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Co-movements and contagion between international stock index futures markets

Claudiu Tiberiu Albulescu[1] · **Daniel Goyeau**[2] · **Aviral Kumar Tiwari**[3]

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Abstract In this paper, we explore the co-movements and contagion between six international stock index futures markets. In contrast to the empirical studies which dominate the literature and focus on the case of spot markets, relatively little is known about the returns and the volatility dynamics of the futures markets. To address this deficiency, we employ a time–frequency approach and discover that the co-movements between the international markets manifest especially in the long run. Nevertheless, the contagion phenomenon associated with the very short-run horizon is present in particular in the case of the European markets, due to their higher level of integration. The rolling wavelet correlation increases after severe turbulence episodes, but fluctuates over time and across frequencies. Our findings can guide the international investors in stock index futures markets to accurately diversify their portfolio in crisis periods.

Keywords Stock index futures · Co-movements · Contagion · Rolling wavelet correlation · Portfolio diversification · Continuous Wavelet Transform

JEL Classification G11 · G15 · C49 · F36

✉ Claudiu Tiberiu Albulescu
claudiu.albulescu@upt.ro; claudiual@yahoo.com

1 Management Department, Politehnica University of Timisoara, 2, P-ta. Victoriei, 300006 Timisoara, Romania

2 CRIEF, University of Poitiers, 2, Rue Jean Carbonnier, Bat. A1, BP 623, 86022 Poitiers, France

3 Faculty of Management, IBS Hyderabad, IFHE University, Dontanpalli, Hyderabad 501203, India

1 Introduction

The deregulation of financial markets and their increasing integration throughout the world has generated interest in empirically examining the common behavior of international stock markets. This issue has gained importance at least for the following reasons. First, studies on financial markets co-movements provide information about potential benefits of international portfolio diversification, related to risks mitigation (Markowitz 1952). These benefits are higher when the correlation between the stock returns is low. Second, studying the co-movements of international financial markets is important for risk managers, as the empirical investigation of the spillover effects offers insights into building accurate asset pricing models (Arouri et al. 2011). Indeed, the transmission of shocks among financial markets is assumed to be higher in times of crisis. Finally, analyzing the financial markets correlation is important for supervision authorities and international financial institutions, facilitating coordinated rescue measures for contagious financial systems (Ahmad et al. 2013).

In stark contrast to the significant volume of work on international stock markets co-movements, studies approaching the stock index futures markets remain limited, with few exceptions only (Becker et al. 1993; Aggarwal and Park 1994; Booth et al. 1996; Pan and Hsueh 1998; Sarno and Valente 2005; In and Kim 2006; Karim et al. 2011; Todorova et al. 2014). The analysis of co-movements in futures markets presents several advantages over the spot markets. First, it allows for the mitigation of the stale quote problem found in the spot index prices (Boudoukh et al. 1994; Pan and Hsueh 1998). Thus, by expanding the co-movements issues toward the futures markets, the non-synchronous problem existing on the spot markets is avoided. In addition, the price discovery takes place in stock index futures markets (Kawaller et al. 1993). Indeed, the existing empirical evidence strongly suggests that futures prices typically lead spot prices and that they respond rapidly and differently to new information (Chan 1992; Rittler 2012), even if a strong feedback relationship between spot and futures markets was documented (see, e.g., In and Kim 2006). Furthermore, Bollen and Whaley (2013) show that the amount of noise in the futures price is constant in average, and it is independent of data frequencies for estimating the returns. Finally, the use of futures products in order to study the co-movements of international financial markets is further motivated by a better transactional efficiency.

Against this background, the main aim of our paper was to explore the co-movements (associated with the medium-run and the long-run horizon) and the contagion phenomenon (associated with the short-run horizon or high frequencies) within six international stock index futures markets (Australia, France, Germany, Japan, the UK, and the USA), using the continuous wavelet transform (CWT) and the rolling wavelet correlation approach. The focus on futures and not on spot markets provides to the international investors more precise information regarding the international financial markets co-movements, due to the reasons debated above. In addition, the findings generated by our rolling wavelet correlation analysis provide benefits to international investors and risk managers who are specialized on derivatives trading.

While previous studies on futures markets co-movements focus either on the index returns or on the volatility, similar to Lee (2004), we attempt to take a more holistic perspective on these issues, analyzing the co-movements and contagion both in terms of returns and volatility. The volatility spillover is essential for the characterization of market dynamics, valuation of assets, choices that affect portfolio allocation decisions, and also for the assessment of the vulnerability of financial markets (Ewing et al. 2002; Baele 2005; Khalifa et al. 2011; Arouri et al. 2011; Huang 2012). Thus, the possibility that changes in volatility in one market may spillover to other markets cannot be neglected. As Ewing et al. (2002) show, these spillovers are usually attributed to cross-market hedging and changes in common information, which may simultaneously alter expectations across markets.

Our paper also contributes to the existing literature by focusing not only on the time dimension, but also on the frequency dimension of the data. A series of recent papers combined frequency and time domain to study the international stock markets co-movements and discovered that the co-movements are different between frequency scales and periods, being influenced by financial turbulence events (In and Kim 2006; Rua and Nunes 2009; Graham and Nikkinen 2011; Fernández-Macho 2012; Gallegati 2012; Graham et al. 2012, 2013; Loh 2013; Benhmad 2013; Ranta 2013; Aloui and Hkiri 2014; Kiviaho et al. 2014; Tiwari et al. 2015). However, none of the aforementioned papers analyze the stock index futures markets co-movements.

Using wavelet tools to examine the co-movements and contagion has certain salient features over the classic time series analysis. The main advantage of wavelets is the ability to decompose the data into various timescales (investment horizons or cycles). While the time domain analyses allow examination of only two timescales, this new analytical tools provide a different perspective for international investors and risk managers (In and Kim 2006). The method is very useful in portfolio management analysis, where agents interested in daily movements interact, on the markets, with agents concerned with longer time horizons (Rua and Nunes 2009). Unlike other more usual time series approaches which dominate the literature, the tools of wavelet analysis capture at the same time co-movements, nonlinearities, structural breaks, and lead–lag situations between stock index futures markets.

In this context, a third contribution to the literature is related to the use of wavelets for the investigation of co-movements and contagion. Our paper builds thus on the previous research, by moving from the time domain to the time–frequency domain, combining discrete wavelets (i.e., maximal discrete wavelet transform (MODWT)) with the rolling wavelet correlation analysis as in Benhmad (2013). Furthermore, we use the wavelet coherency of the CWT in order to investigate the co-movements, as in Ranta (2013). As compared to the discrete wavelet transform (DWT), the CWT approach offers a better interpretation of the variance, at different timescales. Moreover, the identification of common features in the variable characteristics is simplified. However, different from these previous studies, we also use the wavelet power spectrum, a CWT tool, which offers a time–frequency interpretation of the variance and the identification of common features in the variables' variance, and which is helpful in understanding and analyzing the coherency and phase differences. For the identification of lead–lag relationships between futures markets, we resort to the cross-wavelet phase angle tool.

Finally, we contribute to the existing literature by analyzing the co-movements and the contagion phenomenon within six world's leading futures markets in the context of the sovereign debt crisis. As far as we know, the study of Gallegati (2012) is the only one using the wavelet approach to test the contagion on the spot markets during the sovereign debt crisis. However, none of the previous researchers analyzed the futures markets co-movements before and after different turbulence episodes associated with the development of the sovereign debt crisis.

The rest of the paper is organized as follows. Section 2 describes the literature. Section 3 presents the data and the methodology. The empirical analyses are carried out in Sect. 4. Section 5 concludes.

2 Literature review

Surprisingly, the overall literature on the contagion and co-movements between international stock index futures markets is very limited, and most of the studies analyze the existence of this phenomenon on the spot markets. The findings of low correlations among international stock markets in the early studies suggested potential benefits of the international diversification (for a discussion, see Sergey et al. 2010; Karim et al. 2011). More recent studies, however, indicate increasing co-movements of major stock markets, which amplify during financial turbulence periods (Yang et al. 2003; Climent and Meneu 2003; Choudhry et al. 2007; Syriopoulos 2007; Karim and Majid 2009; Lee 2009; Yiu et al. 2010; Jayasuriya 2011; Kenourgios and Padhi 2012; Dimitriou et al. 2013; Benhmad 2013). These empirical findings are not in line with Tamakoshi et al. (2012), or with Korkmaz et al. (2012), who discover that contemporaneous spillover effects are generally low in crisis periods, both in developed and emerging markets.

However, the mixed results documented in the literature are influenced by both the way contagion is defined and by the empirical methodologies. Essentially, the way of computing the correlation between international stock markets has evolved over time, from the simple Pearson's correlation coefficient (Longin and Solnik 1995; Bonanno et al. 2001; Vandewalle et al. 2001; Tse et al. 2010) toward vector auto-regression methods (VAR) and cointegration techniques (Voronkova 2004; Lin 2008; Mukherjee and Bose 2008). Recent studies approach a two-stage estimator of conditional variance and correlation, to estimate directly the dynamics of the correlation process across time. The dynamic conditional correlation (DCC) model proposed by Engle (2002) and its asymmetric version developed by Cappiello et al. (2006) dominate the financial literature during the last years. Noteworthy studies employing these models and their developments are those of Syriopoulos and Roumpis (2009), Syllignakis and Kouretas (2011), Tamakoshi et al. (2012), Dimitriou et al. (2013), Connor and Suurlaht (2013).

Nevertheless, the above-listed papers are all concerned with time domain only, ignoring thus the possibility that the strength and the direction of the co-movements can vary over different frequencies. Therefore, a new approach, combing time and frequency domain analyses, is better suited for assessing the co-movements and the contagion in financial markets. Consequently, a series of recent papers studies the co-movements in a wavelet framework. Applying a wavelet analysis, Rua and Nunes (2009) discover that the strength of the co-movements of international stock returns depends on the frequency and varies across countries, as well as across sectors. Graham and Nikkinen (2011) show that the co-movement of Finland and the emerging market regions is confined to long-term fluctuations, while the short-run co-movements intensified in the last period. Gallegati (2012) investigate in its turn the level of international stock markets contagion during the US subprime crisis and notice that Brazil and Japan are the only countries in which contagion is observed at all scales. Graham et al. (2013) examine the co-movements of selected Middle East and North Africa (MENA) region stock markets with the US stock market and report a modest degree of co-movement of stock returns between S&P 500 and MENA stock markets at higher frequencies. Using the multi-resolution analysis and a rolling window, Benhmad (2013) investigate the international stock market co-movements and contagion and notice that the contagion dynamics depends on the bull or bear periods of stock markets, on the stock markets maturity, and on regional aspects. Similarly, Ranta (2013) shows that short timescale co-movements increase during the major crisis while long timescale co-movements remain approximately at the same level.

More recently, Aloui and Hkiri (2014) highlight frequent changes in the pattern of the co-movements for all the selected Gulf Cooperation Council (GCC) markets especially after 2007, at relatively higher frequencies. In the same line, Kiviaho et al. (2014) assess the co-movements of European frontier stock markets with the US and more developed markets in Europe in a wavelet framework, and discover that co-movements are relatively weaker for the frontier markets of Central and Southeastern Europe than in the Baltic region, while being stronger at lower frequencies. Tiwari et al. (2015) show in their turn that the PIIGS (Portugal, Ireland, Italy, Greece, and Spain) stock markets are more correlated with Germany than with the UK in the long run, while an opposite result is obtained at high-frequency decomposition levels.

Even though significant wavelet attempts have appeared in the literature on spot markets co-movements, none of these studies addressed the case of the futures markets. Consequently, our research brings insights about the interdependencies of futures markets, conducting a comprehensive examination of returns and volatility spillovers in a wavelet framework and assessing also the rolling wavelet correlation between developed international stock futures markets. In this paper, co-movements are analyzed through low frequencies, while the contagion phenomenon is understood in the sense given by Forbes and Rigobon (2002) and is associated with high frequencies (i.e., with the short-run horizon).

3 Methodology and data

3.1 Methodological aspects

Through wavelets, the correlation levels are assessed at different frequency scales and at different moments in time. Practically, each time series is decomposed in different frequencies, and this decomposition can be made using different wavelet transforms (i.e., discrete, continuous, multiple). Our paper relies both on the CWT methodology, which is computationally complex but facilitates the results' interpretation, and on the MODWT, which allows the rolling wavelet correlation analysis. This section provides only elementary notions about the CWT and the MODWT (for a detailed description, see Torrence and Compo 1998; Grinsted et al. 2004; Aguiar-Conraria et al. 2008; Rua and Nunes 2009; Tiwari et al. 2013).

The wavelet transform decomposes a time series in functions (wavelets) localized in both time and frequency $\psi_{\tau,s}(t)$. For a discrete time series $x(t)$, the CWT is:

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

Torrence and Compo (1998) show that for a discrete time series, the CWT is defined as a convolution and can be efficiently computed as a product in the Fourier space where the Morlet wavelet (with $\omega_0 = 6$) is a good choice in decomposing a signal.

Consequently, the studies using the wavelet coherence for assessing the co-movements of financial series usually resort to the Morlet wavelet and defined as:

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

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

The corresponding Fourier transform is given by:

$$\overset{\wedge}{\psi}(\omega) = \pi^{\frac{1}{4}} \sqrt{2e}^{-\frac{1}{2}(\omega-\omega_0)^2}. \tag{3}$$

The wavelet power spectrum (WPS), which shows the variance of the time series (i.e., signals) across timescale, is defined by $|W_x(\tau, s)|^2$, while the white-noise and red-noise wavelet power spectra are (Torrence and Compo 1998)[1]:

$$D\left(\frac{|W_x(\tau, s)|^2}{\sigma_x^2} < p\right) = \frac{1}{2} P_k \chi_\nu^2(p) \tag{4}$$

where ν is equal to 1 for real and 2 for complex wavelets; P_k is the mean spectrum at the Fourier frequency k.

In addition, the wavelet coherence (WTC) method allows the estimation of the presence of a simple cause–effect relationship between the phenomena recorded in the time series. Torrence and Webster (1999) define the WTC of two time series with $W_x(\tau, s)$ and $W_y(\tau, s)$ wavelet transforms, as the absolute value squared of the smoothed cross-wavelet spectrum, normalized by the smoothed wavelet power spectra:

$$R^2(\tau, s) = \frac{\left|S\left(s^{-1} W_{xy}(\tau, s)\right)\right|^2}{S\left(s^{-1} |W_x(\tau, s)|^2\right) \cdot S\left(s^{-1} \left|W_y(\tau, s)\right|^2\right)} \tag{5}$$

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

However, the CWT suffers from edge effects due to the fact that wavelets are not completely localized in time. Thus, to address this issue, we use the cone of influence (COI). Outside the COI, the edge effects are predominant and can distort the result.

