact in the financial literature.

Table 1
Country and corresponding stock market index.

Country (region)	Stock market index
Argentina	Merval
Australia	SandPASX200
Austria	ATX
Brazil	Ibovespa
Canada	SandPTSX Composite index
Chile	IPSA
China	SSE Composite index
Eurozone	Eurostoxx50
France	Euronext 100
Germany	DAX
India	SandPBSE SENSEX
Indonesia	Jakarta Comp index
Israel	TA-100
Italy	MIB
Japan	Nikey 225
Mexico	IPC
South Korea	Cospi
Taiwan	TSEC
United Kingdom	FTSE 100
United States	Dow Jones

Table 2
Descriptive statistics for the return rates of the considered indices.

	Mean	Std. dev.	Minimum	Maximum	Skewness	Kurtosis
Argentina	0.00036	0.0217	−0.1215	0.1749	−0.0117	4.7726
Australia	0.00019	0.0100	−0.0705	0.0579	−0.3028	4.1863
Austria	0.00024	0.0147	−0.0974	0.0910	−0.5510	5.3184
Belgium	−0.00002	0.0129	−0.0736	0.0978	−0.0273	5.3258
Brazil	−0.00002	0.0178	−0.1139	0.1343	−0.1690	3.2679
Canada	0.00002	0.0110	−0.0932	0.0982	−0.3416	9.9282
Chile	0.00039	0.0098	−0.0698	0.0590	−0.4597	5.0761
China	0.00016	0.0206	−0.1324	0.1478	−0.3704	6.2255
Eurozone	−0.00019	0.0151	−0.0786	0.1035	−0.1052	3.3232
France	−0.00017	0.0135	−0.0856	0.0884	−0.1623	4.1702
Germany	−0.00004	0.0152	−0.0707	0.1128	−0.0482	3.7702
India	0.00045	0.0151	−0.1114	0.1734	0.1263	10.9177
Indonesia	0.00073	0.0140	−0.1038	0.0792	−0.6347	6.0060
Israel	0.00017	0.0110	−0.1000	0.0541	−0.7575	6.9863
Japan	0.00028	0.0158	−0.1141	0.1415	−0.1116	7.7960
Mexico	0.00040	0.0126	−0.0701	0.1031	−0.0868	4.6911
South Korea	0.00046	0.0139	−0.1057	0.0614	−0.5199	4.5341
Taiwan	0.00029	0.0128	−0.0651	0.0577	−0.2090	2.5397
UK	−0.00017	0.0121	−0.0785	0.0805	−0.2998	4.8025
USA	0.00005	0.0112	−0.0993	0.1104	−0.5194	10.3279

3. Methodology

The basis of the network is built using the detrended cross-correlation analysis (DCCA) coefficient correlation to study the cross-correlation dependence between series. DCCA was created by Podobnik and Stanley [46] and is performed according to the following steps. It considers two different datasets x_k and y_k with $k = 1, \ldots, t$ equidistant observations. Based on those variables, DCCA starts by integrating both series, i.e., calculating $(t) = \sum_{k=1}^{t} x_k$ and $y(t) = \sum_{k=1}^{t} y_k$. The next step is to divide the whole samples into boxes of equal length, of dimension n and divide into N-n overlapping boxes. For each box, a local trend ($\tilde{x}_k$ and $\tilde{y}_k$) is considered, using ordinary least squares. The detrended series are calculated, based on the difference between original values and the previously calculated trend. The covariance of the residuals in each box is calculated, given by $f_{DCCA}^2 = \frac{1}{n-1}\sum_{k=i}^{i+n}(x_k - \tilde{x}_k)(y_k - \tilde{y}_k)$. Finally, the detrended covariance is calculated summing all boxes of size n, i.e., $F_{DCCA}^2(n) = \frac{1}{N-n}\sum_{i=1}^{N-n} f_{DCCA}^2$. The process is repeated for all length boxes, allowing identification of the relationship between the DCCA fluctuation function and n. The long-range cross correlation $F_{DCCA}(n)$ is given by the power law: $F_{DCCA}(n) \sim n^{\lambda}$, with the λ parameter as the parameter of interest which quantifies the long-range power-law cross-correlations.

