Quantifying the contagion effect of the 2008 financial crisis between the G7 countries (by GDP nominal)

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Quantifying the contagion effect of the 2008 financial crisis between the G7 countries (by GDP nominal)

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HIGHLIGHTS

- We apply ρ_{DCCA} to analyze the stock market of the G7 countries in GDP (nominal).
- We analyzed the 2008 financial crisis in terms of ρ_{DCCA}, in function of time.
- $\Delta\rho_{DCCA}$ is defined in order to measure the contagion/interdependence effect.

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ABSTRACT

In this paper we quantify the cross-correlation between the adjusted closing index of the G7 countries, by their Gross Domestic Product (nominal). For this purpose we consider the 2008 financial crisis. Thus, we intend to observe the impact of the 2008 crisis by applying the DCCA cross-correlation coefficient ρ_{DCCA} between these countries. As an immediate result we observe that there is a positive cross-correlation between the index, and this coefficient changes with time between weak, medium, and strong values. If we compare the pre-crisis period (before 2008) with the post-crisis period (after 2008), it is noticed that ρ_{DCCA} changes its value. From these facts, we propose to study the contagion (interdependence) effect from this change by a new variable, $\Delta\rho_{DCCA}$. Thus, we present new findings for the 2008 crisis between the members of the G7.

1. Introduction

The study of economic complexity belongs to the field of complex systems. This field has become significant and naturally appeared as an area of interdisciplinary research, called econophysics [1–6]. One of the many ways of studying economics and physics problems is to try understanding the (auto or cross)-correlations in the time series of these non-linear systems [7–14]. The analysis of the cross-correlation between financial time series has been of great importance

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in understanding the financial links between the different markets and assets (exchange rates, stocks, interest rates). In this context, Podobnik and Stanley developed a method to investigate the power law cross-correlation between two simultaneous and non-stationary time series, called *Detrended Cross Correlation Analysis* (DCCA) [15].

The DCCA method was applied to check the cross-correlation between price and volume [16], to study correlations and cross-correlations in Brazilian agrarian commodities and stocks [17], to find a cross-correlation between WTI crude oil and the US dollar [18], and a number of other things [19,20]. The DCCA method is a generalization of the Detrended Fluctuation Analysis (DFA), one of the most popular methods for non-stationary time series auto-correlation analysis [21]. With this knowledge, Zebende combined these two methods and has defined the detrended cross-correlation coefficient, ρ_{DCCA}, which measures the level of cross-correlation between two non-stationary time series [22]. The value of ρ_{DCCA} varies between -1 and 1. When $\rho_{DCCA} = 1$, the time series are perfectly correlated, whereas $\rho_{DCCA} = -1$ means that the time series are perfectly anti-correlated. The value, $\rho_{DCCA} = 0$, represents no correlation between these series. This cross-correlation coefficient is being applied to many areas of knowledge, such as the study of homicide [23], to quantify the level of cross-correlation between the Dow Jones and Nasdaq indexes [24], to verify the cross-correlation between the West Texas Intermediate (WTI) crude oil spot price and some exchange rates around the world [25], and to measure the cross-correlation of the 44 variations of the currencies of the largest economies in the world [26,27].

Kristoufek, in order to ensure the efficiency of ρ_{DCCA}, tested the cross-correlation coefficient using Monte Carlo simulations. It was compared to the Pearson correlation coefficient. The conclusion was that the ρ_{DCCA} remains a promising tool for measuring the dependence of non-stationary time series [28,29]. Other tests with ρ_{DCCA} have also been performed [26,30]. Multifractal extensions of DCCA can be seen in Refs. [31,32,12,33–36,9].

In economics, the search for auto- or cross-correlations between stock markets has been important, especially in a period marked by globalization and financial crises (like in 2008) [37,38]. In this context, in accordance with Ref. [39], there is some pre-existing integration between the economies of countries. During a period of financial instability, this relationship intensifies. This intensity may be sufficient to promote pre-existing structural breaks in transmission collisions between two countries. Thus, the contagion effect is characterized by, e.g., shocks occurring in a certain economy infecting the economy of another country, regardless of the macroeconomic fundamentals of the two or more countries concerned. In contrast, interdependence between countries is characterized by an increase in the level of cross-correlation due to pre-existing economic relations (see Refs. [40–43]).