[1] We use the theoretical distribution of the wavelet power spectrum for computing the significance levels.

Further, we want to assess the phase difference between the components of two time series (i.e., the series are in-phase or out of phase). Therefore, we need to estimate the mean and confidence interval of the phase difference. Following Grinsted et al. (2004), the phase relationship is computed using the circular mean of the phase over regions that are outside the COI, with greater than 5 % statistical significance. The circular mean of a set of angles ($a_t, t = 1, \ldots, n$) is defined as follows:

$$a_m = \arg(A, B) \tag{6}$$

where $A = \sum_{t=1}^{n} \cos(a_t)$ and $B = \sum_{t=1}^{n} \sin(a_t)$.

Different from the CWT, the DWT is characterized by simplicity and allows for data decomposition of many variables in the same time. The Daubechies' (1992) least asymmetric wavelet filter LA(8) is usually used, because it provides an accurate time alignment between the wavelet coefficients at various scales and the original time series. Daubechies' (1992) wavelet filter coefficients are $h_1 = (h_{1,0}, \ldots, h_{1,L-1}, 0, \ldots, 0)^T$.

If we consider $g_1 = (g_{1,0}, \ldots, g_{1,L-1}, 0, \ldots, 0)^T$ the scaling filter coefficients defined through $g_{1,l} = (-1)^{l+1} h_{1,L-1-1}$, and $x(t)$ the time series, for scales with $N \geq L_j$, the time series can be filtered using h_j as follows:

$$W_{j,t} = 2^{j/2} \tilde{W}_{j,2^j(t+1)+1}, \left[(L-2)\left(1 - \frac{1}{2^j}\right) \right] \leq t \leq \left[\frac{N}{2^j} - 1 \right] \tag{7}$$

where $L_j = (2^j - 1)(L - 1) + 1$, and $\tilde{W}_{j,t} = \frac{1}{2^{j/2}} \sum_{2^{j/2}}^{L_j - 1} h_{j,l} x_{t-1}, t = L_j - 1, \ldots, N - 1$.

The $\tilde{W}_{j,t}$ associated coefficients with changes on a scale of length $\tau_j = 2^{j-1}$ are performed by subsampling every 2^jth of the $\tilde{W}_{j,t}$ coefficients.

However, this approach suffers because it cannot handle any sample size, it is not translation-invariant, and it cannot provide an increase in resolution. Therefore, we use an alternative approach, the MODWT, where the output signal is never subsampled and which does not decimate the number of scaling and wavelet coefficients at every level of transform (Percival and Walden 2000).

The wavelet coefficients $\tilde{w}_{j,t}$ and the scaling coefficients $\tilde{V}_{j,t}$ at levels $j = 1, \ldots, J$, are $\tilde{W}_{j,t} = \sum_{l=0}^{L-1} \tilde{g}_l \tilde{v}_{j-1,t-1 \bmod N}$ and $\tilde{v}_{j,t} = \sum_{l=0}^{L-1} \tilde{h}_i \tilde{v}_{j-1,t-1 \bmod N}$. The wavelet and scaling filters, $\tilde{g}_l, \tilde{h}_l$, are rescaled as $\tilde{g}_j = g_j / 2^{j/2}$, $\tilde{h}_j = h_j / 2^{j/2}$. The differences between the generalized averages of the scale data $\tau = 2^{j-1}$ are the non-decimated wavelet coefficients. Due to the fact that the maximum decomposition level J is given by log2(N), we use the MODWT up to a level $J = 6$ (the detail component d1, ..., d5 and the smoothed component s5) and the smallest L that gives reasonable results (the filter's length is $L = 8$).

Thus, applying the MODWT to a stochastic time series produces a scale-by-scale decomposition (Ranta 2013). After decomposing the data according to the MODWT, we are able to apply the rolling correlation to the wavelet decomposed coefficients at different frequencies, following Gencay et al. (2002). We carry out a cross-pairwise rolling correlation analysis on a scale-by-scale basis, between the selected stock index futures. The window is established at 125 days (half a year trading) and is rolled forward one day at a time, resulting in a time series of wavelet correlation.[2]

Following Ranta (2013), we perform a t test to compare the level of correlation before and after the episodes of financial turbulence occurred in the context of the sovereign debt crisis, in order to check for the existence of the contagion phenomenon.[3] Before that, we test whether the two data samples, including 75 days before and after the moment of the incident, have equal variance or not. For this purpose, we use an F test with the null hypothesis assuming equal variance. The length of each sample may seem short, but the small data sample and the intent to avoid the overlapping of the samples between two different crisis events are the reasons behind our choice.

3.2 Data and descriptive statistics

The analysis utilizes daily close-to-close stock index futures returns data—$R_t = \ln(P_{c,t}/P_{c,t-1}) \times 100$, from six international markets: Australia (ASX 200 futures—ASXF), France (CAC 40 futures—CACF), Germany (DAX 30 futures—DAXF), Japan (Nikkey 225 futures—NF), the UK (FTSE 100 futures—FTSEF), and the USA (S&P 500 futures—SPF). The sample period starts on October 15, 2009 and ends on August 27, 2013, including 944 observations (days of no trading on any of the observed futures markets are left out in order to avoid non-synchronous problems).[4] The stock index futures volatility (ASXFV, CACFV, DAXFV, FTSEFV, NFV, and SPFV) was computed as the logarithmic difference between the highest and the lowest price, recorded during the day: $V_t = \ln(H_t/L_t) \times 100$.[5] Fig. 7 (Appendix 1) presents the returns and volatility for all selected stock index futures.

The data are obtained from Fusion Media (www.investing.com).[6] All stock index futures contracts have a cycle of contract maturities of March, June, September, and December. Attention is directed to the nearest futures contract because it is typically

2 The choice of the length of the window is no straightforward task. It is influenced by the data sample and by the previous works. A longer window implies the loss of time information, and a shorter window implies the loss of frequency information. The choice of the window's length is based on the previous works of Benhmad (2013) and Ranta (2013).

3 Alternatively, one can also test the stability of the relation before and after a crisis event through the wavelet detail coefficients. However, the t test can be considered as a robustness analysis, which is easier to interpret.

4 The use of daily data is common in wavelet analysis applied to financial data, due to their accessibility. Moreover, the number of observations in our sample is adequate for wavelet analysis. As Rua (2013) shows, the wavelet approach compensates the small-frequency data problem and can be applied even on annual data, by applying a tighter resolution.

5 We have retained this simple volatility measure for two reasons. First, the well-known volatility estimators of Garman and Klass (1980) and Rogers and Satchell (1991) are focused on the variance and not on the volatility, which represent the obvious interest for financial applications. Second, the weights assigned to the quadratic unbiased variance estimators in the Garman and Klass (1980) model are often criticized in the literature. In addition, comparing different technique for volatility estimation is out of the purpose of the present paper.

6 The data are widely disseminated by data vendors and market makers and can truly be viewed as public information available to all investors (for a discussion about the benefits of using freely available data, see Giot 2005).

more liquid than the next nearest contract (Booth et al. 1996). The descriptive statistics of the data are presented in Table 1.

With the exception of the ASXF, the skewness indicates that all stock index futures returns are negatively skewed. Similarly, all series demonstrate excess kurtosis, i.e., all series are leptokurtic. The observed high kurtosis is suggestive of a time-varying variance and can be noticed in particular for volatility series. As expected, the European stock index futures present a higher standard deviation in the analyzed period, as compared to the other indexes (both in terms of returns and volatility), except for the Japanese index.

4 Empirical results

4.1 Co-movements and rolling wavelet correlation for stock index futures returns

The empirical analyses start with the wavelet results and continue with the rolling wavelet correlation estimations and tests. We first address the co-movements and the contagion in terms of index returns. We discuss the common movements in the series in three major periodicities, namely the short run (2–8 days cycle), the medium run (8–32 days cycle), and the long run (32–128 days cycle), in order to facilitate the interpretation of the results.

Figure 1 describes the wavelet power spectrum of the stock index returns, presented in a contour plot with three dimensions: time (horizontal axis), frequency (vertical axis), and color code (ranging from blue to red, where red means high power).

The WPS is helpful in identifying the similarities in the evolution of the data series across timescale. Without being a direct proof of either co-movements or lead–lag relationships, the results of the WPS can be interpreted as a first sign of interdependences between the selected stock index returns. The left side of the plot represents the local wavelet power spectrum (LWPS) or simply the WPS. On the right side of each plot, we have the global wavelet power spectrum (GWPS) which gives the averaged variance contained in all wavelet coefficients of the same frequency.

First, we notice similarities in terms of the variance between the NF, ASXFm and FTSEF on the one hand, and between the SPF, DAXF, and CACF on the other hand. While the first group of indexes shows strong oscillations of the futures markets in the long run, the second group is characterized by a strong variance in the short run and medium run. This evidence is confirmed also by the GWPS. Second, the LWPS highlights an important variation in data series after the observation 400 (on July 21, 2011, the European leaders extended an additional €109 billion rescue package for Greece). Other episodes of oscillations in data series are located after the observation 150 (which corresponds to the onset of the sovereign debt crisis, in May 2, 2010) and around the observation 600 (on January 14, 2012, the rating agency Standard & Poor's announced its rating actions on 16 Eurozone countries). However, in the case of the last event, the oscillations are observed only for the SPF, DAXF, and CACF.

While the WPS offers some insights about the probable co-movements of the series, the wavelet coherence, together with phase difference, provides not only a good tool

Table 1 Statistical properties of the data

	Return (R_t)						Volatility (V_t)					
	ASXFL	CACF	DAXF	FTSEF	NF	SPF	ASXFV	CACFV	DAXFV	FTSEFV	NFV	SPFV
Mean	0.002	0.015	0.033	0.030	0.033	0.042	1.481	2.025	1.914	1.536	1.970	1.524
Std. dev.	1.009	1.519	1.441	1.187	1.391	1.110	0.865	1.207	1.221	0.955	1.242	0.934
Min	−5.121	−7.917	−8.848	−6.668	−6.341	−7.495	0.222	0.000	0.000	0.000	0.539	0.336
Max	7.749	7.411	6.327	8.395	7.740	5.301	10.81	10.91	10.54	11.54	16.78	10.14
Skewness	0.026	−0.276	−0.444	−0.305	−0.038	−0.523	3.713	2.234	2.354	2.907	4.308	2.787
Kurtosis	8.994	6.307	7.115	9.006	5.583	7.232	31.39	11.99	11.93	22.46	37.27	17.78

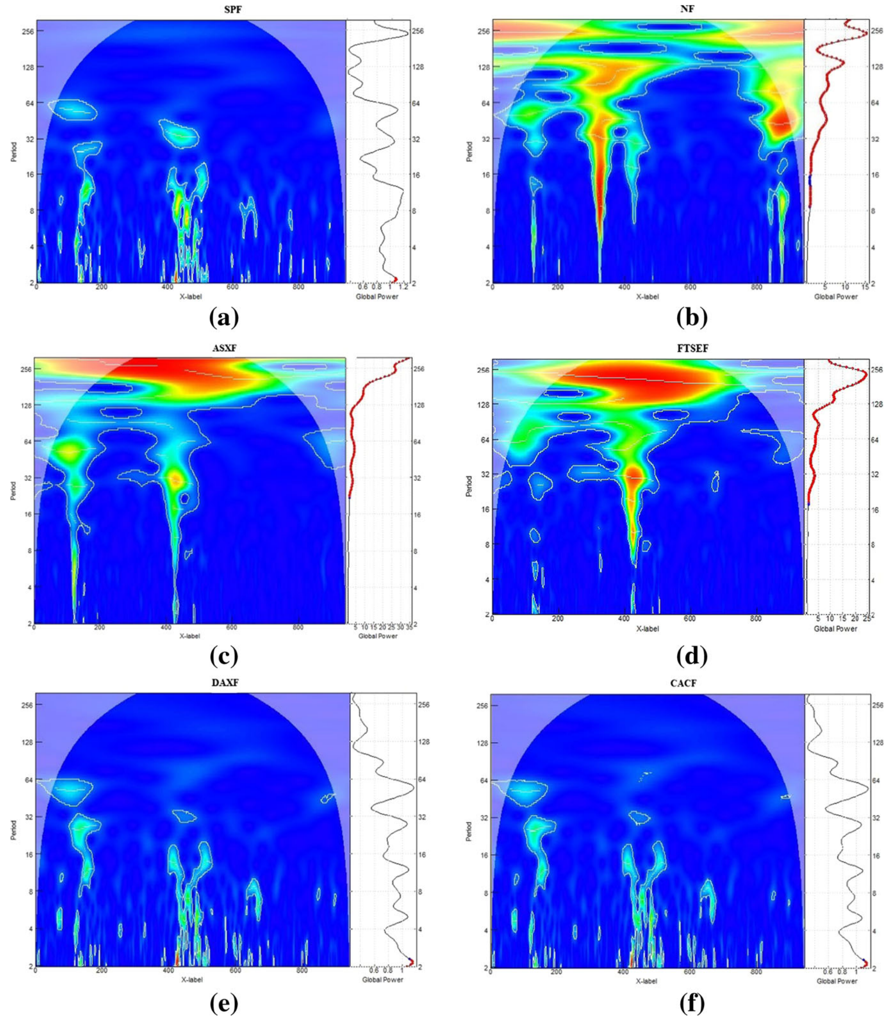

Fig. 1 Wavelet power spectrum (returns). *Notes*: The *figure* describes the local and the global power spectrum of stock indexes returns. The *white contour* designates the 5 % significance level. The cone of influence, where edge effects might distort the picture, is shown as a *lighter shade*. The *color code* for the power ranges from *blue* (low power) to *red* (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, since October 15, 2009 to August 27, 2013. As we have irregular data, the rank of the observations is presented on the *horizontal axis*: The observation 200 corresponds to September 9, 2010; 400 corresponds to June 29, 2011; 600 corresponds to April 17, 2012; and 800 corresponds to February 1, 2013. **a** SPF, **b** NF, **c** ASXF, **d** FTSEF, **e** DAXF, **f** CACF

for a descriptive analysis of the contagion but also for examining the co-movements and lead–lag relationships. We document that the selected indexes present common movements especially in the medium run and long run. The co-movements for the SPF pairs are presented in Fig. 2, while the WTC results for the remaining pairs are