The DCCA method measures the covariation between series. However, to understand the degree of the relationship it is more suitable to use the correlation coefficient created by Zebende [45], given by $\rho_{DCCA} = \frac{F_{DCCA}^2}{F_{DFA\{x\}}F_{DFA\{y\}}}$, where $\mathrm{DFA}_{\{xi\}}$

and $DFA_{\{yi\}}$ represent the DFA method [55] for the series {xi} and {yi}, respectively. This has had several applications in economics and finance [56–60].

That coefficient, which is considered efficient by Kristoufek [61], has the desired properties of a correlation coefficient: $-1 \leq \rho_{DCCA} \leq 1$; $\rho_{DCCA} = 0$ when there is no cross-correlation between series; a positive or negative value meaning evidence of cross-correlation or anti cross-correlation and Kwapień et al. [62] propose the q-dependent detrended cross-correlation coefficient, i.e., ρ_q (q ∈ R) based on the so-called q-dependent fluctuation functions.

The Podobnik et al. [63] procedure is used to test the significance of this correlation coefficient, considering the different sample sizes used in this study. Besides that, based on Silva et al. [64], we consider a high degree of ρ_{DCCA} correlation coefficient ≥ 0.66. In this study, we consider the existing network connection in significant correlations and the correlation grades already mentioned. A variation of ρDCCA is the $\Delta\rho$DCCA introduced by Silva et al. [65], which is used to measure the contagion effect, with the work of Wang et al. [66] or Ferreira et al. [58] applying that new concept. Additionally, Balocchi et al. [67] reconcile the ρDCCA with ARFIMA models and Kristoufek [68] shows that the DCCA coefficient is more efficient than the Pearson coefficient in measuring the cross correlation between two non-stationary series.

For the analysis of communities, we then apply the Louvain method for community detection to identify closely interconnected stock markets within the graphs proposed by Blondel et al. [69], named modularity.

To analyze centrality we will consider the weighted degree and the PageRank. Regarding the weighted degree, let us consider that $\Gamma(i)$ is the neighborhood of vertex i. The weighted degree of vertex i is given by the sum of the weights of all in-or-out arcs connected to vertex i, $k_{wi} = \sum_{j\in\Gamma(i)} w_{ij}$.

PageRank measures the importance of a node (sector) by counting the number and quality of arcs (if the network is addressed). PageRank is a measure of quantity and quality because it captures both the number of arcs a node can have and the importance of the node in the network. A node (stock market) can be important if it receives an arc from an important node, according to Page et al. [70], PageRank is defined as:

1. At t = 0, an initial probability distribution is assumed, usually $PR(i; 0) = 1/N$, where N is the total number of nodes;
2. At each time step, the PageRank of node i is computed as $PR(i; t+1) = \frac{1-d}{N} + d\sum_{j\in M(i)} \frac{PR(j;t)w_{ij}}{S(j)}$, where M(i) are the in-neighbors of i, w_{ij} is the weight of the link between the nodes i and j, S is the sum of the weights of the outgoing edges from j, and the damping factor d is set to its default value, 0.85.

4. Results

Firstly, we build the network formed by the values of the significance test of Podobnik et al. [63], linking the edges for a ρDCCA ≥ 0.66. The objective of using a ρDCCA ≥ 0.66 is to propose a filtering method to verify which edges remained even for a high ρDCCA value. So we can verify which stock exchanges are most influential. For this, the total value of the weighted degree of a given market together with the ρDCCA filtering will be used.

Fig. 1 shows the example of the networks for a time scale of 4 days, considering the values of ρDCCA and using the significance test of Podobnik et al. [63], with the top panel representing the period before the crisis and the bottom panel the period after the crisis. The larger the node size and the darker the blue tint, the greater the weighted degree value. This helps in visualizing the most important nodes corresponding to the financial indices of the respective countries. We can see that the larger knots in darker blue are European markets, mainly France, Germany, Belgium, the Eurozone as whole and UK. In the background, American countries and China predominate.

During the pre-crisis period, the agglomeration coefficient of the network was 0.48 and the density coefficient 0.47, while after the crisis our network has higher coefficients: 0.98 for the agglomeration and 0.97 for the density. This shows that during the period analyzed, the twenty stock exchanges maintained relationships with each other, for a time scale of 4 days. Regarding the analysis for a time scale of 28 days and 135 days, the results are similar (see appendix 1, which shows the results of the correlation coefficient for all pairs of indices, for both subperiods).