As we know, the 2008 financial crisis was the second largest crisis for capitalism after the Great Depression of 1929. It began in the USA with the collapse of the speculative bubble in the housing market, caused mainly by the abundance of real estate loans and financial innovations. As a result of the 2008 crisis, industrial production and GDP declined rapidly in the last quarter of 2008 in several countries. The height of the crisis was the bankruptcy of the Lehman Brothers investment bank on September 15, 2008, after the refusal of the Federal Reserve (the "Fed", the US central bank) to rescue that institution. After this event, the financial markets went into a panic situation, since it had been expected that the Fed would help all institutions which were failing. This led to a significant increase in the preference for liquidity, especially in the case of commercial banks. The increased demand for liquidity triggered a process of selling financial assets on a large scale, leading to a Minskyan process of asset deflation, with a sudden and violent fall in the prices of financial assets, and a contraction of bank credit for commercial and industrial transactions. This credit evaporation resulted in a rapid and deep fall in industrial production and international trade worldwide. Therefore, in the last quarter of 2008, industrial production experienced a very significant reduction, see for example Fig. 1 2008 (black line). After the Lehman Brothers event, several countries adopted fiscal and monetary policies to reduce the effects of the crisis on their economies. These included Brazil, which carried out fiscal stimulus and monetary policies to reduce the effects of the economic crisis. But, because of these policies, Brazil has, over the last year, suffered economically. It is known that blue chip companies play a key role in the national economy [44]. In this sense, IBOVESPA (the blue chips sum) has suffered successive drops (see the last years in Fig. 1 IBO).

Taking into account the above, in this paper we apply the Detrended Cross-Correlation Coefficient, ρ_{DCCA}, to indicate whether or not there was a contagion/interdependence effect in the 2008 financial crisis. We propose to study financial indexes relevant to the group of seven largest economies, G7, measured by their Gross Domestic Product (GDP) (nominal) according to the International Monetary Fund list. These are:

- **CAC 40** (Currency in EUR), the most widely-used indicator of the Paris market, reflects the performance of the 40 largest equities listed in France, measured by free-float market-capitalization and liquidity.
- **DAX** (Currency in EUR), the German Stock Index is a total return index of 30 selected German blue chip stocks traded on the Frankfurt Stock Exchange. The equities use free float shares in the index calculation.
- **DJI** (Currency in USD), the Dow Jones Industrial Average is a price-weighted average of 30 blue-chip stocks that are generally the leaders in their industry.
- **FTSE 100** (Currency in GBP), the FTSE 100 index is a capitalization-weighted index of the 100 most highly capitalized companies traded on the London Stock Exchange. The equities use an investibility weighting in the index calculation.
- **IBOVESPA** (Currency in BRL), a gross total return index weighted by market value to the free float and comprises the most liquid stocks traded on the São Paulo Stock Exchange.
- **Nikkei 225** (Currency in JPY), the Nikkei-225 Stock Average is a price-weighted average of 225 top-rated Japanese companies listed in the First Section of the Tokyo Stock Exchange.
- **SSE Composite Index** (Currency in CNY), the Shanghai Stock Exchange Composite Index is a capitalization-weighted index. The index tracks the daily price performance of all A-shares and B-shares listed on the Shanghai Stock Exchange.