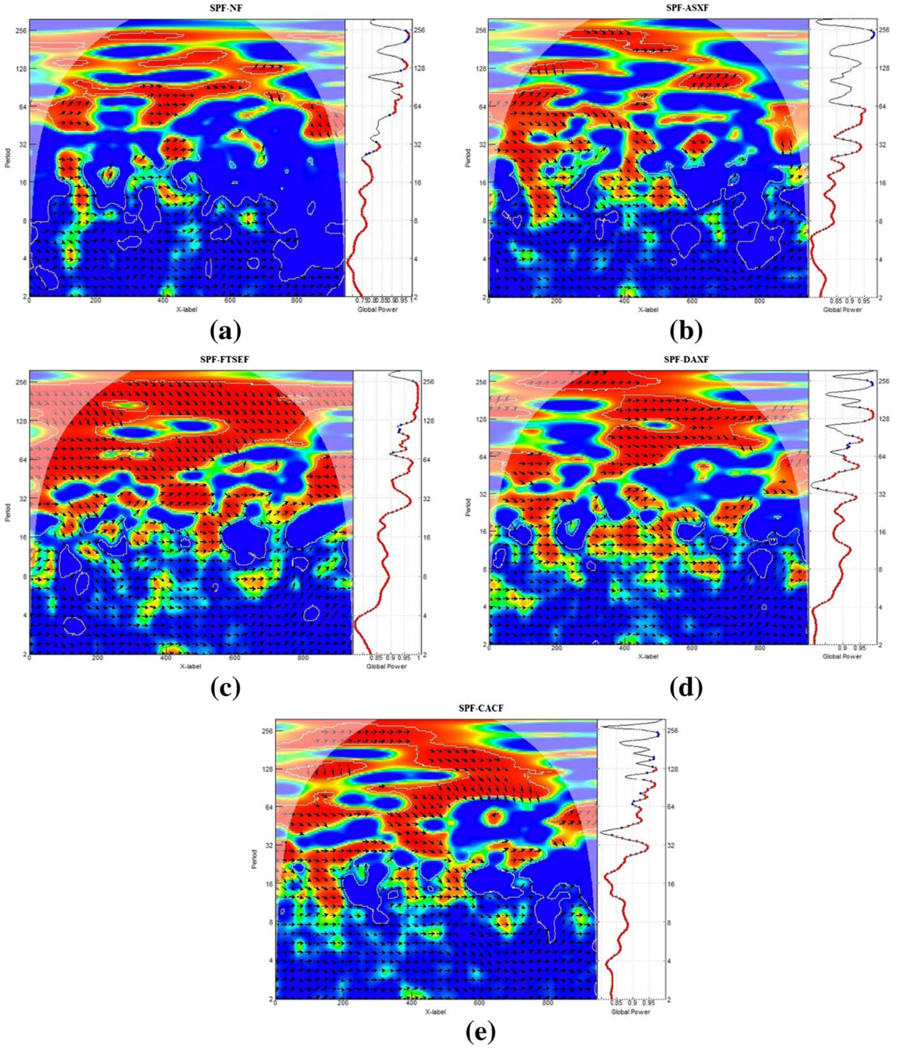

Fig. 2 Wavelet coherence (returns). *Notes*: The *white contour* designates the 5 % significance level estimated from the Monte Carlo simulations using the phase randomized surrogate series. The cone of influence, where edge effects might distort the picture, is shown as a *lighter shade*. The *color code* for power ranges from *blue* (low power) to *red* (high power). *Y-axis* measures frequencies or scale, and *X-axis* represents the time period studied, since October 15, 2009 to August 27, 2013. As we have irregular data, the rank of the observations is presented on the *horizontal axis*: The observation 200 corresponds to September 9, 2010; 400 corresponds to June 29, 2011; 600 corresponds to April 17, 2012; and 800 corresponds to February 1, 2013. 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. **a** SPF–NF pair, **b** SPF–ASXF pair, **c** SPF–FTSEF, **d** SPF–DAXF, **e** SPF–CACF

presented in Fig. 8 (Appendix 2). In addition, we notice the presence of the contagion phenomenon, associated with high frequencies (short run). All pairs of indexes show that the main identified turbulence episode (July 21, 2011) produces its effects in terms of contagion (2–4 days cycle).

The contagion is stronger in the case of the European futures markets (see the last three plots of Fig. 8), which is not surprising, given the fact that the sovereign debt crisis manifested in the European Union. In the case of FTSEF–DAXF and FTSEF–CACF pairs of indexes, the arrows point to the right and up, showing that the FTSEF index is leading. For the DAXF–CACF pair, apparently none of the two markets is leading the other.

However, the co-movements between the selected markets manifest especially in the medium run and long run. In all the cases, the arrows point to the right, indicating that the futures markets are in-phase (an increase in one index is accompanied by an increase in other indexes too). If we look to the SPF index, we notice that the co-movements are more intense in relation with the European indexes as compared to the Asia–Pacific indexes (Fig. 2).

In the medium run (8–32 days cycle), co-movements manifest around the turbulence periods identified based on the WPS (observations 150, 400, and 600). In almost all the cases, the arrows point right and up, showing that the FTSEF, DAXF, and CACF are the leading indexes in the analyzed period. Given the fact that the sovereign debt crisis started in Europe, the results explain the shocks spillover in the international futures markets. However, they contrast to most of the findings in the literature, which show that the American stock market is leading the other markets. In the medium run, the European stock index futures lead also the Japanese and the Australian markets.

The WTC analysis shows that in the long run (32–128 days cycle), co-movements are stronger, indicating an important integration of futures market around the world. We notice that the SPF and FTSEF indexes present large co-movements and that the British market is leading the American one. We also notice a similar situation in the case of the other two European indexes, namely the DAXF and CACF. Finally, for all time horizons (2–128 days cycle), the German and French markets present a high level of contagion and integration. For the DAXF–CACF pair of indexes, the CACF is leading in general, especially for long time horizons.

The wavelet coherence brings additional information about co-movements and lead–lag relationships but does not provide the possibility to see whether the level of correlation is significantly different between frequencies or whether the correlation increases after turbulence episodes. Consequently, we carry out a pairwise rolling correlation analysis on a scale-by-scale basis for the 15 pairs of indexes. The decomposed wavelet timescales (d) 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).

Figure 3 presents the rolling correlation series for the SPF pairs at different frequencies, including the original, undecomposed stock index futures sample, while Fig. 9 (Appendix 2) presents the wavelet rolling correlation for the remaining pairs of indexes. At all levels of decomposition, we observe oscillations of the rolling wavelet correla-

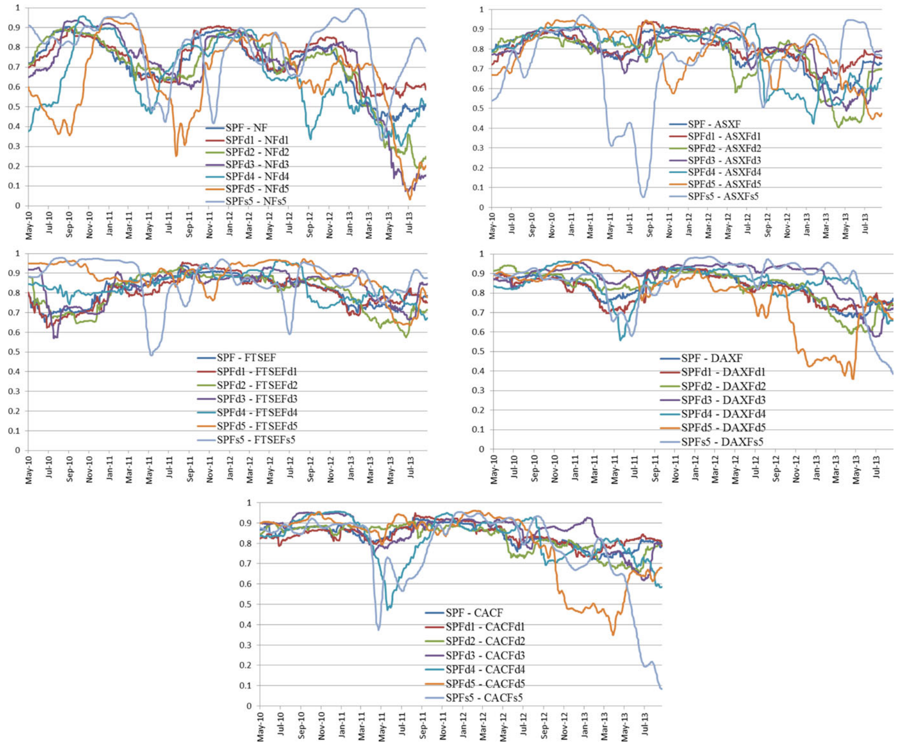

Fig. 3 Rolling wavelet correlation (returns)

tion of selected indexes. In all the cases, we notice an increase in the level of correlation after May 2, 2010, with a peak in September 2010. Another increase in the correlation level is identified after July 21, 2011, with a peak in December 2011. However, after January 14, 2012, the level of correlation decreases, even if the announcement of the rating agencies were unfavorable for the confidence of the investors.

We notice consistent results between the WTC and the rolling wavelet correlation analysis, regarding the co-movements of the American and European stock indexes. In both cases, the co-movements are high and present small oscillations only in the long run. For the SPF–FTSEF pair, the correlation level is almost constant, with a slight intensification after July 21, 2011. The European indexes are strongly correlated. Nevertheless, the level of correlation, especially in the long run, is influenced by the appearance of financial turbulence episodes. In general, the long-run co-movements are prone to fluctuations around turbulence episodes. In all the cases, we observe a decrease in the correlation level in normal times, in particular in 2013. This relationship is stronger for the SPF–NF pair of indexes.

In order to compare the level of correlation before and after a crisis event, we perform a two-step equal samples t test (75 observations in each sample). For the rolling wavelet correlation, the window is established at 125 days and implies a loss of 125 observations at the beginning of the sample. Consequently, we are not able to compare, based on the t test, the level of correlation before and after the first crisis event from our sample (namely the outburst of the sovereign debt crisis, on May 2, 2010).[7] Therefore, we focus our investigation on the two remaining events, identified in the WPS analysis, namely July 21, 2011 and January 14, 2012.

The first analyzed event is represented by the turbulences determined by the additional rescue package awarded to Greece on July 21, 2011. Table 2 highlights several interesting aspects around this moment. First, for all pairs of indexes, the rolling correlation increases after the crisis event at d1 and d2 levels of decomposition, with few exceptions. Second, at d3 and d4 levels, the correlation is higher in general after July 21, 2011, but the results are mixed. Third, at d5 level, in many situations, the correlation decreases, including the correlation between the European stock futures indexes. Finally, if we compare the rolling correlation between the raw data and the wavelet decomposed data, we notice similarities only for high frequencies. For the medium and low frequencies, the results are mixed. Moreover, in the very long run, we document an opposite situation, where the rolling wavelet correlation decreases.

Moving to the second identified crisis episode (January 14, 2012), we discover a totally different situation (Table 3).

In this case, both for the undecomposed data and for the d1 level of decomposition, the rolling wavelet correlation decreases, with one exception (the pair SPF–NF). These results confirm our previous findings. However, in the medium run, the results are mixed, while in the long run the correlation increases.

Our findings based on the wavelet analyses, rolling correlation, and *t* test for the futures index returns can be summarized as follows:

- The WPS describes similarities in terms of variance between the NF, ASXF, and FTSEF on the one hand, and between the SPF, DAXF, and CACF on the other hand. At the same time, the WPS documents a contagion phenomenon around July 21, 2011.
- The WTC shows that the co-movements manifest especially in the medium run and long run, and are very strong in the case of the European indexes, proving thus a high level of integration of these markets. In addition, the European indexes lead in general the American one.
- The rolling wavelet correlation analysis confirms the theoretical assumptions regarding the increase in the correlation after financial incidents. It also shows that the level of correlation between the European markets, but also between the American and the European indexes is very high, and does not oscillate considerably in times of crisis.
- The *t* test demonstrates that for the first analyzed event, the level of correlation increases in general in the short run and medium run, while for the second identified episode of turbulence, we have an opposite situation, where the correlation increases in the long run.

These findings can be influenced by the choice of the rolling window length and by the fact that the sovereign debt crisis affected in particular the European countries. Therefore, we proceed to an identical analysis, considering this time the volatility

[7] After computing the rolling correlation, this crisis event remains located at the beginning of our sample. Thus, we cannot compare the correlation before and after May 2, 2010.

Table 2 Rolling wavelet correlation of futures volatility before and after July 21, 2011 (t test)

	Raw data			d1 (2–4 days)			d2 (4–8 days)			d3 (8–16 days)		
	Corr. before *Var. before*	Corr. after *Var. after*	t-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	t-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	t-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	t-stat *F-stat*
SPF–NF	**0.642**	**0.706**	**−3.35****	**0.525**	**0.632**	**−8.65****	**0.506**	**0.585**	**−5.69****	0.705	0.694	0.74
	0.000	*0.026*	*0.01***	*0.000*	*0.010*	*0.06***	*0.000*	*0.014*	*0.01***	*0.007*	*0.009*	*0.80*
SPF–ASXF	**0.750**	**0.894**	**−17.0****	**0.687**	**0.784**	**−13.1****	**0.648**	**0.656**	**−0.92**	**0.691**	**0.813**	**−7.60****
	0.001	*0.003*	*0.42***	*0.002*	*0.001*	*1.04*	*0.004*	*0.001*	*3.14***	*0.002*	*0.017*	*0.12***
SPF–FTSEF	**0.818**	**0.931**	**−23.7****	**0.712**	**0.809**	**−20.3****	**0.727**	**0.807**	**−16.0****	**0.866**	**0.907**	**−5.13****
	0.000	*0.001*	*0.03***	*0.001*	*0.000*	*2.36***	*0.000*	*0.001*	*0.39***	*0.000*	*0.004*	*0.18***
SPF–DAXF	**0.776**	**0.900**	**−23.8****	0.649	0.612	*6.64***	**0.618**	**0.732**	**−17.1****	**0.829**	**0.914**	**−10.8****
	0.000	*0.001*	*0.05***	*0.000*	*0.002*	*0.05***	*0.000*	*0.003*	*0.01***	*0.002*	*0.001*	*1.64**
SPF–CACF	**0.753**	**0.883**	**−14.6****	**0.650**	**0.728**	**−15.0****	**0.622**	**0.755**	**−14.7****	**0.754**	**0.882**	**−12.5****
	0.000	*0.005*	*0.09***	*0.001*	*0.000*	*1.43*	*0.000*	*0.005*	*0.15***	*0.005*	*0.002*	*1.84***
NF–ASXF	**0.572**	**0.665**	**−4.41****	**0.429**	**0.510**	**−8.05****	**0.460**	**0.525**	**−4.66****	0.690	0.647	*3.17***
	0.000	*0.032*	*0.02***	*0.002*	*0.005*	*0.38***	*0.000*	*0.014*	*0.02***	*0.001*	*0.012*	*0.13***
NF–FTSEF	**0.578**	**0.700**	**−6.36****	**0.322**	**0.546**	**−18.1****	**0.578**	**0.603**	**−3.57****	**0.621**	**0.632**	**−0.70**
	0.000	*0.027*	*0.01***	*0.000*	*0.010*	*0.09***	*0.000*	*0.003*	*0.18***	*0.007*	*0.011*	*0.67*
NF–DAXF	0.768	0.736	*2.54***	**0.527**	**0.606**	**−11.8****	0.767	0.671	14.3**	**0.764**	**0.770**	**−0.34**
	0.000	*0.011*	*0.02***	*0.000*	*0.002*	*0.13***	*0.000*	*0.003*	*0.03***	*0.015*	*0.004*	*3.33***
NF–CACF	**0.650**	**0.716**	**−3.80****	**0.384**	**0.596**	**−13.7****	**0.656**	**0.663**	**−1.30**	**0.658**	**0.677**	**−1.18**
	0.000	*0.022*	*0.22***	*0.000*	*0.016*	*0.05***	*0.000*	*0.001*	*0.70*	*0.013*	*0.005*	*2.36***
ASXF–FTSEF	**0.646**	**0.878**	**−18.7****	**0.582**	**0.727**	**−17.3****	**0.504**	**0.683**	**−14.6****	**0.545**	**0.749**	**−8.31****
	0.001	*0.009*	*0.17***	*0.000*	*0.004*	*0.11***	*0.000*	*0.010*	*0.10***	*0.002*	*0.042*	*0.07***
ASXF–DAXF	**0.669**	**0.820**	**−22.2****	0.534	0.468	*7.98***	**0.491**	**0.569**	**−17.3****	**0.602**	**0.758**	**−11.1****
	0.000	*0.003*	*0.04***	*0.000*	*0.004*	*0.09***	*0.000*	*0.001*	*0.15***	*0.001*	*0.013*	*0.12***

