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Contagion and dynamic correlation of the main European stock index futures markets: a time-frequency approach

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Abstract

In this paper, we examine the financial contagion and dynamic correlation between three European stock index futures, namely FTSE 100, DAX 30 and CAC 40. For this purpose we resort to a continuous wavelet transform framework and we cover the aftermath of the sovereign debt crisis period. More precisely, we analyze the power spectrum of the series, the wavelet coherency and the average dynamic correlation before and after turbulence episodes occurred after the outburst of the sovereign debt crisis. Our results show that the stock index futures are highly correlated and this correlation increases around financial distress episodes. The contagion phenomenon, associated with a high-frequency correlation, manifested especially after the additional rescue package awarded to Greece. All in all, the dynamic correlation is influenced by the frequency decomposition level and fluctuates considerably in the very long-run.

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Keywords: Stock index futures; European financial markets integration; Portfolio diversification; Contagion; Wavelets

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1. Introduction

The stock markets integration has drawn attention among academics, practitioners and policy makers, especially at the European Union (EU) level. Numerous studies have focused on the cross-border interdependence, analyzing the co-movements and contagion between spot markets. This issue has lately gained importance at least for the following reasons. First, the co-movement of stock market returns is crucial for portfolios risk assessment, which highlights the necessity of diversifying investments, so as to disperse the risks. The benefits of risks diversification are higher when the correlation between the stock returns is low. Noteworthy studies addressing this topic are those of Rua and Nunes (2009), Sergey et al. (2010), Syllignakis and Kouretas (2011) and Dajcman et al., (2012).

Second, stock markets co-movements and correlations provide particular clues about spillover effects. This issue is important for risk managers because the transmission of shocks among financial markets is assumed to be higher in times of crisis (Dimitriou et al., 2013). In this line, most of the research studies discovered that correlations between markets were growing during and after periods of high volatility (Longin and Solnik, 1995; Morana and Beltratti, 2008; Tamakoshi and Hamori, 2013). Finally, studying the stock markets correlation is important also for supervision authorities and international financial institutions (Ahmad et al., 2013). Additional information is released, allowing the policy makers to undertake coordinated rescue measures for contagious financial systems.

Even if a large part of the literature showed that international market are more and more correlated and the co-movements increase in high volatility periods, there are also studies which provided mixed results. This is due to the way of defining contagion and/or to the econometric techniques employed in this demarche. In the last years, a general accepted definition of the contagion has emerged, being advanced by Forbes and Rigobon (2002). Accordingly, the contagion is associated with a significant increase in the degree of co-movements among financial markets, during and immediately after episodes of high financial turbulence. In addition, an ample development of the empirical techniques was recorded. Nowadays, most of the papers rely on the Dynamic Conditional Correlation (DCC) model proposed by Engle (2002), which has emerged from the autoregressive conditional heteroskedasticity (ARCH) model. Cappiello et al. (2006) developed this technique and proposed an asymmetric approach called Asymmetric Dynamic Conditional Correlation (ADCC) model. Important studies which used these methods both for developed and emerging stock markets, especially in the context of the recent financial crisis, are those of Chen et al., (2002), Chiang et al., (2007), Lin (2012), Min and Hwang (2012) and Ahmad et al., (2013). The European stock markets represented a case study for the works of Voronkova (2004), Hardouvelis et al., (2006), Syllignakis and Kouretas (2011) and Connor and Suurlaht (2013).

In this context, the contribution of our paper to the literature is threefold. First, we assess the contagion and dynamic correlation of futures and not spot markets. The use of stock index futures prices has several obvious advantages Pan and Hsueh (1998). On the one hand, it overcomes the nonsynchronous problem existing on the spot markets. However, this issue is not of great interest for the present study, as only the European stock markets are analyzed. On the other hand, the general sentiment is that the price discovery takes place in stock index futures markets instead of occurring in underlying spot markets. Recently, Karim and Jais (2011) studied the effect of the subprime crisis on the integration of stock index futures markets and discovered that the 2007 subprime crisis does not seem to affect the long-run co-movements among the stock index futures markets.

Second, our paper employs a novel approach, namely the Continuous Wavelet Transform (CWT). The wavelet transformation, which combines the time and frequency domain, was used in several researches approaching the co-movements of international stock markets. This method is very useful in portfolio management analysis, where agents focusing on daily movements interact, on the markets, with agents concerned with longer time horizons. Notable studies in this area are those of Rua and Nunes (2009), Graham and Nikkinen (2011), Graham et al., (2012), Dajcman et al., (2012) and Ranta (2013). However, none of these studies addressed the correlation of futures markets.