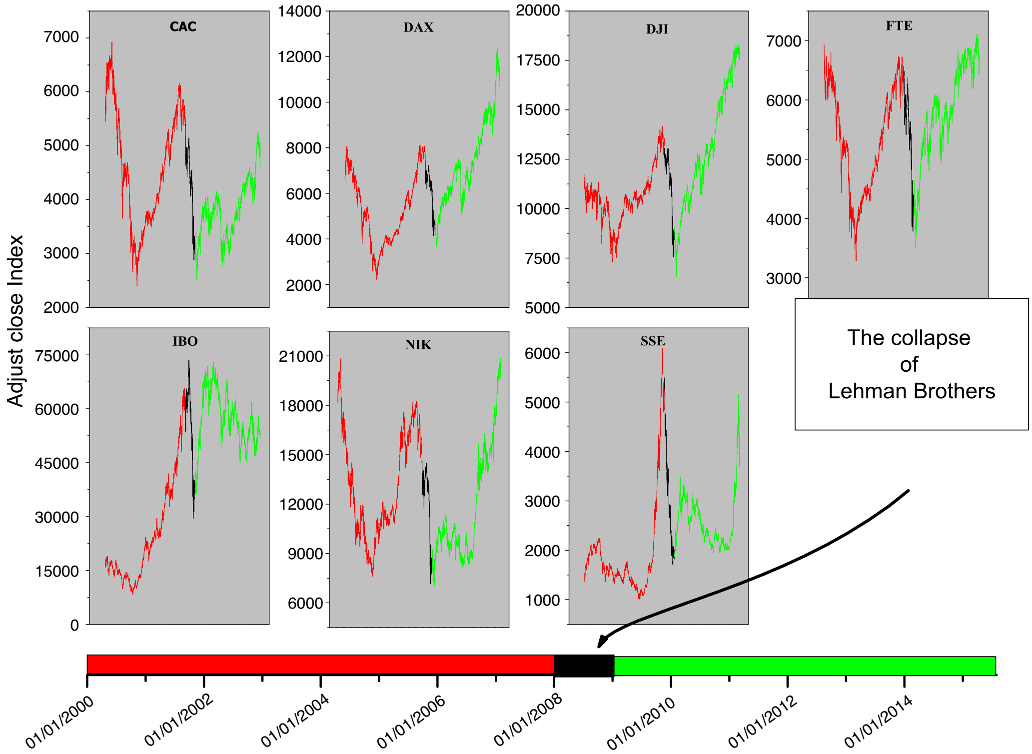

Fig. 1. (Color on-line) Adjusted closing index for the G7 in GDP (nominal) between January 01, 2000 to July 15, 2015. The red line represents the data before 2008, the black line during 2008, and the green line the period after 2008.

To accomplish this task, we organize this paper according to the following sequence. In Section 2 we discuss the methodology, in Section 3 we present the data and results, and in Section 4 we draw some conclusions.

2. Methodology

The detrended cross-correlation coefficient is a new method to quantify the level of cross-correlation between two non-stationary time series [22]. This method is based on detrended fluctuation analysis (DFA) [21] and detrended cross-correlation analysis (DCCA) [15] Thus, for a better understanding of ρ_{DCCA}, we present the algorithm below in five steps:

Step I: Consider two time series, $\{x_t\}$ and $\{y_t\}$, with $t = 1, 2, \ldots, N$ (the length of the time series). We integrate these time series, obtaining two new series:

$$xx_k = \sum_{t=1}^{k} x_t \quad \text{and} \quad yy_k = \sum_{t=1}^{k} y_t, \qquad k = 1, 2, \ldots, N. \tag{1}$$

Step II: We divide these two integrated time series, $\{xx_t\}$ and $\{yy_t\}$, into $(N - n)$ overlapping boxes of equal length n, with $4 \leq n \leq \frac{N}{4}$.

Step III: We calculate the local trend of each box by a least-squares fit of each series, $xP_i(k)$ and $yP_i(k)$, and we calculate the covariance of the residuals in each box by:

$$f_{xy}^2(n, i) = \frac{1}{(n+1)} \sum_{k=i}^{i+n} (xx_k - xP_i(k))(yy_k - yP_i(k)). \tag{2}$$

Step IV: The average over all $(N - n)$ overlapping boxes is calculated to obtain the new covariance function:

$$F_{xy}^2(n) = \frac{1}{(N-n)} \sum_{i=1}^{N-n} f_{xy}^2(n, i). \tag{3}$$

Step V: Lastly, we calculate the cross-correlation coefficient ρ_{DCCA} by:

$$\rho_{DCCA}(n) = \frac{F_{xy}^2(n)}{F_{xx}(n) F_{yy}(n)}. \tag{4}$$

Table 1
The G7 from the point of view of GDP (nominal). List by the International Monetary Fund (2014). Value in Millions of US$.

Country (region)	GDP (nominal)	Stock market index (symbol)
Brazil	2,353,025	Ibovespa (IBO)
China	10,380,380	SSE Composite (SSE)
United Kingdom	2,945,146	FTSE 100 (FTE)
France	2,846,889	CAC 40 (CAC)
Germany	3,859,547	DAX (DAX)
Japan	4,616,335	Nikkei 225 (NIK)
USA	17,418,925	DJI (DJI)

Table 2
Skewness of the return.