Table 2 continued

	Raw data			d1 (2–4 days)			d2 (4–8 days)			d3 (8–16 days)		
	Corr. before *Var. before*	Corr. after *Var. after*	*t*-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	*t*-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	*t*-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	*t*-stat *F-stat*
ASXF–CACF	0.657	0.855	−22.5**	0.563	0.628	−14.4**	0.523	0.624	−14.9**	0.544	0.765	−12.4**
	0.000	0.005	0.06**	0.000	0.000	0.81	0.001	0.002	0.43**	0.001	0.022	0.04**
FTSEF–DAXF	0.801	0.906	−23.8**	0.642	0.675	−9.22**	0.797	0.800	-1.37	0.865	0.898	−7.59**
	0.000	0.001	0.10**	0.000	0.000	0.59*	0.000	0.000	0.48	0.000	0.000	0.44**
FTSEF–CACF	0.801	0.936	−28.4**	0.681	0.831	−38.6**	0.760	0.836	−20.4**	0.826	0.919	−14.5**
	0.000	0.001	0.14**	0.000	0.000	0.26**	0.000	0.000	0.11**	0.001	0.001	0.87
DAXF–CACF	0.880	0.949	−23.7**	0.782	0.826	−8.39**	0.860	0.884	−5.97**	0.915	0.950	−8.99**
	0.000	0.000	0.68	0.001	0.000	3.40**	0.000	0.000	0.60*	0.000	0.000	4.97**

	d4 (16–32 days)			d5 (32–64 days)			s5 (64–128 days)		
	Corr. before *Var. before*	Corr. after *Var. After*	*t*-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	*t*-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	*t*-stat *F-stat*
SPF–NF	0.582	0.670	−5.90**	0.908	0.759	21.9**	0.946	0.832	21.6**
	0.016	0.000	34.8**	0.002	0.000	3.05**	0.000	0.001	0.65
SPF–ASXF	0.885	0.908	−3.74**	0.954	0.951	−2.71**	0.980	0.812	18.9**
	0.001	0.001	0.87	0.000	0.000	3.92**	0.000	0.005	0.16**
SPF–FTSEF	0.882	0.906	−4.67**	0.795	0.933	−16.2**	0.909	0.968	−3.80**
	0.000	0.001	0.12**	0.006	0.000	12.6**	0.017	0.000	40.5**
SPF-DAXF	0.889	0.909	−4.05**	0.881	0.891	−1.23	0.974	0.892	28.5**
	0.000	0.001	0.16**	0.003	0.001	2.51**	0.000	0.000	0.50**
SPF–CACF	0.880	0.867	2.74**	0.917	0.892	3.78**	0.932	0.859	10.4**
	0.001	0.000	8.01**	0.002	0.000	2.29**	0.002	0.000	4.36**

Table 2 continued

	d4 (16–32 days)			d5 (32–64 days)			s5 (64–128 days)		
	Corr. before *Var. before*	Corr. after *Var. After*	t-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	t-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	t-stat *F-stat*
NF–ASXF	**0.720**	**0.744**	$\mathbf{-1.98}^{*}$	0.901	0.818	13.7**	0.927	0.670	23.2**
	0.006	0.003	1.70*	0.002	0.000	6.50**	0.006	0.002	2.77**
NF–FTSEF	**0.509**	**0.628**	$\mathbf{-9.13}^{**}$	0.731	0.725	0.68	0.873	0.784	5.85**
	0.011	0.001	9.50**	0.003	0.001	2.12**	0.015	0.002	6.43**
NF–DAXF	**0.633**	**0.783**	$\mathbf{-8.72}^{**}$	**0.891**	**0.897**	**−0.94**	0.979	0.943	7.06**
	0.019	0.002	8.62**	0.002	0.001	2.31**	0.000	0.001	0.12**
NF–CACF	**0.599**	**0.718**	$\mathbf{-9.03}^{**}$	0.868	0.828	6.74**	0.927	0.785	11.9**
	0.011	0.001	9.07**	0.001	0.001	0.62*	0.003	0.007	0.47**
ASXF–FTSEF	0.874	0.848	2.83**	**0.794**	**0.954**	$\mathbf{-16.0}^{**}$	0.873	0.779	4.47**
	0.000	0.006	0.06**	0.007	0.000	51.8**	0.021	0.012	1.79*
ASXF–DAXF	**0.895**	**0.918**	$\mathbf{-4.37}^{**}$	**0.925**	**0.951**	$\mathbf{-7.17}^{**}$	0.970	0.841	15.7**
	0.000	0.001	0.70	0.000	0.000	6.76**	0.001	0.003	0.66
ASXF–CACF	0.878	0.871	1.12**	**0.899**	**0.969**	$\mathbf{-17.5}^{**}$	0.960	0.784	12.1**
	0.000	0.002	0.16**	0.001	0.000	20.4**	0.000	0.015	0.01**
FTSEF–DAXF	0.920	0.909	2.44*	0.828	0.904	−8.68**	0.873	0.848	1.43
	0.000	0.001	0.04**	0.005	0.000	38.1**	0.021	0.000	31.6**
FTSEF–CACF	**0.875**	**0.905**	$\mathbf{-5.49}^{**}$	**0.907**	**0.955**	$\mathbf{-10.1}^{**}$	0.927	0.876	6.37**
	0.000	0.001	0.13**	0.001	0.000	20.0**	0.004	0.000	4.57**
DAXF–CACF	0.965	0.963	1.55	0.972	0.970	1.61	0.958	0.924	22.3**
	0.000	0.000	0.12**	0.000	0.000	14.1**	0.000	0.001	0.44**

(i) ** and * indicate the rejection of the null hypothesis of equal means at 1 and 5 % critical values, respectively; (ii) since the null hypothesis is that the mean difference is equal to zero, we perform a two-sided test and we report two-tailed values; (iii) the cases where the correlation grows higher after distress moments are marked in bold; (iv) the variance of the samples (before and after the financial incident) is reported in italics, as well as the F test for equal variances (in this case, ** and * indicate the rejection of the null hypothesis of equal variances at 1 and 5 % critical values, respectively)

Table 3 Rolling wavelet correlation of futures returns before and after January 14, 2012 (t test)

	Raw data			d1 (2–4 days)			d2 (4–8 days)			d3 (8–16 days)		
	Corr. before *Var. before*	Corr. after *Var. after*	t-stat F-stat	Corr. before *Var. before*	Corr. after *Var. after*	t-stat F-stat	Corr. before *Var. before*	Corr. after *Var. after*	t-stat F-stat	Corr. before *Var. before*	Corr. after *Var. after*	t-stat F-stat
SPF–NF	**0.773**	**0.777**	**−0.33**	**0.783**	**0.789**	**−0.47**	**0.688**	**0.844**	**−21.1****	**0.645**	**0.834**	**−22.4****
	0.006	0.002	2.32**	0.010	0.003	2.75**	0.003	0.001	3.05**	0.003	0.002	1.59*
SPF–ASXF	0.888	0.850	15.8**	0.909	0.846	17.0**	**0.860**	**0.863**	**−0.82**	**0.869**	**0.890**	**−13.0****
	0.000	0.000	0.07**	0.000	0.000	0.07**	0.000	0.000	0.39**	0.000	0.000	2.31**
SPF–FTSEF	0.905	0.879	16.7**	0.924	0.874	17.2**	0.888	0.879	8.01**	**0.868**	**0.888**	**−6.80****
	0.000	0.000	0.05**	0.000	0.000	0.09**	0.000	0.000	0.65	0.000	0.000	0.52**
SPF–DAXF	0.917	0.894	18.9**	0.925	0.893	16.8**	0.908	0.895	11.3**	**0.933**	**0.942**	**−7.65****
	0.000	0.000	0.03**	0.000	0.000	0.05**	0.000	0.000	0.21**	0.000	0.000	1.87**
SPF–CACF	0.903	0.873	20.5**	0.917	0.877	17.7**	0.877	0.861	10.7**	**0.905**	**0.905**	**−0.45**
	0.000	0.000	0.09**	0.000	0.000	0.07**	0.000	0.000	0.93	0.000	0.000	1.16
NF–ASXF	0.869	0.767	11.3**	0.908	0.815	11.3**	**0.816**	**0.827**	**−1.02**	**0.794**	**0.799**	**−0.41**
	0.000	0.000	0.09**	0.000	0.004	0.03**	0.004	0.004	0.95	0.009	0.005	1.80*
NF–FTSEF	0.878	0.774	15.8**	0.894	0.789	14.7**	**0.828**	**0.832**	**−5.45**	**0.795**	**0.831**	**−3.34****
	0.000	0.003	0.04**	0.000	0.003	0.02**	0.002	0.001	1.41**	0.006	0.001	4.45**
NF–DAXF	0.867	0.791	14.2**	0.867	0.787	13.6**	**0.824**	**0.848**	**−4.43****	**0.841**	**0.865**	**−2.73****
	0.000	0.002	0.06**	0.000	0.002	0.04**	0.001	0.000	5.07**	0.004	0.001	2.60**
NF–CACF	0.882	0.816	12.6**	0.896	0.820	13.0**	**0.808**	**0.848**	**−6.76****	**0.830**	**0.894**	**−6.24****
	0.000	0.001	0.11**	0.000	0.002	0.06**	0.002	0.000	28.9**	0.007	0.000	7.47**
ASXF–FTSEF	0.918	0.862	13.4**	0.927	0.872	15.3**	0.909	0.880	4.13**	0.940	0.925	4.08**
	0.000	0.001	0.01**	0.000	0.000	0.01**	0.000	0.001	0.14**	0.000	0.000	0.29**
ASXF–DAXF	0.858	0.856	0.81	0.891	0.876	8.95**	**0.810**	**0.850**	**−7.80****	**0.877**	**0.892**	**−10.3****
	0.000	0.000	0.33**	0.000	0.000	0.14**	0.000	0.001	0.75	0.000	0.000	1.31**

Table 3 continued

	Raw data			d1 (2–4 days)			d2 (4–8 days)			d3 (8–16 days)		
	Corr. before *Var. before*	Corr. after *Var. after*	t-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	t-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	t-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	t-stat *F-stat*
ASXF–CACF	0.883	0.852	8.50	0.911	0.876	13.4	**0.814**	**0.841**	**−5.29**	**0.886**	**0.888**	**−0.52**
	0.000	*0.000*	*0.16*****	*0.000*	*0.000*	*0.15*****	*0.001*	*0.000*	*1.61**	*0.000*	*0.000*	*1.78**
FTSEF–DAXF	0.925	0.913	15.3**	0.942	0.920	15.9**	**0.914**	**0.917**	**−1.83***	0.927	0.919	8.51**
	0.000	*0.000*	*0.05*****	*0.000*	*0.000*	*0.26*****	*0.000*	*0.000*	*0.22*****	*0.000*	*0.000*	*1.77**
FTSEF–CACF	0.936	0.913	18.9**	0.953	0.920	17.1**	**0.910**	**0.912**	**−1.24**	0.928	0.926	2.75**
	0.000	*0.000*	*0.11*****	*0.000*	*0.000*	*0.15*****	*0.000*	*0.000*	*1.18*	*0.000*	*0.000*	*0.38*****
DAXF–CACF	0.959	0.953	9.41**	0.965	0.955	13.5**	**0.957**	**0.958**	**−1.36**	**0.961**	**0.962**	**−0.37**
	0.000	*0.000*	*0.34*****	*0.000*	*0.000*	*0.02*****	*0.000*	*0.000*	*8.10*****	*0.000*	*0.000*	*2.45*****

	d4 (16–32 days)			d5 (32–64 days)			s5 (64–128 days)		
	Corr. before *Var. before*	Corr. after *Var. after*	t-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	t-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	t-stat *F-stat*
SPF–NF	**0.787**	**0.825**	**−4.16****	**0.445**	**0.841**	**−29.1****	**0.795**	**0.803**	**−0.67**
	0.000	*0.005*	*0.17*****	*0.013*	*0.000*	*105*****	*0.004*	*0.005*	*0.86*
SPF–ASXF	0.872	0.857	4.45**	**0.681**	**0.829**	**−13.2****	**0.731**	**0.844**	**−11.6****
	0.000	*0.000*	*1.40*	*0.005*	*0.003*	*1.44*	*0.001*	*0.005*	*0.36*****
SPF–FTSEF	0.903	0.898	1.22	**0.848**	**0.947**	**−14.7****	0.937	0.850	27.8**
	0.000	*0.000*	*3.15*****	*0.003*	*0.000*	*40.4*****	*0.000*	*0.000*	*1.06*
SPF–DAXF	0.916	0.909	2.42*	0.869	0.839	6.87**	**0.913**	**0.965**	**−8.57****
	0.000	*0.000*	*3.72*****	*0.000*	*0.000*	*0.46*****	*0.002*	*0.000*	*9.47*****
SPF–CACF	0.911	0.883	7.02**	**0.876**	**0.973**	**−17.3****	**0.891**	**0.920**	**−5.00****
	0.000	*0.000*	*3.49*****	*0.000*	*0.000*	*5.67*****	*0.002*	*0.000*	*6.43*****