Third, we focus on the recent period, covering the years after the start of the sovereign debt crisis. Most of the previous empirical works addressed the Asian or the subprime crisis episodes. Nevertheless, the period following the sovereign debt crisis is of particular interest for the European stock markets. Consequently, we focus on the three largest markets in order to see to what extent the identified turbulence episodes (associated with rescue decisions or rating downgrades) impacted upon their dynamic correlation level.

The rest of this paper is structured as follows. Section 2 provides the empirical framework and data description. Section 3 provides the empirical results. Finally, Section 4 outlines the conclusions of the study.

2. Data and empirical design

2.1. Data

To examine the co-movements between the selected European futures markets (UK, Germany and France), we use the FTSE 100, DAX 30 and CAC 40 stock index futures contracts (Real Time Stock Indices Futures), from the www.investing.com database. This study employs daily closing data of the stock index futures markets, covering the period October 15, 2009 to August 27, 2013. Days of no trading on any of the observed stock markets are excluded from the analysis. Consequently, our data sample contains 944 observations. The stock index futures returns are calculated as differences of natural logarithmic daily closing prices:

$$R_t = \ln\left(\frac{C_t}{C_{t-1}}\right) \tag{1}$$

where: R_t is the index return and C_t is the index closing price.

Fig. 1 presents the stock index returns for the futures contracts. We can see a strong variation in the index returns in the mid of 2010 (in May 2010 we had the sovereign debt crisis setup), in the mid of 2011 and at the beginning of 2012. However, this simple analysis does not allow identifying common movements in data series, lead-lag relationships or different changes associated with different frequencies (defined as the rapidity of movements in the data series). Therefore, a wavelet transform framework is more suited for this analysis.

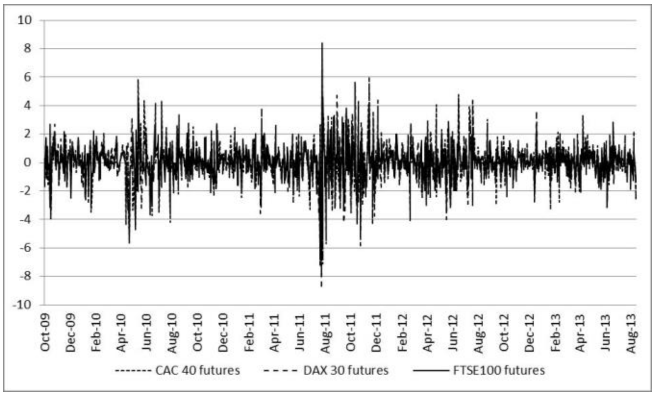


Fig. 1. Daily returns of the stock index futures

2.2. Continuous Wavelet Transform

Through wavelets, the correlation levels are assessed at different scales and at different moments in time. For a detailed presentation of the CWT and wavelet coherence, see the works of Grinsted et al., (2004), Rua and Nunes (2009) and Tiwari et al., (2013a). We further on briefly describe this methodology.

The wavelet transform decomposes a time series in functions called wavelets (small waves), localized both in time and frequency $\psi_{\tau,s}(t)$. These small waves result from a mother wavelet that can be expressed as a function of time positions and scales:

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right) \tag{2}$$

where: $\frac{1}{\sqrt{s}}$ is a normalization factor.

The continuous wavelet transform of a time series $x(t)$ with respect to $\psi(t)$ is given by:

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{s}}\int_{-\infty}^{+\infty} x(t)\psi^{*}\left(\frac{t-\tau}{s}\right)dt \tag{3}$$

Thus, the CWT for a $x(t)$ series becomes:

$$W_x(\tau,s) = \frac{1}{\sqrt{s}}\sum_{t=1}^{N} x(t)\psi^{*}\left(\frac{t-\tau}{s}\right) \tag{4}$$

Torrence and Compo (1998) proposed the Fourier space for the wavelet transform. For the financial series, the Morlet wavelet decomposition is indicated (Tiwari et al., 2013b).

$$\psi(t) = \pi^{-\frac{1}{4}} e^{i\omega_0 t} e^{-\frac{1}{2}t^2} \tag{5}$$

where: ω_0 is the frequency dimension and t is the time dimension.