Fig. 2 reveals the communities extracted with the modularity property, using the modularity algorithm of Blondel et al. [69]. For the period before the crisis (upper panel), the algorithm retrieved three communities: one formed by European stock markets, another formed by American markets and the third formed by Asian countries and Australia. Regarding the post-crisis period (lower panel), just two communities were formed: one by European and American stock markets and another formed by Asian markets and Australia. This does not mean that the stock markets of a given community do not influence one belonging to the other community. The algorithm only divides the stock markets that correlate most with each other. For example, in the period after the crisis, there is a notable influence of European markets on American markets and a community representing Asian countries, with the Chinese stock exchange being dominant, since this has the highest weighted degree among the Asian markets.

Combining both subperiods, the reduction from three to two communities means that stock markets seem to increase their levels of integration, since American and European indices now form just one community. This is not a new result: for example, Ang and Chen [71] and Ang and Bekaert [72] found an increase in correlations between financial assets' returns across international markets after a shock. The fact that Asian markets and the Australian one remain in a different community means those markets are not fully integrated with the others.

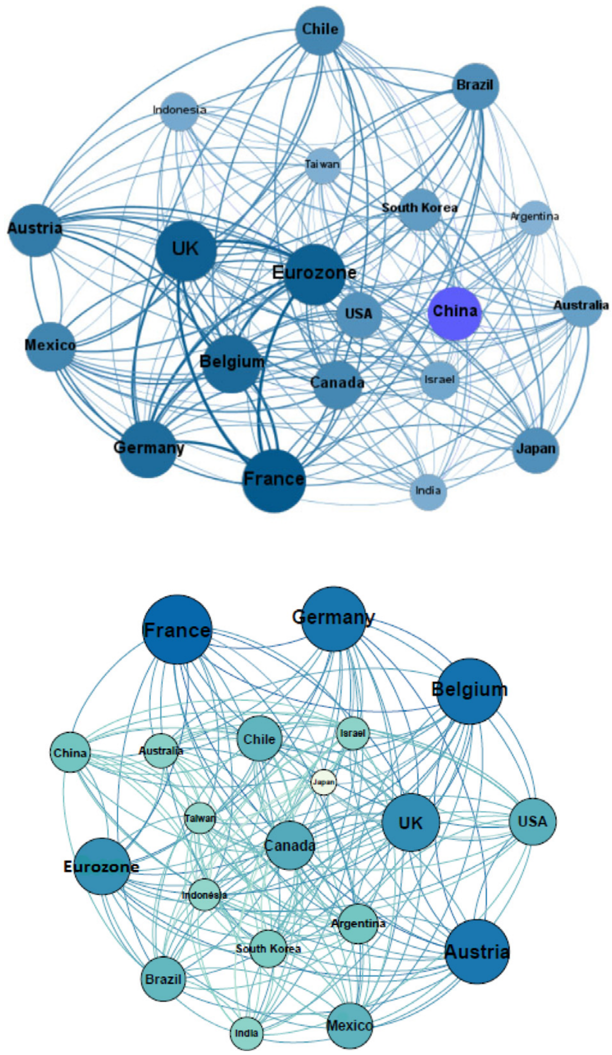

Fig. 1. Networks constructed for a time scale of 4 days and considering the significance test of Podobnik et al. [63]. Note that the larger the knot and the darker the blue the larger the weighted degree. The upper panel is for the pre-crisis period and the lower panel for the period after the crisis.

Considering a higher level of correlation (ρDCCA $>$ 0.66), it is natural that the size of the network is smaller, since a correlation with a more demanding level is being considered. It is noticeable that the longer the time scale, the more integrated the market is, and there are more connections between the corresponding stock markets. In the scales of n = 4, n = 14, n = 28 and n = 60 (Figs. 3–6), the clear predominance of the European markets is noted. Thus, considering a higher level of integration (measured by a higher level of correlation), European markets are not only among the most integrated, but also those that can be considered as influencing other markets. Fig. 7, representing a time scale of n = 135, shows the participation of several stock markets in different continents, emphasizing the European markets. The strong connectivity of European countries was detected before and after the subprime crisis. The crisis had two effects on the network: an increase in the connectivity in the network with the presence of a larger number of countries for all scales and an increased presence of South Korea and Taiwan. Additionally, the network remained practically the same before the crisis for smaller scales, having a change in scales 60 and 135 (see Figs. 3–5).