Table 3 continued

	d4 (16–32 days)			d5 (32–64 days)			s5 (64–128 days)		
	Corr. before *Var. before*	Corr. after *Var. after*	*t*-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	*t*-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	*t*-stat *F-stat*
NF–ASXF	**0.741**	**0.767**	**−3.26****	**0.593**	**0.662**	**−5.47****	**0.210**	**0.572**	**−23.7****
	0.001	*0.003*	*0.29***	*0.010*	*0.001*	*5.63***	*0.013*	*0.004*	*3.03***
NF–FTSEF	**0.826**	**0.840**	**−1.51**	**0.736**	**0.866**	**−8.50****	**0.606**	**0.738**	**−9.74****
	0.000	*0.006*	*0.02***	*0.017*	*0.000*	*83.4***	*0.013*	*0.000*	*40.7***
NF–DAXF	**0.850**	**0.875**	**−3.17****	**0.912**	**0.968**	**−8.72****	**0.766**	**0.868**	**−8.10****
	0.000	*0.004*	*0.10***	*0.003*	*0.000*	*32.1***	*0.011*	*0.000*	*37.4***
NF–CACF	**0.861**	**0.918**	**−7.65****	**0.605**	**0.864**	**−12.4****	**0.645**	**0.808**	**−9.28****
	0.001	*0.003*	*0.38***	*0.031*	*0.000*	*45.9***	*0.028*	*0.000*	*142***
ASXF–FTSEF	0.888	0.862	7.82**	0.851	0.815	9.37**	**0.843**	**0.864**	*−3.56***
	0.000	*0.000*	*1.02*	*0.000*	*0.000*	*0.79*	*0.001*	*0.001*	*0.89*
ASXF–DAXF	0.846	0.805	11.4**	0.685	0.591	12.0**	**0.539**	**0.791**	**−21.5****
	0.000	*0.000*	*0.70*	*0.002*	*0.002*	*0.86*	*0.001*	*0.008*	*0.18***
ASXF–CACF	0.878	0.864	4.74	**0.793**	**0.832**	**−7.03**	**0.632**	**0.788**	**−16.5**
	0.000	*0.000*	*0.58**	*0.001*	*0.000*	*4.55***	*0.000*	*0.006*	*0.01***
FTSEF–DAXF	**0.871**	**0.881**	**−2.39***	**0.790**	**0.868**	**−8.91****	**0.838**	**0.910**	**−7.95****
	0.000	*0.000*	*1.71**	*0.004*	*0.000*	*6.57***	*0.005*	*0.000*	*8.70***
FTSEF–CACF	0.903	0.889	3.36**	**0.816**	**0.910**	**−12.8****	**0.872**	**0.953**	**−11.6****
	0.000	*0.000*	*2.85***	*0.003*	*0.000*	*4.86***	*0.003*	*0.000*	*9.48***
DAXF–CACF	**0.924**	**0.929**	**−1.76**	**0.782**	**0.868**	**−9.42****	**0.859**	**0.977**	**−10.9****
	0.000	*0.000*	*1.56*	*0.005*	*0.000*	*19.4***	*0.008*	*0.000*	*932***

(i) ** and * indicate the rejection of the null hypothesis of equal means at 1 and 5 % critical values, respectively; (ii) since the null hypothesis is that the mean difference is equal to zero, we perform a two-sided test and we report two-tailed values; (iii) the cases where the correlation grows higher after distress moments are marked in bold; (iv) the variance of the samples (before and after the financial incident) is reported in italics, as well as the *F* test for equal variances (in this case, ** and * indicate the rejection of the null hypothesis of equal variances at 1 and 5 % critical values, respectively) and not the returns spillovers. This supplementary analysis can be considered as a robustness check of our findings, since in periods with high fluctuations of returns, the prices volatility is also high (Fig. 7 in "Appendix 1").

4.2 Co-movements and rolling wavelet correlation for stock index futures volatility

The WPS shows that the two groups presenting small and high oscillations in the long run are different as compared to the previous case (Fig. 4).

The variances in terms of volatility are very strong in the medium run and long run, only for the European indexes. In this case, the DAXFV and CACFV present high oscillations in the long run, while the SPFV does not. Furthermore, the identification of the contagion associated with turbulence episodes is not as clear as in the case of the returns series. However, we observe stronger variability in the short run, after the observations 150 and 400.

The WTC analysis provides additional insights, proving that the co-movements in terms of volatility are stronger in the medium run and long run and manifest for the entire time horizon. The co-movements are considerable between the SPFV and the other selected indexes (Fig. 5), but also between the stock index futures European markets (Fig. 10 in "Appendix 3").

Two supplementary conclusions can be drawn from the WTC analysis. First, there is no evident leading market in terms of volatility spillovers. Second, for high frequencies, there is no strong sign of contagion after the identified turbulence episodes.

As compared to the correlation in terms of returns, in the case of the volatility, we observe stronger oscillations and also important differences between decomposition levels (Fig. 6). Further, Fig. 11 (Appendix 3) shows that the correlation is quite small in normal times as compared to crisis events. Indeed, the correlation level grows higher after the sovereign debt crisis start-up and decreases at the beginning of 2011.

In all the cases, the rolling wavelet correlation reaches its peak immediately after July 21, 2011. However, the level of correlation in terms of volatility between the European futures markets on the one hand and the Asia–Pacific markets on the other hand is reduced and fluctuates from one period to another and between frequencies. At the same time, the correlation of the European stock index futures is less strong in terms of volatility, but does not oscillate considerably.

Nevertheless, in order to see whether our findings are consistent, we need to check whether the correlation increases or decreases after crisis events, performing equal sample t tests. The results for the first retained crisis event are presented in Table 4.

We can notice similar findings with those reported in the case of the returns' correlation. For the raw data series, as well as for the d1 and d2 levels of decomposition, there is clear evidence that the correlation level increases. The d3 and d4 decomposition levels emphasize also an increase in the level of correlation. However, the d5 level of decomposition shows mixed results, where the correlation level decreases for the European stock index futures. These findings prove the robustness of the results obtained in the case of the returns correlation.

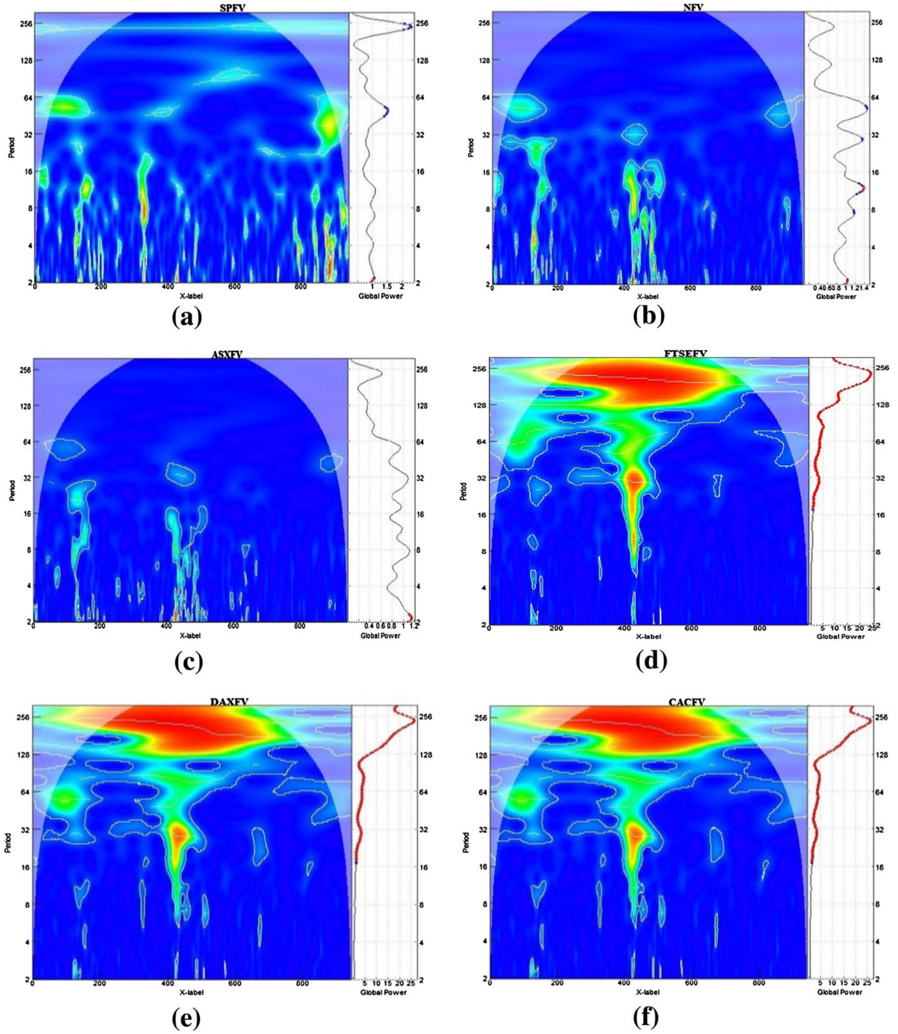

Fig. 4 Wavelet power spectrum (volatility). *Notes*: The *figure* describes the local and the global power spectrum of stock indexes returns. The *white contour* designates the 5 % significance level. The cone of influence, where edge effects might distort the picture, is shown as a *lighter shade*. The *color code* for the power ranges from *blue* (low power) to *red* (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, since October 15, 2009 to August 27, 2013. As we have irregular data, the rank of the observations is presented on the *horizontal axis*: The observation 200 corresponds to September 9, 2010; 400 corresponds to June 29, 2011; 600 corresponds to April 17, 2012; and 800 corresponds to February 1, 2013. **a** SPFV, **b** NFV, **c** ASXFV, **d** FTSEFV, **e** DAXFV, **f** CACFV

Regarding the second turbulence moment retained in the analysis, the results are less consistent (Table 5). While for the d1 level of decomposition the correlation decreases in terms of returns, we notice mixed results in terms of volatility. Furthermore, for d2

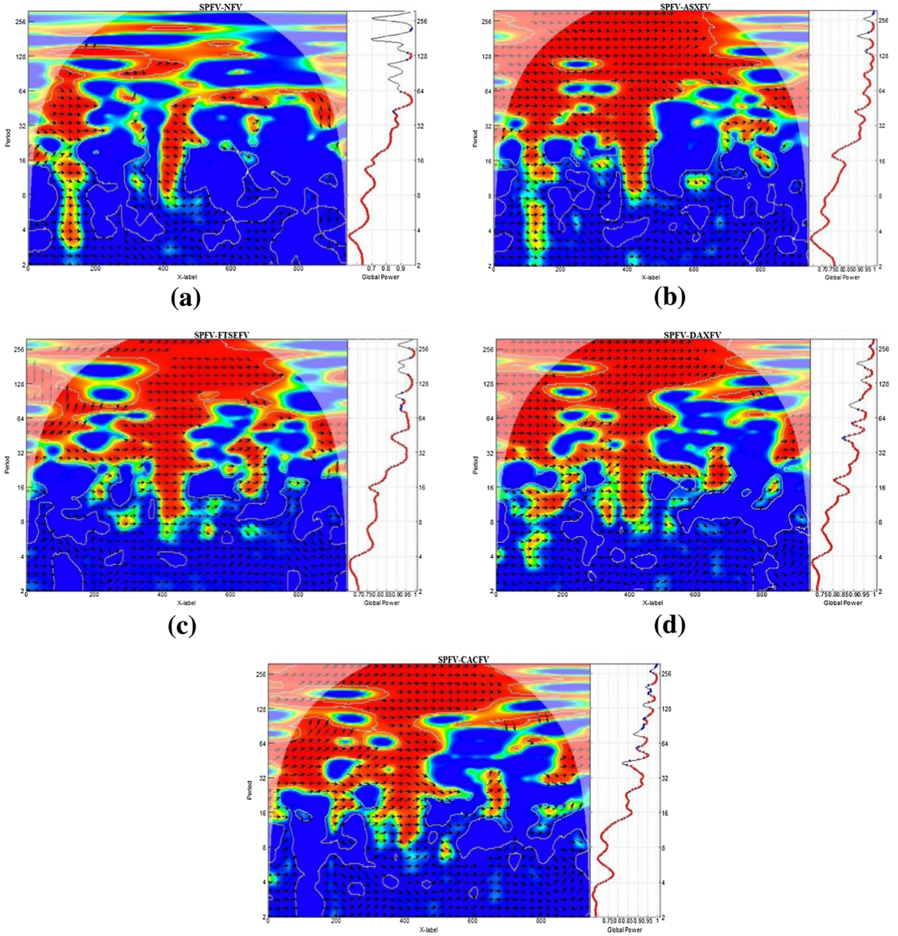

Fig. 5 Wavelet coherence (volatility). *Notes*: The *white contour* designates the 5 % significance level estimated from the Monte Carlo simulations using the phase randomized surrogate series. The cone of influence, where edge effects might distort the picture, is shown as a *lighter shade*. The *color code* for power ranges from *blue* (low power) to *red* (high power). *Y-axis* measures frequencies or scale, and *X-axis* represents the time period studied, since October 15, 2009 to August 27, 2013. As we have irregular data, the rank of the observations is presented on the *horizontal axis*: The observation 200 corresponds to September 9, 2010; 400 corresponds to June 29, 2011; 600 corresponds to April 17, 2012; and 800 corresponds to February 1, 2013. 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. **a** SPFV–NFV pair, **b** SPFV–ASXFV pair, **c** SPFV–FTSEFV, **d** SPFV–DAXFV; **e** SPFV–CACFV

and d3, we observe in general a decrease in the correlation level, while the returns correlation shows the opposite. However, at d5 level of correlation, the results are similar, proving thus only a partial robustness of the t test results.