The corresponding Fourier transform is given by:

$$\hat{\psi}(\omega) = \pi^{\frac{1}{4}}\sqrt{2e}^{-\frac{1}{2}(\omega-\omega_0)^2} \tag{6}$$

The wavelet power spectrum, which shows the co-movements of two series, is defined by $\left|W_x(\tau,s)\right|^2$ and the complex argument of $W_x(\tau,s)$ represents the local phase. According to Torrence and Compo (1998), the white-noise and red-noise wavelet power spectra can be defined as follows:

$$D\left(\frac{\left|W_x(\tau,s)\right|^2}{\sigma_x^2} < p\right) = \frac{1}{2}P_k \chi_\nu^2(p) \tag{7}$$

where: ν is equal to 1 for real and 2 for complex wavelets.

The wavelet coherence (WTC) is defined as the ratio of the cross-wavelet spectrum to the product of the spectrum of each series (see Torrence and Webster, 1999) and helps us to see the reciprocal influences of two series and the lead-lag relationships between different stock index futures returns. For two time series with $W_x(\tau,s)$ and $W_y(\tau,s)$ wavelet transforms, the WTC is:

$$R^2(\tau,s) = \frac{\left|S\left(s^{-1}W_{xy}(\tau,s)\right)\right|^2}{S\left(s^{-1}\left|W_x(\tau,s)\right|^2\right)\cdot S\left(s^{-1}\left|W_y(\tau,s)\right|^2\right)} \tag{8}$$

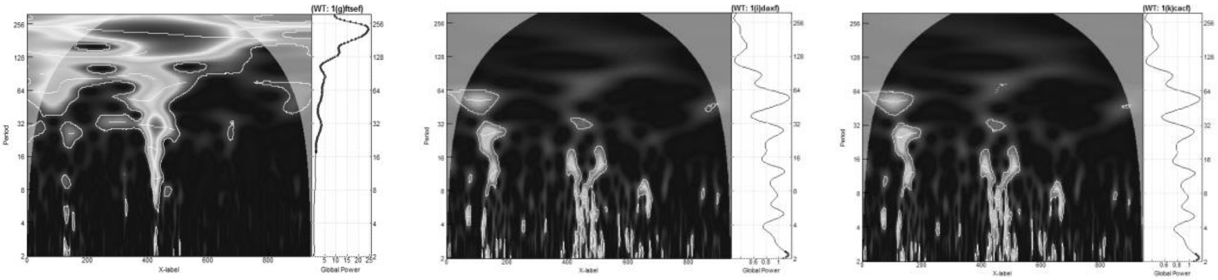
where: $S\,(.)$ is a smoothing operator and s is the wavelet scale.

3. Results

3.1. Wavelet Power Spectrum and Wavelet Coherence

Fig. 2 describes the wavelet power spectrum of the stock index futures returns, presented in a contour plot with three dimensions: time, frequency and color code. In order to identify the series co-movements and to see if the strength of the co-movements changes across frequencies and over time, we look to the contour plot. The Local Wavelet Power Spectrum (LWPS) is located in the left side of the plot, while on the right side of each plot the Global Wavelet Power Spectrum (GWPS) is represented. The LWPS shows the local spectrum of a time series signal and the GWPS gives the average variance contained in all wavelet coefficients with equal frequency.

The WPS shows a clear common movement between DAX 30 Futures Index (DAXF) and CAC 40 Futures Index (CACF), while the FTSE 100 Futures Index (FTSEF) presents different patterns. While the first two indexes present a strong variance in the short-run, FTSE 100 shows strong oscillations in the long-run (64-256 days cycle). This observation is confirmed by both the LWPS and the GWPS.