Index (symbol)	Before	2008	After
FTSE 100 (FTE)	−0.24	0.12	−0.18
Ibovespa (IBO)	−0.20	0.22	−0.03
Nikkei 225 (NIK)	−0.16	−0.23	−0.56
DJI (DJI)	−0.10	0.23	−0.19
CAC 40 (CAC)	−0.09	0.34	0.01
DAX (DAX)	−0.04	0.53	0.08
SSE Composite (SSE)	0.11	0.28	−0.52

This cross-correlation coefficient, as we can see, depends on the box length n (the time scale). One of the advantages of this cross-correlation coefficient is that it measures the correlations between two non-stationary time series at different time scales. The DCCA cross-correlation coefficient ranges from $-1 \leq \rho_{DCCA} \leq 1$. A value of $\rho_{DCCA} = 1$ means a perfect correlation, $\rho_{DCCA} = -1$ means a perfectly anti-correlation, and $\rho_{DCCA} = 0$ means there is no correlation between the series. With the detrended cross-correlation defined, we will describe the data and the results in the next section.

3. Data and results

We collected the daily adjusted closing index of the seven largest economies in the world, measured in GDP (nominal) according to the International Monetary Fund, (see Table 1 and Fig. 1). Our data were collected between January 01, 2000 and July 15, 2015.[1]

In order to better study the crisis, we split the data into three periods: before 2008 (pre-crisis), 2008, and after 2008 (post-crisis). We consider the pre-crisis period to be from January 01, 2000 to December 31, 2007 and the post-crisis to be the period from January 01, 2009 to July 15, 2015. These cut-offs were found to coincide qualitatively with the peak and subsequent fall of the adjusted closing value index (with the bankruptcy of Lehman Brothers Holdings Inc. on September 15, 2008) (Fig. 1). We are interested in a fluctuation analysis, in this sense we define below the returns of the time series by:

$$r_i(t) = \log_{10} \frac{P_i(t)}{P_i(t-1)}. \tag{5}$$

$P_i(t)$ is the value of the index i at day t. With $r_i(t)$ we can see the relative changes (fluctuations) and compare them directly with other variables, even this variable has very different base values. Fig. 2 shows the return for the G7. Visually, the returns show that there is a greater fluctuation in 2008 (black line), the year of the crisis. Therefore, we calculated the descriptive statistics for this variable. From our data we see that the average value is zero with standard deviation of approximately 0.01 for all returns index, before, at the crisis, and post-crisis. The skewness [45], Eq. (6), is presented in Table 2.

$$SK \equiv \frac{N}{(N-1)(N-2)} \sum_{i=1}^{N} \left(\frac{r_i - \overline{R}}{\sigma} \right)^2, \tag{6}$$

N denotes the number of observations, σ the standard deviation, and $\overline{R}$ the average of the return r.

The skewness characterizes the degree of asymmetry of a distribution around its mean. For most cases, SK was negative for the period before and after the crisis. During the crisis, there is a greater fluctuation in return, which is evidenced by the positive skewness (except for the Nikkei 225). A positive (negative) skewness indicates that the tail on the right (left) side is longer or fatter than the left (right) side. And if we look at the post-crisis we can see that the asymmetry back to the negative value (in general), but this value tends to zero (identifying an adjustment of the stock market).

With the results above we cannot identify the contagion/interdependence relations, but with ρ_{DCCA} we can. Thus, we calculate the ρ_{DCCA} for all pairs (see Table 3 for symbols) of returns.

[1] As described on the web site: www.yahoofinance.com.

Table 3
Cross-correlation symbols.