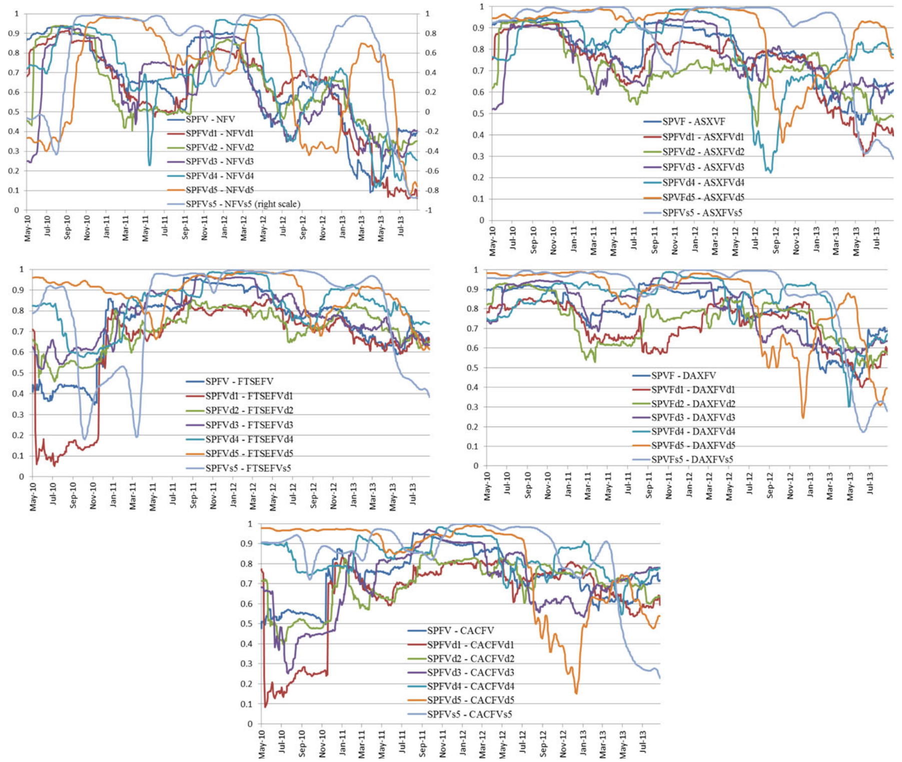

Fig. 6 Rolling wavelet correlation (volatility)

Summarizing all the aforementioned aspects, the findings in terms of volatility correlation show that:

- Only the European stock index futures present strong oscillations in the long run (WPS results).
- The co-movements in terms of volatility are stronger in the medium run and long run according to the WTC. However, no lead–lag relationships were identified.
- The rolling correlation fluctuates more in terms of volatility, both in time and between frequencies. Nevertheless, in this case also, the European stock markets present a stronger correlation. In addition, for all pairs of indexes, the peak of the correlation is attained after July 21, 2011.
- The *t* test demonstrates the robustness of the findings only for the first analyzed crisis event, while in the case of the second turbulence episode, the results are partially robust when we compare the correlation in terms of returns and volatility.

All in all, our results show that the international investors on futures markets cannot make their decisions only in terms of time series analysis. Indeed, the correlation level increases after severe turbulence moments (i.e., July 21, 2011), but the stock index futures markets provide opportunities for potential benefits from international portfolio

Table 4 Rolling wavelet correlation of futures volatility before and after July 21, 2011 (*t* test)

	Raw data			d1 (2–4 days)			d2 (4–8 days)			d3 (8–16 days)		
	Corr. before *Var. before*	Corr. after *Var. after*	*t*-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	*t*-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	*t*-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	*t*-stat *F-stat*
SPFV–NFV	0.642	0.706	−3.35**	0.525	0.632	−8.65**	0.506	0.585	−5.69**	0.705	0.694	0.74
	0.000	0.026	0.01**	0.000	0.010	0.06**	0.000	0.014	0.01**	0.007	0.009	0.80
SPFV–ASXFV	0.750	0.894	−17.0**	0.687	0.784	−13.1**	0.648	0.656	−0.92	0.691	0.813	−7.60**
	0.001	0.003	0.42**	0.002	0.001	1.04	0.004	0.001	3.14**	0.002	0.017	0.12**
SPFV–FTSEFV	0.818	0.931	−23.7**	0.712	0.809	−2 0.3**	0.727	0.807	−16.0**	0.866	0.907	−5.13**
	0.000	0.001	0.03**	0.001	0.000	2.36**	0.000	0.001	0.39**	0.000	0.004	0.18**
SPFV–DAXFV	0.776	0.900	−23.8**	0.649	0.612	6.64**	0.618	0.732	−17.1**	0.829	0.914	−10.8**
	0.000	0.001	0.05**	0.000	0.002	0.05**	0.000	0.003	0.01**	0.002	0.001	1.64*
SPFV–CACFV	0.753	0.883	−14.6**	0.650	0.728	−15.0**	0.622	0.755	−14.7**	0.754	0.882	−12.5**
	0.000	0.005	0.09**	0.001	0.000	1.43	0.000	0.005	0.15**	0.005	0.002	1.84**
NFV–ASXFV	0.572	0.665	−4.41**	0.429	0.510	−8.05**	0.460	0.525	−4.66**	0.690	0.647	3.17**
	0.000	0.032	0.02**	0.002	0.005	0.38**	0.000	0.014	0.02**	0.001	0.012	0.13**
NFV–FTSEFV	0.578	0.700	−6.36**	0.322	0.546	−18.1**	0.578	0.603	−3.57**	0.621	0.632	−0.70
	0.000	0.027	0.01**	0.000	0.010	0.09**	0.000	0.003	0.18**	0.007	0.011	0.67
NFV–DAXFV	0.768	0.736	2.54**	0.527	0.606	−11.8**	0.767	0.671	14.3**	0.764	0.770	−0.34
	0.000	0.011	0.02**	0.000	0.002	0.13**	0.000	0.003	0.03**	0.015	0.004	3.33**
NFV–CACFV	0.650	0.716	−3.80**	0.384	0.596	−13.7**	0.656	0.663	−1.30	0.658	0.677	−1.18
	0.000	0.022	0.22**	0.000	0.016	0.05**	0.000	0.001	0.70	0.013	0.005	2.36**
ASXFV–FTSEFV	0.646	0.878	−18.7**	0.582	0.727	−17.3**	0.504	0.683	−14.6**	0.545	0.749	−8.31**
	0.001	0.009	0.17**	0.000	0.004	0.11**	0.000	0.010	0.10**	0.002	0.042	0.07**
ASXFV–DAXFV	0.669	0.820	−22.2**	0.534	0.468	7.98**	0.491	0.569	−17.3**	0.602	0.758	−11.1**
	0.000	0.003	0.04**	0.000	0.004	0.09**	0.000	0.001	0.15**	0.001	0.013	0.12**

Table 4 continued

	Raw data			d1 (2–4 days)			d2 (4–8 days)			d3 (8–16 days)		
	Corr. before *Var. before*	Corr. after *Var. after*	*t*-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	*t*-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	*t*-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	*t*-stat *F-stat*
ASXFV–CACFV	**0.657**	**0.855**	**−22.5****	**0.563**	**0.628**	**−14.4****	**0.523**	**0.624**	**−14.9****	**0.544**	**0.765**	**−12.4****
	0.000	*0.005*	*0.06***	*0.000*	*0.000*	*0.81*	*0.001*	*0.002*	*0.43***	*0.001*	*0.022*	*0.04***
FTSEFV DAXFV	**0.801**	**0.906**	**−23.8****	**0.642**	**0.675**	**−9.22****	**0.797**	**0.800**	**−1.37**	**0.865**	**0.898**	**−7.59****
	0.000	*0.001*	*0.10***	*0.000*	*0.000*	*0.59**	*0.000*	*0.000*	*0.48*	*0.000*	*0.000*	*0.44***
FTSEFV CACFV	**0.801**	**0.936**	**−28.4****	**0.681**	**0.831**	**−38.6****	**0.760**	**0.836**	**−20.4****	**0.826**	**0.919**	**−14.5****
	0.000	*0.001*	*0.14***	*0.000*	*0.000*	*0.26***	*0.000*	*0.000*	*0.11***	*0.001*	*0.001*	*0.87*
DAXFV–CACFV	**0.880**	**0.949**	**−23.7****	**0.782**	**0.826**	**−8.39****	**0.860**	**0.884**	**−5.97****	**0.915**	**0.950**	**−8.99****
	0.000	*0.000*	*0.68*	*0.001*	*0.000*	*3.40***	*0.000*	*0.000*	*0.60**	*0.000*	*0.000*	*4.97***

	d4 (16–32 days)			d5 (32–64 days)			s5 (64–128 days)		
	Corr. before *Var. before*	Corr. after *Var. After*	*t*-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	*t*-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	*t*-stat *F-stat*
SPFV–NFV	**0.582**	**0.670**	**−5.90****	0.908	0.759	21.9**	0.946	0.832	21.6**
	0.016	*0.000*	*34.8***	*0.002*	*0.000*	*3.05***	*0.000*	*0.001*	*0.65*
SPFV–ASXFV	**0.885**	**0.908**	**−3.74****	**0.954**	**0.951**	**−2.71****	0.980	0.812	18.9**
	0.001	*0.001*	*0.87*	*0.000*	*0.000*	*3.92***	*0.000*	*0.005*	*0.16***
SPFV–FTSEFV	**0.882**	**0.906**	**−4.67****	**0.795**	**0.933**	**−16.2****	**0.909**	**0.968**	**−3.80****
	0.000	*0.001*	*0.12***	*0.006*	*0.000*	*12.6***	*0.017*	*0.000*	*40.5***
SPFV–DAXFV	**0.889**	**0.909**	**−4.05****	**0.881**	**0.891**	**−1.23**	0.974	0.892	28.5**
	0.000	*0.001*	*0.16***	*0.003*	*0.001*	*2.51***	*0.000*	*0.000*	*0.50***
SPFV–CACFV	0.880	0.867	2.74**	0.917	0.892	3.78**	0.932	0.859	1 0.4**
	0.001	*0.000*	*8.01***	*0.002*	*0.000*	*2.29***	*0.002*	*0.000*	*4.36***

Table 4 continued

	d4 (16–32 days)			d5 (32–64 days)			s5 (64–128 days)		
	Corr. before *Var. before*	Corr. after *Var. After*	t-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	t-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	t-stat *F-stat*
NFV–ASXFV	**0.720**	**0.744**	**−1.98***	0.901	0.818	13.7**	0.927	0.670	23.2**
	0.006	*0.003*	*1.70**	*0.002*	*0.000*	*6.50***	*0.006*	*0.002*	*2.77***
NFV–FTSEFV	**0.509**	**0.628**	**−9.13****	0.731	0.725	0.68	0.873	0.784	5.85**
	0.011	*0.001*	*9.50***	*0.003*	*0.001*	*2.12***	*0.015*	*0.002*	*6.43***
NFV–DAXFV	**0.633**	**0.783**	**−8.72****	**0.891**	**0.897**	**−0.94**	0.979	0.943	7.06**
	0.019	*0.002*	*8.62***	*0.002*	*0.001*	*2.31***	*0.000*	*0.001*	*0.12***
NFV–CACFV	**0.599**	**0.718**	**−9.03****	0.868	0.828	6.74**	0.927	0.785	11.9**
	0.011	*0.001*	*9.07***	*0.001*	*0.001*	*0.62**	*0.003*	*0.007*	*0.47***
ASXFV–FTSEFV	0.874	0.848	2.83**	**0.794**	**0.954**	**−16.0****	0.873	0.779	4.47**
	0.000	*0.006*	*0.06***	*0.007*	*0.000*	*51.8***	*0.021*	*0.012*	*1.79**
ASXFV–DAXFV	**0.895**	**0.918**	**−4.37****	**0.925**	**0.951**	**−7.17****	0.970	0.841	15.7**
	0.000	*0.001*	*0.70*	*0.000*	*0.000*	*6.76***	*0.001*	*0.003*	*0.66*
ASXFV–CACFV	0.878	0.871	1.12**	**0.899**	**0.969**	**−17.5****	0.960	0.784	12.1**
	0.000	*0.002*	*0.16***	*0.001*	*0.000*	*20.4***	*0.000*	*0.015*	*0.01***
FTSEFV DAXFV	0.920	0.909	2.44*	0.828	0.904	−8.68**	0.873	0.848	1.43
	0.000	*0.001*	*0.04***	*0.005*	*0.000*	*38.1***	*0.021*	*0.000*	*31.6***
FTSEFV CACFV	**0.875**	**0.905**	**−5.49****	**0.907**	**0.955**	**−10.1****	0.927	0.876	6.37**
	0.000	*0.001*	*0.13***	*0.001*	*0.000*	*20.0***	*0.004*	*0.000*	*4.57***
DAXFV–CACFV	0.965	0.963	1.55	0.972	0.970	1.61	0.958	0.924	22.3**
	0.000	*0.000*	*0.12***	*0.000*	*0.000*	*14.1***	*0.000*	*0.001*	*0.44***

(i) ** and * indicate the rejection of the null hypothesis of equal means at 1 and 5 % critical values, respectively; (ii) since the null hypothesis is that the mean difference is equal to zero, we perform a two-sided test and we report two-tailed values; (iii) the cases where the correlation grows higher after distress moments are marked in bold; (iv) the variance of the samples (before and after the financial incident) is reported in italics, as well as the F test for equal variances (in this case, ** and * indicate the rejection of the null hypothesis of equal variances at 1 and 5 % critical values, respectively)

Table 5 Rolling wavelet correlation of futures volatility before and after January 14, 2012 (t test)