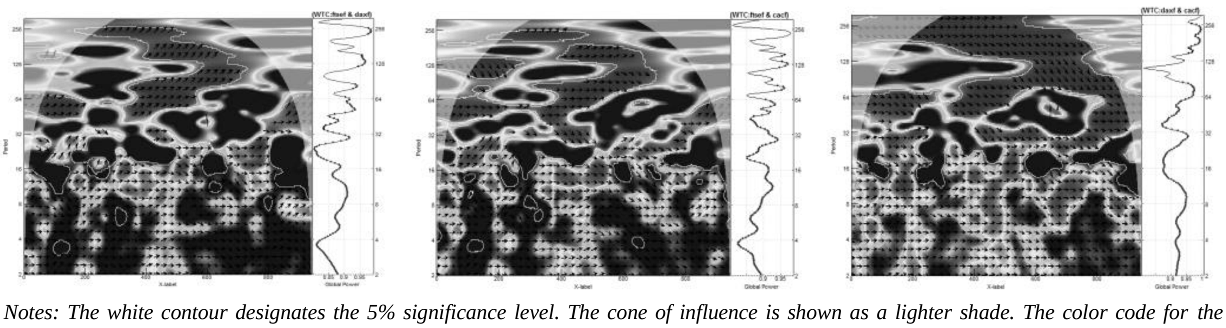


Notes: The white contour designates the 5% significance level. The cone of influence is shown as a lighter shade. The color code for the power ranges from black (low power) to white (high power). The isolated regions within the white lines indicate the significant power at 5% significance level. Y-axis measures frequencies or scales, from the shortest scale (2 days) to the longest scale (256 days). X-axis represents the time-period studied. As we have irregular data, the rank of observations is presented on the horizontal axis: 200 corresponds to September 9, 2010; 400 corresponds to June 29, 2011; 600 corresponds to April 17, 2012; 800 corresponds to February 1, 2013.

Fig. 2. Wavelet power spectrum of the stock index futures returns

In all cases, we observe two zones of strong oscillations in the series in the short- and medium-runs. The first event is located around the observation 150, which corresponds to the setup of the sovereign debt crisis (May 2010). The second event of strong oscillation in the series occurs immediately after the observation 400 (on July 21, 2011, the European leaders extended an additional €109 billion rescue package for Greece). For the DAXF and CACF, we also observe a third area of high oscillations, before the observation 600. On January 14, 2012, the rating agency Standard & Poor's announced its rating actions on 16 Eurozone members, following completion of its review.

Even if the WPS offers some information about the common movements of the series at different frequencies and moments in time, it does not tell much about the contagion phenomenon. The wavelet coherence fills in this gap, being an efficient approach for cross-analyses. The WTC allows to estimate the phase spectrum (movements in the same or opposite direction), but also the lead-lag situation (which series influences the other). Fig. 3 presents the WTC for the three selected indexes.



Notes: The white contour designates the 5% significance level. The cone of influence is shown as a lighter shade. The color code for the power ranges from black (low power) to white (high power). The phase differences between the two series are indicated by arrows. Arrows pointing to the right mean that the variables are in-phase (move in the same direction, having cyclical effects on each other). If the arrows point to the right and up, then the first market index is leading (the first index causes the second one). If the arrows point down, the first index is lagging. Arrows pointing to the left mean that the variables are out-of-phase (have anti-cyclical effects on each other). If the arrows point to the left and up, the first index is leading, and if they point to the left and down, the first index is lagging.

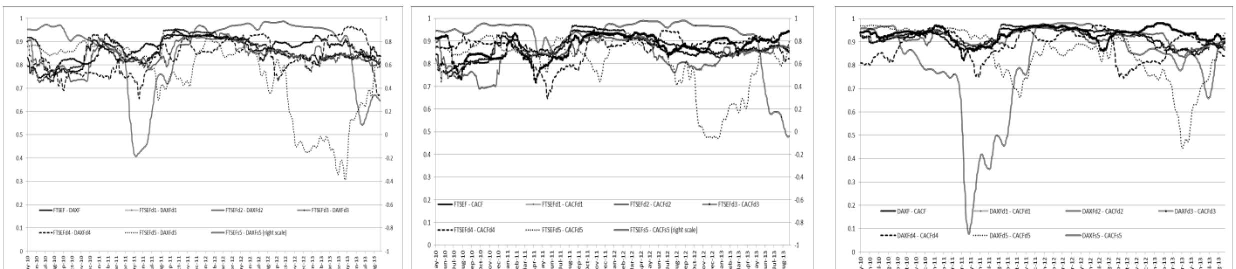
Fig. 3. Wavelet coherence of the stock index futures returns

The WTC demonstrate the co-movements in the series in both short- and long-runs. If the long-run co-movements (64-256 days cycle) are present for the entire analyzed time horizon, the short-run ones (2-16 days cycle) are located around the events identified with the WPS approach and are very strong (white color). In all the cases, the variables are in-phase (arrows point to the right). If we analyze pair-by-pair indexes, we obtain additional information. For the FTSEF–DAXF pair, in the short-run, around 21 July 2011, but also in the long-run for the entire time horizon, the arrows point up. This means that the FTSEF leads the DAXF index. In the case of the FTSEF–CACF pair, we observe a similar situation. However, in this case, in the medium-run (24-32 days cycle), around 21 July 2011, FTSEF is lagging. Finally, for the DAXF–CACF pair, we observe that in general CACF is leading, especially for long time horizons.