Tables 3 and 4 identify country rankings, for both subperiods, according to the centrality of Page Rank and the Weighted Degree, considering the different time scales under analysis. In the period before the crisis, the results show that the Eurozone as a whole has in important role in the network. France and the UK are other European countries prominent in almost all time scales, in both the indicators used in the analysis. The US stock market appears in the lead of the network for shorter time scales, when considering the Page Rank. A brief note for the presence of Mexico in the table in the pre-crisis period, for higher time scales. And according to the centrality of the weighted degree and Page Rank, shows the predominance of European markets, mainly the French, British, German, Belgian and Austrian ones and the Eurozone

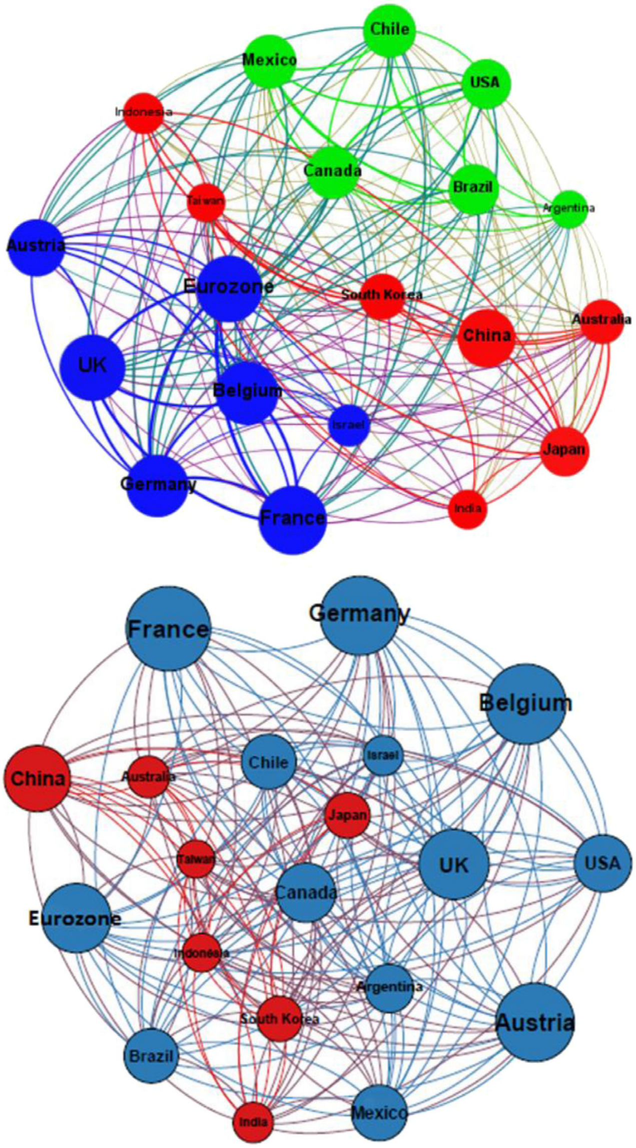

Fig. 2. Communities extracted with the modularity property. The upper panel is for the period before the crisis and the lower panel for the period after the crisis.

as a whole. Few variations among the first five positions are noted. This really shows the predominance of the European stock markets when compared with the remaining countries under analysis. The fact that in recent years the European Union in general and the Eurozone in particular suffered a severe financial crisis could be one of the explanations of these results.

5. Concluding remarks

The subprime crisis was the biggest crisis since 1929, and has caused the fall of several stock exchanges worldwide, increased unemployment and reduced Gross Domestic Product (GDP) all over the world. In the ten years since its outbreak, other financial phenomena such as the Eurodebt crisis and the United Kingdom's decision to leave the European Union (Brexit referendum) have taken place and this has affected the dynamics of the world financial markets. Therefore, this work analyzed twenty world stock exchanges using a multiscale network with the intention to verify how these stock markets are related after those ten years, compared to the situation in the pre-crisis period.