	Raw data			d1 (2–4 days)			d2 (4–8 days)			d3 (8–16 days)		
	Corr. before *Var. before*	Corr. after *Var. after*	t-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	t-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	t-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	t-stat *F-stat*
SPFV–NFV	0.834	0.737	1 0.8**	0.784	0.786	3.55**	0.786	0.781	0.50	0.817	0.756	2.81
	0.000	0.013	0.01**	0.001	0.000	1.63*	0.004	0.003	1.45	0.015	0.019	0.81
SPFV–ASXFV	0.907	0.872	22.1**	0.815	0.812	1.01	**0.699**	**0.723**	**−7.63****	0.933	0.848	8.84**
	0.000	0.000	0.65	0.000	0.000	1.05	0.000	0.000	1.89**	0.000	0.006	0.00**
SPFV–FTSEFV	0.932	0.907	15.8**	**0.804**	**0.824**	**−7.02****	0.822	0.799	8.09**	0.960	0.919	7.95**
	0.000	0.000	0.43**	0.000	0.000	0.56*	0.000	0.000	0.14**	0.000	0.002	0.01**
SPFV–DAXFV	0.894	0.890	1.76	**0.647**	**0.787**	**−15.6****	**0.759**	**0.783**	**−4.87****	0.940	0.878	8.64**
	0.000	0.000	0.84	0.002	0.003	0.78	0.000	0.001	0.21**	0.000	0.003	0.04**
SPFV–CACFV	0.912	0.870	15.9**	**0.783**	**0.802**	**−6.19****	0.813	0.790	5.30**	0.925	0.836	9.90**
	0.000	0.000	0.98	0.000	0.000	6.27**	0.000	0.001	0.24**	0.000	0.005	0.10**
NFV–ASXFV	0.869	0.748	9.15**	**0.670**	**0.758**	**−1 0.2****	0.717	0.676	4.04**	**0.823**	**0.843**	**−0.92**
	0.000	0.012	0.02**	0.004	0.000	4.93**	0.004	0.003	1.45	0.024	0.009	2.64**
NFV–FTSEFV	0.868	0.705	13.6**	**0.674**	**0.676**	**−0.46**	0.700	0.642	5.81**	0.802	0.753	1.98*
	0.000	0.010	0.01**	0.000	0.000	0.64	0.001	0.005	0.35**	0.021	0.023	0.94
NFV–DAXFV	0.844	0.711	11,8**	0.701	0.682	3.52**	0.644	0.619	3.33**	0.833	0.753	4.41**
	0.000	0.009	0.01**	0.001	0.000	2.60**	0.001	0.003	0.39**	0.007	0.017	0.41**
NFV–CACFV	0.877	0.720	12.5**	0.776	0.737	6.49**	0.718	0.652	7.26**	0.821	0.729	2.16**
	0.000	0.011	0.01**	0.001	0.001	1.21**	0.001	0.004	0.27**	0.013	0.013	1.05
ASXFV–FTSEFV	0.911	0.868	13.8**	0.766	0.757	2.49*	0.772	0.744	6.12**	0.950	0.902	7.26**
	0.000	0.000	0.08**	0.000	0.000	0.17**	0.000	0.001	0.27**	0.000	0.003	0.03**
ASXFV–DAXFV	**0.822**	**0.824**	**−0.68**	**0.481**	**0.662**	**−15.0****	**0.623**	**0.687**	**−13.7****	0.880	0.795	8.68**
	0.000	0.000	0.56*	0.002	0.008	0.29**	0.000	0.001	0.58*	0.000	0.007	0.02**

Table 5 continued

	Raw data			d1 (2–4 days)			d2 (4–8 days)			d3 (8–16 days)		
	Corr. before *Var. before*	Corr. after *Var. after*	*t*-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	*t*-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	*t*-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	*t*-stat *F-stat*
ASXFV–CACFV	0.871	0.838	1 0.2**	**0.663**	**0.723**	**−12.5****	0.703	0.736	−7.53**	0.911	0.826	9.71**
	0.000	*0.000*	*0.26***	*0.000*	*0.000*	*0.73*	*0.001*	*0.000*	*2.36***	*0.000*	*0.005*	*0.01***
FTSEFV DAXFV	0.904	0.896	4.22**	**0.697**	**0.791**	**−16.4****	**0.789**	**0.793**	**−1.94**	0.923	0.868	9.68**
	0.000	*0.000*	*1.42*	*0.000*	*0.001*	*0.54***	*0.000*	*0.000*	*0.38***	*0.000*	*0.002*	*0.01***
FTSEFV CACFV	0.937	0.897	16.6**	0.835	0.817	9.50**	0.843	0.806	15.1**	0.937	0.870	11.1**
	0.000	*0.000*	*0.26***	*0.000*	*0.000*	*0.47***	*0.000*	*0.000*	*0.23***	*0.000*	*0.002*	*0.06***
DAXFV–CACFV	0.946	0.936	8.11**	**0.835**	**0.864**	**−7.91****	**0.864**	**0.886**	**−9.91****	0.960	0.952	5.50**
	0.000	*0.000*	*0.41***	*0.000*	*0.000*	*1.27*	*0.000*	*0.000*	*0.70*	*0.000*	*0.000*	*0.04***
	d4 (16–32 days)			d5 (32–64 days)			s5 (64–128 days)					
	Corr. before *Var. before*	Corr. after *Var. After*	*t*-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	*t*-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	*t*-stat *F-stat*			
SPFV–NFV	**0.776**	**0.928**	**−9.01****	**0.758**	**0.852**	**−7.07****	**0.597**	**0.888**	**−8.53****			
	0.019	*0.001*	*10.2***	*0.000*	*0.012*	*0.07***	*0.064*	*0.023*	*2.76***			
SPFV–ASXFV	0.969	0.946	4.02**	**0.972**	**0.993**	**−2 0.0****	**0.834**	**0.996**	**−11.9****			
	0.000	*0.001*	*0.59∗*	*0.000*	*0.000*	*6.24***	*0.013*	*0.000*	*2125***			
SPFV–FTSEFV	**0.969**	**0.969**	**−0.07**	**0.966**	**0.987**	**−19.6****	**0.960**	**0.990**	**−7.15****			
	0.000	*0.000*	*1.90***	*0.000*	*0.000*	*8.16***	*0.001*	*0.000*	*103***			
SPFV–DAXFV	0.964	0.941	4.58**	**0.926**	**0.969**	**−14.7****	**0.942**	**0.989**	**−9.92****			
	0.000	*0.001*	*0.67*	*0.000*	*0.000*	*4.59***	*0.001*	*0.000*	*13.2***			
SPFV–CACFV	0.952	0.922	5.40**	**0.950**	**0.972**	**−8.57****	**0.935**	**0.991**	**−7.21****			
	0.000	*0.001*	*0.66*	*0.000*	*0.000*	*1.09*	*0.004*	*0.000*	*55.0***			

Table 5 continued

	d4 (16–32 days)			d5 (32–64 days)			s5 (64–128 days)		
	Corr. before *Var. before*	Corr. after *Var. After*	t-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	t-stat *F-stat*	Corr. before *Var. before*	Corr. after *Var. after*	t-stat *F-stat*
NFV–ASXFV	**0.777**	**0.964**	**−12.5****	**0.785**	**0.844**	**−3.65****	**0.390**	**0.880**	**−14.9****
	0.016	*0.000*	*36.9***	*0.003*	*0.016*	*0.22***	*0.052*	*0.028*	*1.87***
NFV–FTSEFV	**0.743**	**0.932**	**−9.74****	**0.732**	**0.855**	**−8.16****	**0.585**	**0.900**	**−9.61****
	0.026	*0.002*	*12.4***	*0.001*	*0.015*	*0.08***	*0.057*	*0.023*	*2.48***
NFV–DAXFV	**0.814**	**0.927**	**−8.76****	**0.889**	**0.900**	**−0.98**	**0.636**	**0.864**	**−6.95****
	0.010	*0.001*	*6.27***	*0.002*	*0.007*	*0.29***	*0.063*	*0.017*	*3.52***
NFV–CACFV	**0.781**	**0.918**	**−9.84****	**0.851**	**0.859**	**−1.31**	**0.586**	**0.880**	**−8.15****
	0.013	*0.001*	*11.7***	*0.003*	*0.011*	*0.26***	*0.075*	*0.021*	*3.51***
ASXFV–FTSEFV	0.953	0.950	0.49	**0.952**	**0.990**	**−19.6****	**0.773**	**0.994**	**−10.9****
	0.002	*0.000*	*3.14***	*0.000*	*0.000*	*62.9***	*0.030*	*0.000*	*8062***
ASXFV–DAXFV	0.960	0.916	6.41**	**0.944**	**0.975**	**−27.2****	**0.924**	**0.990**	**−11.8****
	0.000	*0.002*	*0.27***	*0.000*	*0.000*	*13.5***	*0.002*	*0.000*	*65.3***
ASXFV–CACFV	0.934	0.914	2.96**	**0.975**	**0.987**	**−14.0****	**0.810**	**0.997**	**−10.2****
	0.001	*0.001*	*1.05*	*0.000*	*0.000*	*1.91***	*0.024*	*0.000*	*4118***
FTSEFV DAXFV	**0.967**	**0.977**	**−2.65****	**0.922**	**0.984**	**−22.1****	**0.906**	**0.977**	**−8.54****
	0.000	*0.000*	*4.41***	*0.000*	*0.000*	*76.2***	*0.004*	*0.000*	*18.7***
FTSEFV CACFV	**0.968**	**0.971**	**−0.82**	**0.946**	**0.988**	**−17.8****	**0.900**	**0.991**	**−1 0.5****
	0.000	*0.000*	*4.34***	*0.000*	*0.000*	*78.4***	*0.005*	*0.000*	*514***
DAXFV–CACFV	**0.979**	**0.982**	**−2.64****	**0.979**	**0.990**	**−14.7****	**0.913**	**0.988**	**−8.82****
	0.000	*0.000*	*6.54***	*0.000*	*0.000*	*9.54***	*0.005*	*0.000*	*257***

(i) ** and * indicate the rejection of the null hypothesis of equal means at 1 and 5 % critical values, respectively; (ii) since the null hypothesis is that the mean difference is equal to zero, we perform a two-sided test and we report two-tailed values; (iii) the cases where the correlation grows higher after distress moments are marked in bold; (iv) the variance of the samples (before and after the financial incident) is reported in italics, as well as the F test for equal variances (in this case, ** and * indicate the rejection of the null hypothesis of equal variances at 1 and 5 % critical values, respectively)

diversification and hedging strategies. In times of crisis, it is recommended to extend the variety of investments and the risk management strategies, especially for the short- and medium-term investments.

5 Concluding remarks

This paper investigates the co-movements and contagion between developed international stock futures markets. Traditional financial researches usually analyzed the co-movements of the spot markets, leaving aside the stock index futures. However, investors specialized in derivatives trading may participate in multiple markets with the purpose of portfolio diversification, risk management, and speculation. In spite of few efforts regarding the futures markets co-movements, previous studies are limited in that they apply time series analysis, even though maybe more than two periods characterize the spillovers between futures markets.

The present study fills an important gap in the literature and proposes a new methodology for assessing co-movements and contagion in times of crisis, between selected futures markets. We combine the wavelet transform with the rolling correlation approach to see whether the level of correlation changes over time and frequencies. Finally, based on an equal sample t test, we assess whether the level of correlation increases or not after turbulence episodes.

On the whole, our results point to the existence of an important correlation of the stock index futures markets, especially in the medium run and long run. In addition, during the analyzed period, the European markets lead the other selected markets. These results are documented especially for the returns' co-movements. The rolling wavelet correlation shows that the co-movements increase after turbulences episodes and remains strong in the case of the European markets. We also notice that the correlation in terms of volatility oscillates more that the correlation in terms of returns, in both time and across frequencies. With reference to the results of the t tests for sovereign debt crisis events (i.e., additional package for Greece on July 21, 2011), we notice that the contagion phenomenon cannot be neglected, even if the WPS and the WTC do not prove strong variation in the very short run. All in all, our results show that the co-movements can be detected only at certain levels of decomposition. After severe crisis events, the contagion increases (higher correlation at d1 and d2), while the integration level decreases (smaller correlation at d5).

Our results are important for building accurate asset pricing models and for understanding the interaction between international stock index futures. More precisely, the market practitioners and investors can derive some useful trading implications from our results. For example, in the case of the capital asset pricing model (CAPM), if the relationship between the return of a portfolio and its beta becomes stronger at low frequencies, then the predictions of the CAPM model are more relevant in the long run.

In terms of risk mitigation, our results state that it is recommended for the European investors, for example, to diversify their portfolio in times of crisis, toward Asia–Pacific markets, which present a lower level of correlation with the European ones. In addition, policy makers who are forced to intervene in the case of turbulence episodes can also refer to our empirical findings. The contagion level grows stronger after financial stress episodes, especially if the markets are dominated by the speculative traders, concerned with short time trading horizons. In our research, we demonstrate that the spillover effect is very strong between the European markets, at all levels of decomposition.

Appendix 1: Returns and volatility for selected stock index futures

See Fig. 7.

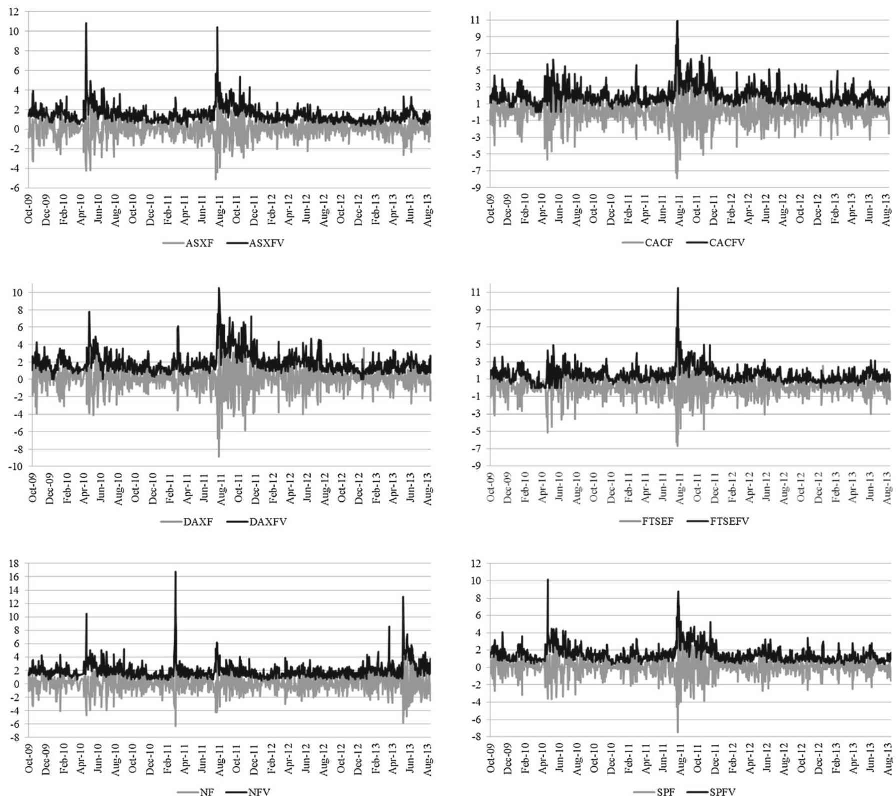

Fig. 7 Stock index futures returns and volatility

Appendix 2: Futures indexes: additional results (returns)

See Figs. 8 and 9.