3.2. Wavelet decomposition and dynamic correlation of stock index futures

The purpose of the dynamic correlation analysis is the identification of the correlation level at different scales, but also of the contagion phenomenon (strong correlation at high-frequency scales). Therefore, we carry out a pairwise rolling cross-correlation analysis on a scale-by-scale basis, with a window length of 125 rolling days. Benhmad (2013) and Ranta (2013) have chosen a 250 days rolling window in their analysis, but they performed robustness checks employing a 125 days rolling window. We have decided to work with a narrow window (half a year trading days) due to the small data sample included in our analysis.

The decomposed wavelet time scales range from scale 1 to scale 5 and are associated with the 2-4 days cycle (d1), 4-8 days cycle (d2), 8-16 days cycle (d3), 16-32 days cycle (d4) and 32-64 days cycle (d5) respectively. These scales represent different frequency components of the original series (raw data), in details, while the smoothed component (s5) is associated with the very long-run (64-128 days cycle). Fig. 4 presents the rolling wavelet correlation series for the FTSEF, DAXF and CACF at different frequencies, including the un-decomposed sample.



(a) FTSEF-DAXF (b) FTSEF-CACF (c) DAXF-CACF

Fig. 4. Wavelet coherence of the stock index futures returns

The stock index futures are highly correlated at all decomposition levels. The correlation level increases in the second part of 2010 and 2011, confirming thus the WPS analysis. In the long-run (d5 and s5 decomposition levels), the stock index futures returns oscillate considerably, dropping before a financial incident and growing strongly immediately after. This observation is valid for the FTSEF–DAXF correlation, but also for the DAXF–CACF co-movements. However, there is no clear evidence that the correlation increases after each crisis event at all decomposition level. Moreover, we cannot prove the contagion phenomenon between these markets, associated with a high-frequency correlation, occurred in the aftermath of the sovereign debt crisis. Consequently, we compare the average dynamic correlation before and after each financial incident identified in the wavelet analysis.

3.3. Comparison of the dynamic correlation: a t-test approach

In order to compare the level of correlation before and after a crisis event, we perform a two steps equal sample *t*-test. First, we test if the samples have equal variance, using an *F*-test (the null hypothesis states that the variances are the same). Second, we perform a two sample *t*-test, assuming equal or unequal variances (the null hypothesis states in this case that the means are the same). We investigate all decomposition levels and we retain a 75 days period before and after the main incidents. The length of the sample is relatively short. However, we made this choice due to the small data sample and because we want to avoid the overlapping of the samples between two different crisis events. The two events identified in the previous analysis are the moment of the additional rescue package for Greece (July 21, 2011) and the moment of the ratings downgrade by Standard & Poor's (January 14, 2012). We have excluded the event associated with the outburst of the debt crisis (May 2, 2010), as it is placed at the beginning of our data sample. Table 1 provides the results of the *t*-test.

Table 1. Level of correlation before and after crisis events (*t*-test)