(a) red	(b) white	(c) green
CAC X DAX □	CAC X IBO □	CAC X SSE □
CAC X FTE ○	CAC X NIK ○	DAX X SSE ○
DAX X FTE △	DAX X IBO △	IBO X SSE △
CAC X DJI ◇	DAX X NIK ▽	NIK X SSE ▽
DAX X DJI ◁	IBO X NIK ◇	DJI X SSE ◇
DJI X FTE ▷	DJI X IBO ◁	FTE X SSE ◁
	DJI X NIK ▷	
	FTE X IBO ⬡	
	FTE X NIK ☆	

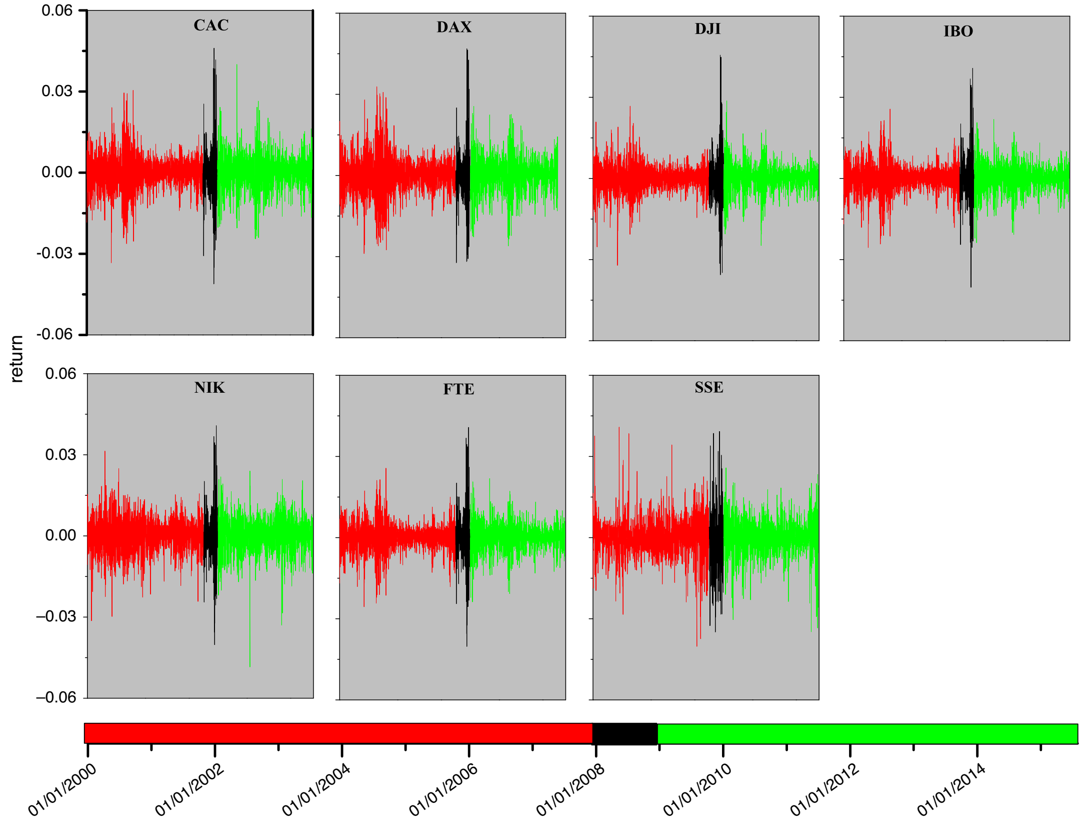

Fig. 2. (Color on-line) Returns from daily adjusted closing index for G7 between January 01, 2000 to July 15, 2015. The red line represents the data before 2008, the black line during 2008, and the green line the period after 2008.

Table 4
Detrended cross-correlation conditions for analysis.

ρ_{DCCA}		
Weak	Medium	Strong
$0.000 \mapsto 0.333$	$0.333 \mapsto 0.666$	$0.666 \mapsto 1.000$

The detrended cross-correlation coefficients between the G7 are presented in three periods, e.g., we consider the period before the crisis, Fig. 3(a), during 2008, Fig. 3(b), and after the crisis, Fig. 3(c). In this figure we can see ρ_{DCCA} as a function of time.