During the pre-crisis period, European and North American indices show predominance in the network, despite the main role of the European markets. In the post-crisis period, European stock exchanges are predominant. The importance

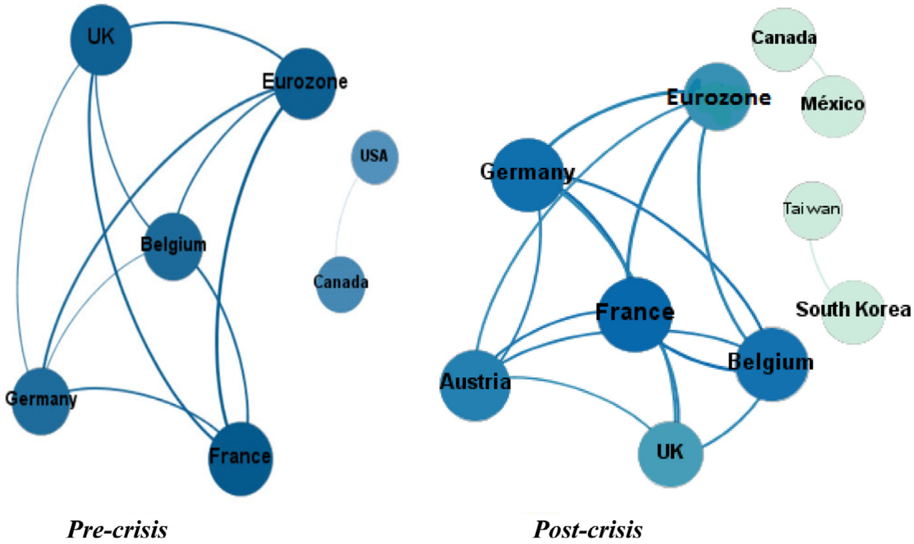

Fig. 3. Relationships with $\rho_{DCCA} > 0.66$ for a time scale of $n = 4$. In this network, the darker blue represents the higher weighted degree of the respective stock market. On the left the pre-crisis period and on the right the post-crisis one.

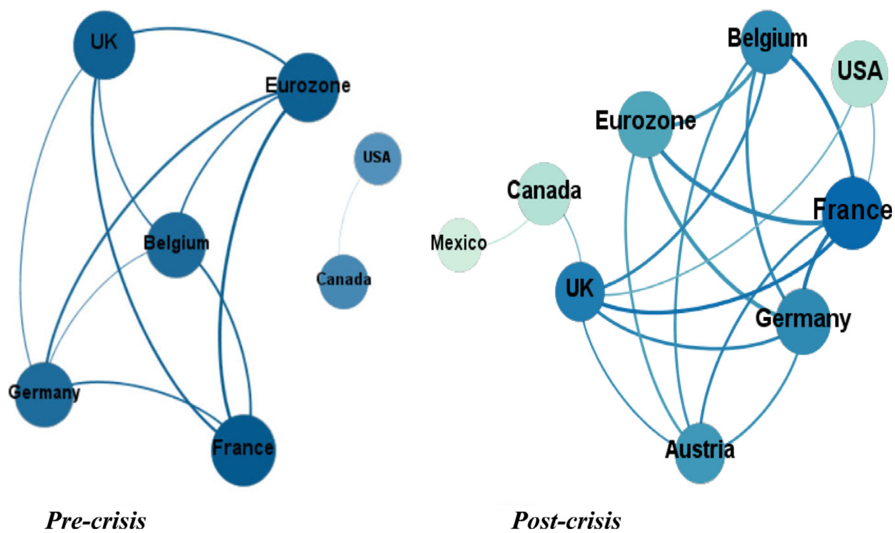

Fig. 4. Relationships with $\rho_{DCCA} > 0.66$ for a time scale of $n = 14$. In this network, the darker blue represents the higher weighted degree of the respective stock market. On the left the pre-crisis period and on the right the post-crisis one.

of the Eurozone in the network is noticeable, namely in the lower scales. This means that, in the short run, the Eurozone is an important market regarding the connection with others. The difference between the subperiods, namely the fact that in the post-crisis period North American markets lost importance, could be justified by the crisis itself, because it caused some decrease in stock market integration with European markets. However, and considering the number of communities retrieved, it is possible to conclude on increased integration of European and American markets, after the crisis.