	raw data			d1 (2-4 days cycle)			d2 (4-8 days cycle)		
	Corr. before	Corr. after	*t*-stat	Corr. before	Corr. after	*t*-stat	Corr. before	Corr. after	*t*-stat
July 21, 2011 (additional rescue package to Greece)									
FTSEF–DAXF	*0.821*	*0.915*	*-28.6***	*0.822*	*0.928*	*-22.1***	*0.811*	*0.863*	*-9.63***
FTSEF–CACF	*0.844*	*0.936*	*-34.8***	*0.861*	*0.950*	*-27.5***	*0.841*	*0.884*	*-16.0***
DAXF–CACF	*0.878*	*0.948*	*-27.5***	*0.888*	*0.956*	*-22.8***	*0.889*	*0.925*	*-12.5***
January 14, 2012 (ratings downgrade by Standard & Poor's)									
FTSEF–DAXF	0.925	0.913	15.3**	0.942	0.920	15.9**	*0.914*	*0.917*	*-1.83**
FTSEF–CACF	0.936	0.913	18.9**	0.953	0.920	17.1**	*0.910*	*0.912*	*-1.24*
DAXF–CACF	0.959	0.953	9.41**	0.965	0.955	13.5**	*0.957*	*0.958*	*-1.36*
	d3 (8-16 days cycle)			d4 (16-32 days cycle)			d5 (32-64 days cycle)		
	Corr. before	Corr. after	*t*-stat	Corr. before	Corr. after	*t*-stat	Corr. before	Corr. after	*t*-stat
July 21, 2011 (additional rescue package to Greece)									
FTSEF–DAXF	*0.867*	*0.920*	*-17.1***	*0.757*	*0.866*	*-16.9***	0.824	0.724	19.8**
FTSEF–CACF	*0.705*	*0.902*	*-21.1***	*0.742*	*0.839*	*-10.9***	0.852	0.829	3.29**
DAXF–CACF	*0.867*	*0.933*	*-22.3***	*0.829*	*0.892*	*-9.78***	0.924	0.744	31.7**
January 14, 2012 (ratings downgrade by Standard & Poor's)									
FTSEF–DAXF	0.927	0.919	8.51**	*0.871*	*0.881*	*-2.39**	*0.790*	*0.868*	*-8.91***
FTSEF–CACF	0.928	0.926	2.75**	0.903	0.889	3.36**	*0.816*	*0.910*	*-12.8***
DAXF–CACF	*0.961*	*0.962*	*-0.37*	*0.924*	*0.929*	*-1.76*	*0.782*	*0.868*	*-9.42***

*Notes: (i) ** and * indicate the rejection of the null hypothesis of equal means at 1% and 5% critical values respectively; (ii) Since H0 states that the mean difference is equal to zero (B-A=0), we perform a two-sided test and we report two-tail values; (iii) The cases where A>B are marked in italics.*

Table 1 shows two opposite situations. In the case of the first event (July 21, 2011), we observe that the correlation level increases after the financial distress appearance, both for the un-decomposed and wavelet transformed series. This situation appears in the case of all indexes and is valid in the short- and medium-runs (d1-d4 decomposition level). In the long-run (d5 level), the correlation decreases. This evidence confirms the theoretical intuition and proves the contagion effects existent at high-frequencies. The highest correlation level is recorded at d3 (8-16 days cycle).

An opposite situation can be viewed in the case of the second event (January 14, 2012). The downgrading announcement made by Standard & Poor's, had no contagion effect on the futures markets. Neither in the case of the original data series, nor in the case of high-frequency levels, is the dynamic correlation higher after this episode. Nevertheless, for the d4 and the d5 levels of decomposition, the average correlation increases after January 14, 2012. We see then that the contagion does not manifest after all distress episodes. Consequently, even if the results are influenced by the reduced interval between the chosen events, we state that the correlation level of the markets differs, depending on the frequency level and it is particular to each financial turbulence episode. All in all, the correlation level of the main European futures markets remains very strong in the aftermath of the sovereign debt crisis.

4. Conclusions

The analysis of the dynamic correlation of stock markets is crucial for assessing the stock markets co-movements and contagion, with implications for both portfolio managers and authorities. Futures markets represent a workhorse in this direction, overcoming the nonsynchronous and price formation problem, existing on the spot markets.

In this paper we focus on the main European stock index futures and we target the period after the sovereign debt crisis appearance. Our analysis relies on the CWT and dynamic correlation between these indexes. We have discovered that the WPS identifies co-movements between the three selected indexes, around financial stress episodes. The co-movements are also highlighted by the WTC approach, which shows that in general, the FTSEF leads the DAXF and CACF indexes in the long-run. The dynamic correlation analysis, at different decomposition levels, shows that the European futures markets are strongly correlated, and that the level of correlation fluctuates especially in the long-run. Moreover, the level of correlation increases in general after turbulence episodes. However, the results of the t-test show that the increase in the correlation is influenced by the wavelet decomposition level and is specific to each distress episodes.

Our findings have several policy implications. The fact that the FTSEF leads the European continental indexes in the short-run offers important clues about the contagion phenomenon in the European futures markets. In addition, the risk managers who want to benefit from the portfolio diversification shall have a long-term strategy, as the dynamic correlation level oscillates especially in the long-run. Finally, the increase in the correlation level is not specific to all financial distress episodes. Consequently, a continuous analysis should be performed in order to benefit from a performing strategy of risk diversification.

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