We divided each period into three kinds of partnerships: red for Europe + USA (left panel), green for China (right panel), and white for the other pairs (central panel). The value of ρ_{DCCA} is always positive, independently of crossovers, but with the conditions defined by Table 4:

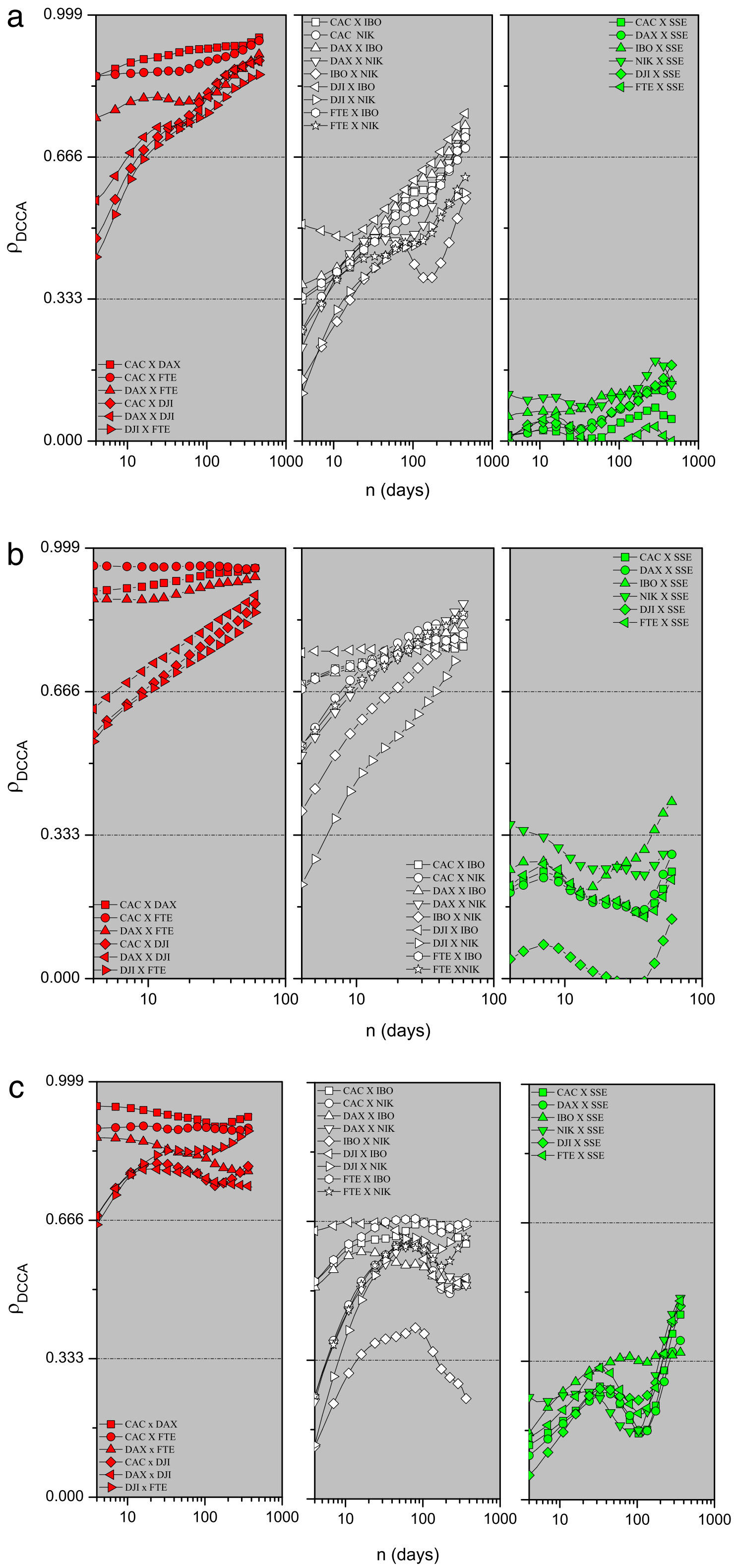

Fig. 3. (Color on-line) Detrended cross-correlation coefficient between the stock market index of the G7 for: (a) before 2008, (b) during the crisis, and (c) after 2008.