If the network is considered for a value of ρDCCA ≥ 0.66, again European stock markets predominate for all the time scales analyzed. As for the variation of time in the scales, the larger the time scale analyzed the greater the financial integration of the stock markets studied and for a time scale of 135 days, the markets of several countries in several continents maintain a strong financial integration.

The number of communities extracted from the network changed from three (European, American and Asian plus Australia) to two communities, with the joining of European and American markets as a single community. Therefore, the analysis of financial networks that vary with time scale can contribute to financial risk containment policies both for financial funds, where the time scale is important and also for hedge funds, helping to control financial stability.

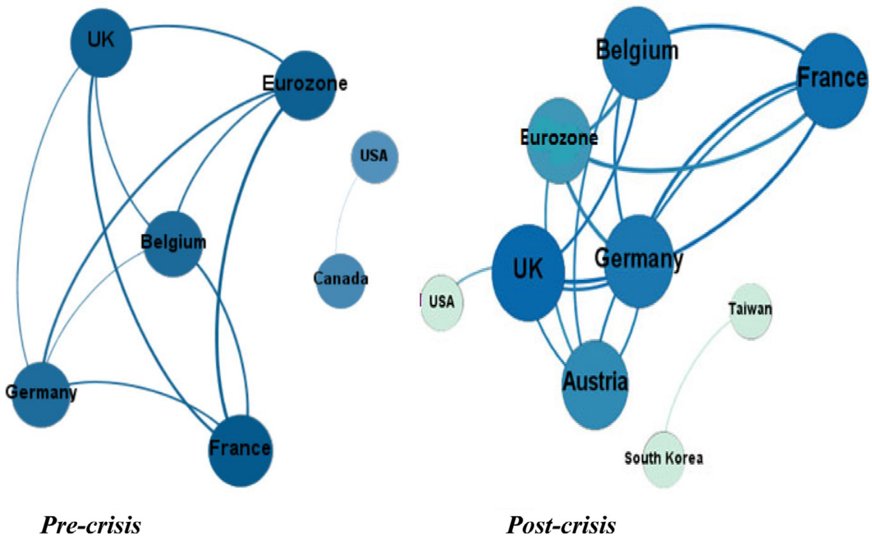

Fig. 5. Relationships with $\rho_{DCCA} > 0.66$ for a time scale of n = 28. In this network, the darker blue represents the higher weighted degree of the respective stock market. On the left the pre-crisis period and on the right the post-crisis one.

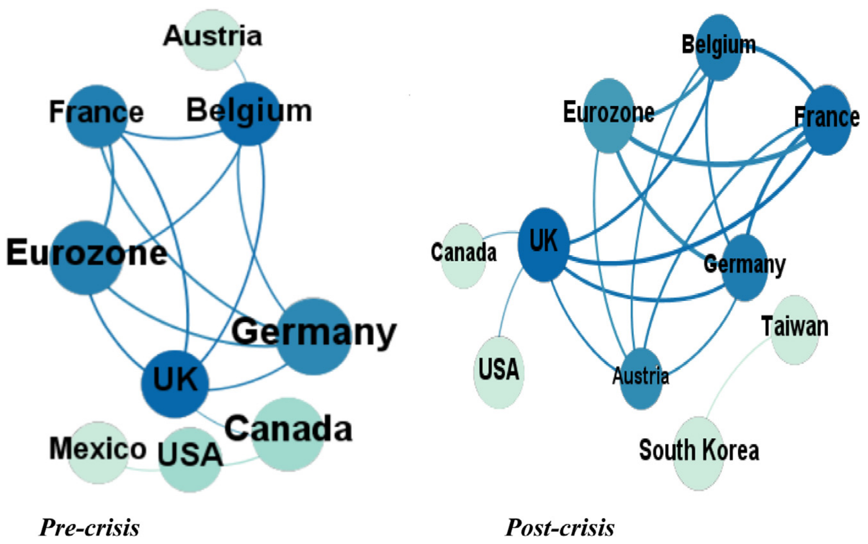

Fig. 6. Relationships with $\rho_{DCCA} > 0.66$ for a time scale of n = 60. In this network, the darker blue represents the higher weighted degree of the respective stock market. On the left the pre-crisis period and on the right the post-crisis one.