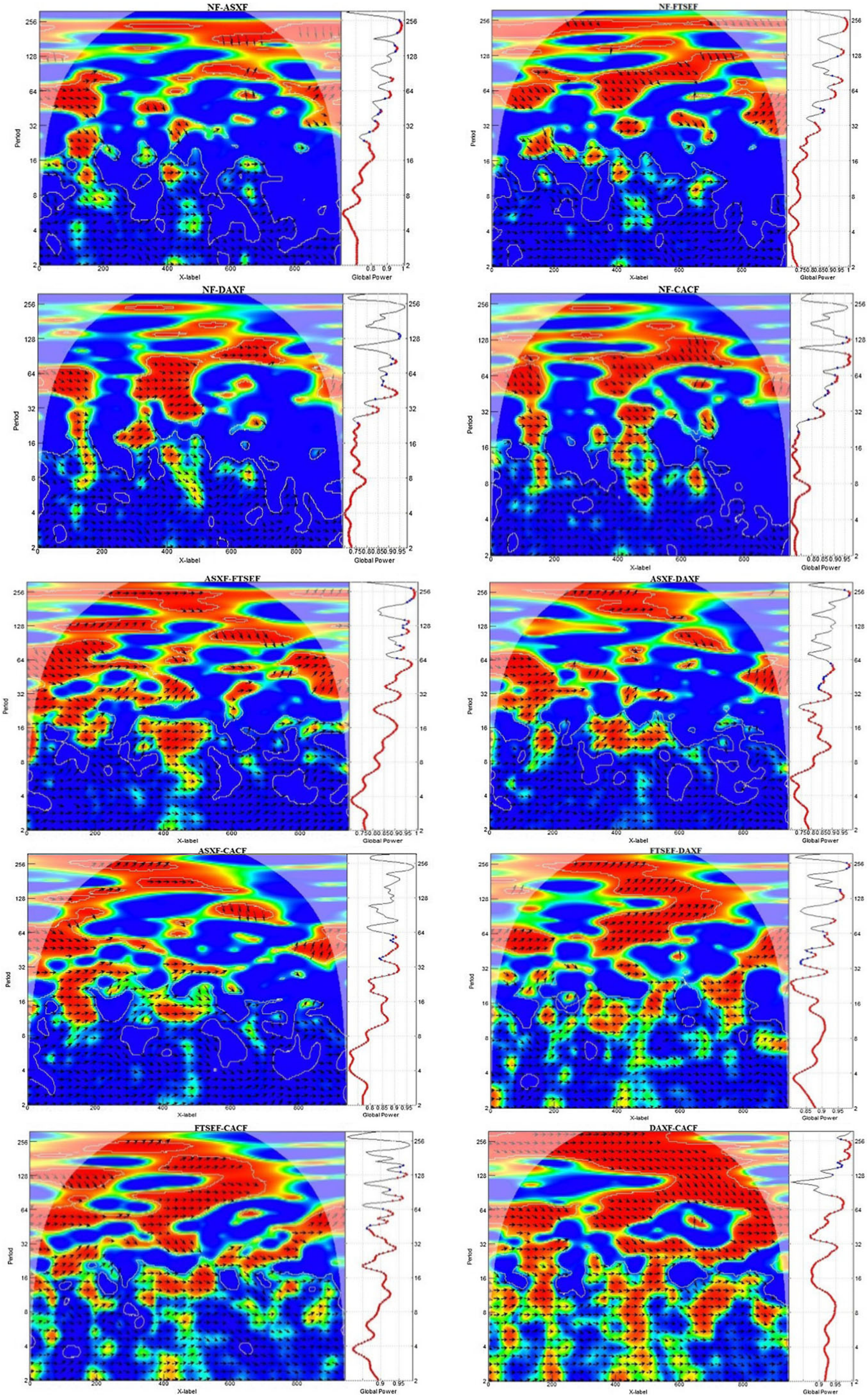

Fig. 8 Wavelet coherence—additional results (returns)

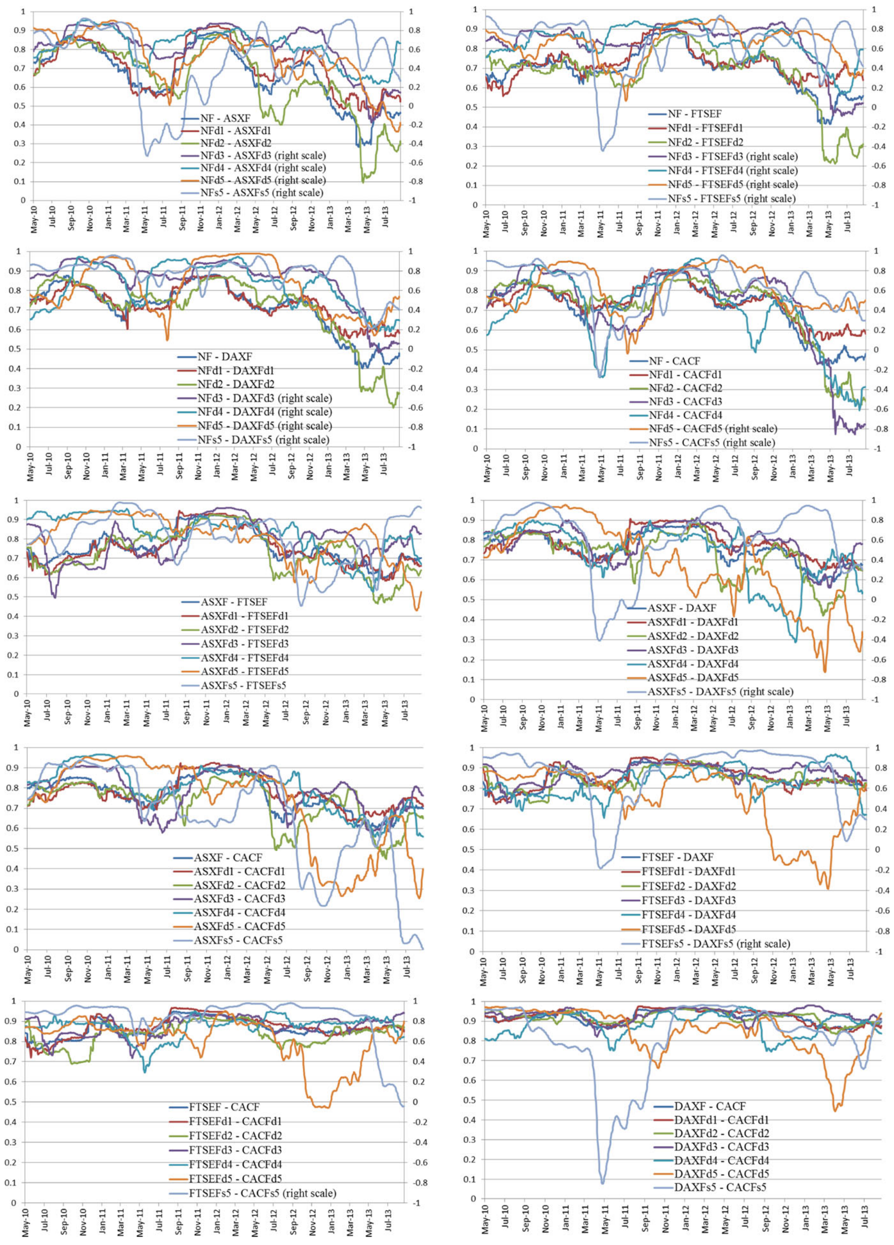

Fig. 9 Rolling wavelet correlation—additional results (returns)

Appendix 3: Futures indexes: additional results (volatility)

See Figs. 10 and 11.

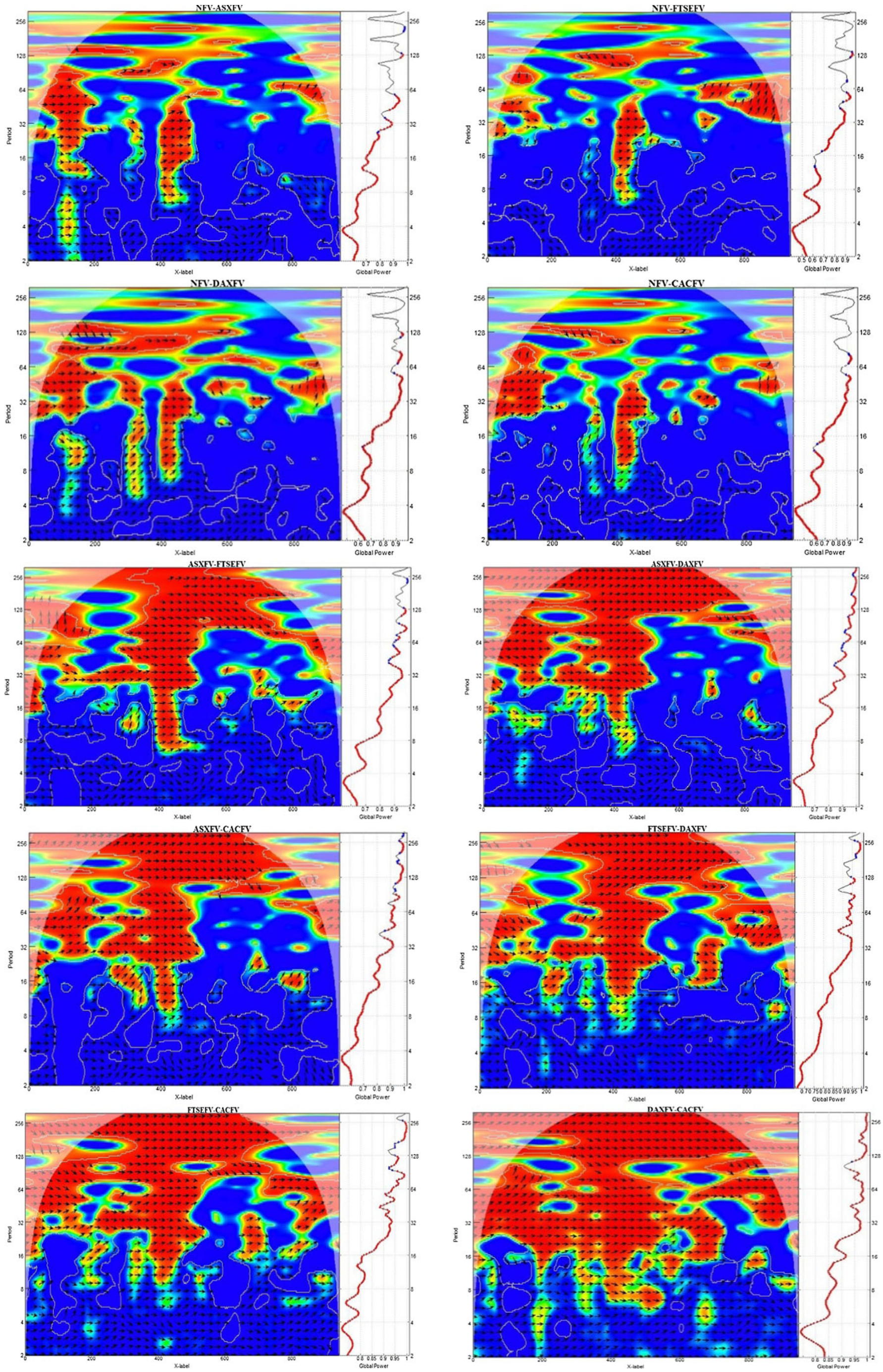

Fig. 10 Wavelet coherence—additional results (volatility)

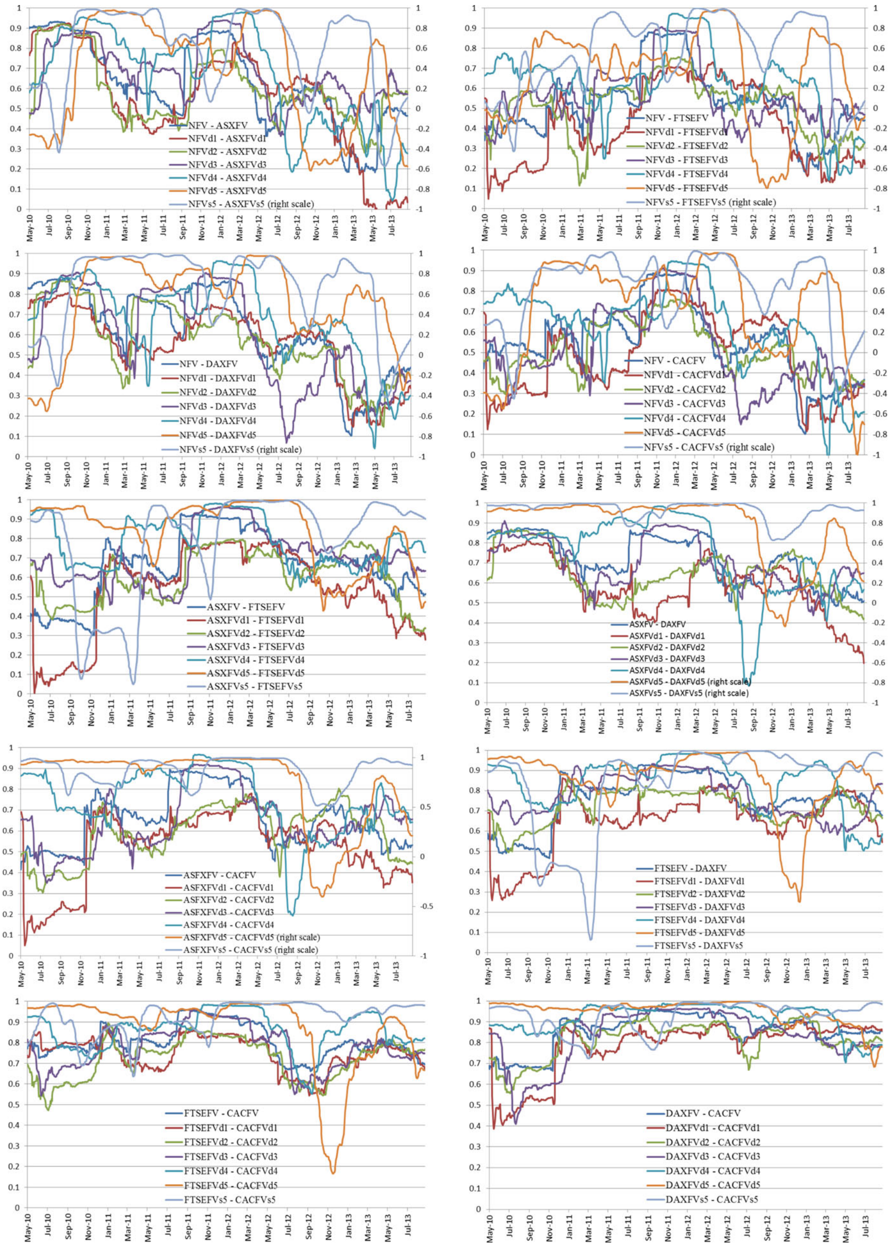

Fig. 11 Rolling wavelet correlation—additional results (volatility)

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