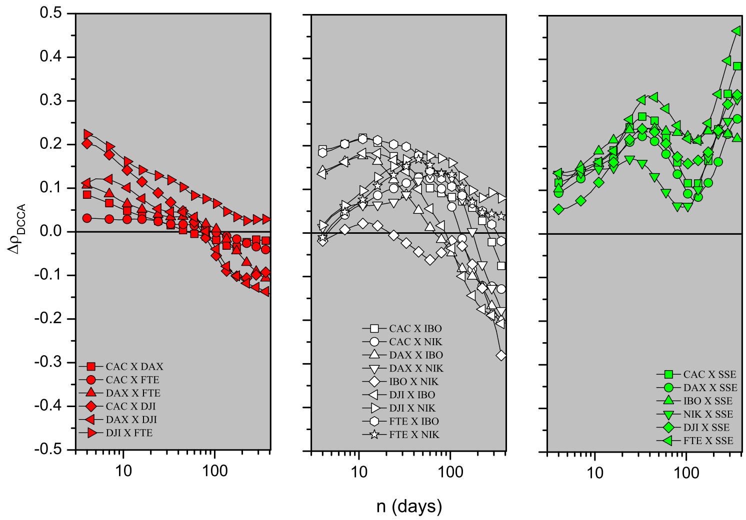

Fig. 4. (Color on-line) $\Delta\rho_{DCCA}$ as a function of time.

For these time periods (before, 2008, and after), we can see that (Fig. 3(a), (b), (c)) the left panel (red) has a greater value of ρ_{DCCA} (strong in the scale of detrended cross-correlation). Thus, for Europe + USA, ρ_{DCCA} shows that their stock markets have a greater interdependence. While for China, right panel (green), the interdependence is smaller because the value of ρ_{DCCA} is weak. The central panel (white) shows an intermediate value (medium) for ρ_{DCCA}.

However, in this paper we wish to study the financial crisis and see its contagion effects in the G7. In this way, let us compare the post-crisis with the pre-crisis period, given that we can see an increase in the ρ_{DCCA} if we compare ρ_{DCCA} value after and before the crisis. Here, we relate the contagion effect to the difference between the post and pre-crisis periods.

For this purpose, we define a new variable, i.e,

$$\Delta\rho_{DCCA}(n) \equiv \rho_{DCCA}^{after}(n) - \rho_{DCCA}^{before}(n). \tag{7}$$

Here, $\rho_{DCCA}^{after}(n)$ is the detrended cross-correlation after the crisis and $\rho_{DCCA}^{before}(n)$ is the detrended cross-correlation before the crisis. This new variable intended to indicate the contagion effect of the crisis or an oscillation of the local/global stock market.

Fig. 4 shows the value of $\Delta\rho_{DCCA}$ as a function of time for the return of the adjust value in G7 countries. In general, we can see an increase in the detrended cross-correlation coefficient, because $\Delta\rho_{DCCA}$ is positive, mainly if $n \leq 30$ days (short time scale).

In Fig. 4, we can actually see an indication of a contagion effect in the 2008 crisis. For example, in the left panel (red), besides a strong cross-correlation between the economies (Europe + USA), there is a clear contagion effect (a positive difference between the post- and the pre-crisis) for $n \leq 30$ days. In the right panel (green), the contagion effect is more evident, because $\Delta\rho_{DCCA}$ is positive in all time scales. This leads us to say that the contagion effect was greater for the Shanghai Stock market in the G7. In the central panel (white) $\Delta\rho_{DCCA}$ is positive for $n \leq 30$ days, except for IBO X NIK, where no contagion effect was observed.

4. Conclusions

In this paper we studied cross-correlations in the G7, in order to analyze the 2008 financial crisis and the contagion effect. For this purpose, we applied the detrended cross-correlation coefficient, ρ_{DCCA}, to the time series of the return of the adjusted closing index for each country. Also, we defined a new variable, $\Delta\rho_{DCCA}$, that introducing directly which is proportion between the post- and pre-crisis, i.e., indicating the contagion effect. Specifically, according to this study, there was an increase in ρ_{DCCA} from its pre- to its post-crisis value, $\rho_{DCCA}^{after} > \rho_{DCCA}^{before}$, at least for $n \leq 30$ days. Thus, the 2008 financial crisis induced in the G7 a greater adhesion of their stock markets, showing that the effect of this crisis spread to almost all these countries, and obviously this shows that any increase or reduction in the stock exchange in a specific country can lead to a similar effect in the others. The Shanghai stock exchange composite index had the highest contagion effect in relation to the other countries, which spread to all time scales.

Lastly, in this paper we introduced a new way to analyze the effects of interdependence and contagion in financial crises. For this purpose, we applied the cross-correlation coefficient and a new variable, $\Delta\rho_{DCCA}$.

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