The results could also be an alert as they could be used for financial risk prevention, in the sense that any crisis in the European Union, mainly in countries like France, Germany, Belgium or Austria, could have a negative influence on several financial markets. The UK also has a relative predominance, which is very important in the current context of Brexit. Therefore, for hedge funds it is vitally important to monitor the economic situation of this region.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.physa.2019.121542.

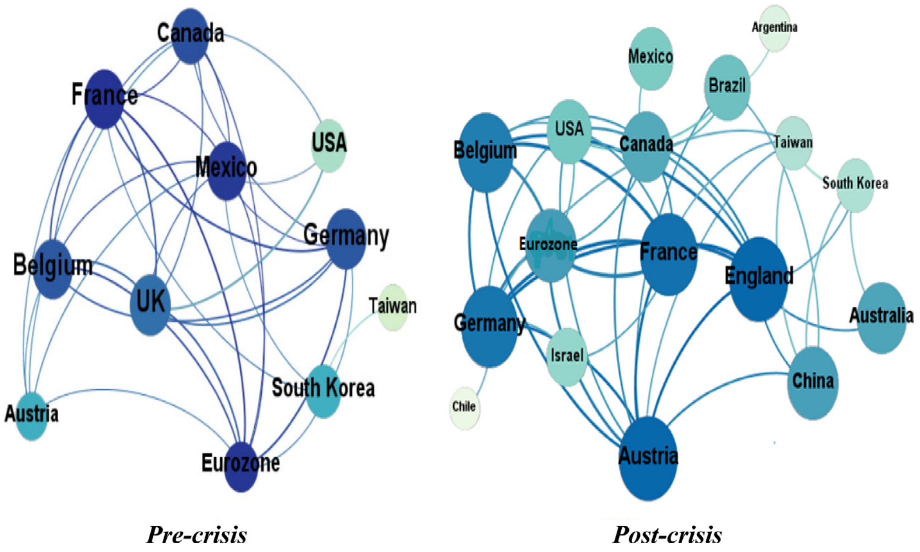

Fig. 7. Relationships with $\rho_{DCCA} > 0.66$ for a time scale of n = 135. In this network, the darker blue represents the higher weighted degree of the respective stock market. On the left the pre-crisis period and on the right the post-crisis one.

Table 3
Country ranking according to the centrality of Page Rank and Weighted Degree, considering different time scales (post-crisis period).

Weighted Degree ranking	Scale 4	Scale14	Scale 28	Scale 60	Scale 135
1	France	France	France	UK	France
2	Eurozone	Eurozone	Eurozone	France	Eurozone
3	UK	UK	UK	Belgium	Mexico
4	Belgium	Germany	Germany	Eurozone	Canada
5	Germany	Belgium	Belgium	Germany	Germany
Page Rank ranking	Scale 4	Scale14	Scale 28	Scale 60	Scale 135
1	Eurozone	Eurozone	Eurozone	Eurozone	Eurozone
2	UK	UK	UK	UK	Mexico
3	USA	USA	USA	Mexico	UK
4	France	France	France	Belgium	France
5	Belgium	Belgium	Belgium	France	Canada

Table 4
Country ranking according to the centrality of Page Rank and Weighted Degree, considering different time scales (pre-crisis period).

Weighted Degree ranking	Scale 4	Scale14	Scale 28	Scale 60	Scale 135
1	France	France	UK	UK	France
2	Germany	UK	Eurozone	France	Eurozone
3	Belgium	Germany	Germany	Germany	Germany
4	Austria	Belgium	Belgium	Belgium	UK
5	Eurozone	Austria	Austria	Austria	Belgium
Page Rank ranking	Scale 4	Scale14	Scale 28	Scale 60	scale 135
1	France	UK	UK	UK	France
2	Germany	France	Eurozone	France	Austria
3	Belgium	Germany	Germany	Germany	Germany
4	Austria	Belgium	Belgium	Belgium	UK
5	Eurozone	Austria	Austria	Austria	Canada

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