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INTERNATIONAL STOCK MARKET INDICES COMOVEMENTS: A NEW LOOK

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ABSTRACT

This study accounts for the time-varying pattern of price shock transmission, exploring stock market linkages using continuous time wavelet methodology. In order to sustain and improve previous results regarding correlation analysis between stock market indices, namely FTSE100, DJIA30, Nikkei225 and Bovespa, we extend here such analysis using the Coherence Morlet Wavelet, considering financial crisis episodes.

Results indicate that the relation among indices was strong but not homogeneous across scales, that local phenomenon's are more felt than others in these markets and that there seems to be no quick transmission through markets around the world, but yes a significant time delay. The relation among these indices has changed and evolved through time, mostly due to financial crisis that occurred at different time periods. Results also favor the view that geographically and economically closer markets exhibit higher correlation and more short run comovements among them. Strong comovement is mostly confined to long-run fluctuations favoring contagion analysis. Copyright © 2011 John Wiley & Sons, Ltd.

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1. INTRODUCTION

Trade and financial liberalization since the nineties determined the process of globalization that has been further enhanced by the recent trend of international stock market indices to become more and more integrated. As a consequence, business cycles synchronization and stock correlations are expected to rise over time and across countries.

Comovement analysis should consider the distinction between short and long-term investors who have different term objectives, especially if we are dealing with international investors who want to diversify risk and derive high returns from their international portfolios (Osborn *et al*., 2010). Candelon *et al*. (2008) argue that from a portfolio diversification point of view, the short-term investor is naturally more interested in the comovement of stock returns at higher frequencies, that is, short-term fluctuations, but the long-term investor focuses on the relationship at lower frequencies (long-term fluctuations).

Diversification strategies performed by international investor's also depend on the nature and magnitude of the existent relationships between different stock markets. Understanding interrelations among the various markets is therefore important to diversify risk and to derive high return. This work investigates

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this relationship, comparing the daily dynamics of four stock market indices around the world. As such the following questions are addressed: (1) Did stock market linkages strengthen in the last decade? If so, what factors can explain such linkages? This analysis should reveal whether there is a dominant economy, thus influencing all other markets. Further, geographically and economically close countries should exhibit higher levels of market linkages due to the presence of similar investor groups and multi-listed companies; (2) What, if any, are the significant long-term linkages between the markets? Did financial crisis stimulate stronger linkages among world markets? Which major stock market (Japan, UK, US) dominated? We would expect the US market to influence all other markets, given the results presented by previous studies, with little influence exerted by these markets on the US market (Floros, 2005; Ozdemir, 2009); (3) How stable have these market linkages been over time? This allows us to examine whether any significant and persistent changes in the degree of market linkages have occurred across the countries analyzed.

This work extends previous literature in the following important aspects. First, we explore the potential time-varying behavior of long run stock market relationships. For investors to be able to adequately exploit knowledge of the structure of stock market co-movements they would need to possess reliable information on the stability of the observed market linkages. While numerous studies draw on the implication of the (non) existence of cointegration for long-run diversification potentials (Taylor and Tonks, 1989)[1], the instability of long-run relationships has not received much attention. In this context, financial crisis are conceivably a potential source of structural breaks in international stock market integration. In fact, some analysts suggest the need for exploring the impact of capital market liberalization and the effects of past episodes of financial crisis as potential sources of instability in the pattern of stock market linkages (Charles and Darné, 2006; Dungey and Martin, 2007). Second, although the importance of contemporaneous information transmission among stock markets is well recognized, there is generally a lack of in-depth analysis of instantaneous price shock transmission in international financial markets. Such investigation certainly helps us understand the nature of these stock market relationships and may carry implications for day trading. Finally, by using a more sophisticated technique, the continuous (Morlet) time wavelet methodology. This may be justified in two different manners: First, wavelets can be used to overcome the problems due to non-stationarity of the series signals; Second, they can be a very useful technique for analyzing financial relations especially when there is a distinction between short and long run relations. The main advantage of the cross-wavelet coherency-phase analysis is its ability to analyze transient dynamics for the association between two time series.

Market co-movements can also lead to market contagion. Financial contagion (Forbes and Rigobon, 2002) is defined as a significant increase in cross-market linkages after a shock to an individual country. There is contagion only if two markets show a significant increase in comovement during crisis periods compared with periods of stability. If cross-market comovements do not increase significantly after the shock, then any continued level of market correlation only suggests the interdependence between the two economies. As such, we include in the analysis special historical periods associated with financial crisis in order to analyze the comovement of stock market indices during these periods of time, if any correlation existed.

This paper is organized as follows. In Section 2 we present a brief literature review about stock market linkages. Section 3 discusses the main advantages of wavelet analysis and presents the continuous wavelet transform, its localization properties and the optimal characteristics of the Morlet wavelet. Wavelet power spectrum, the cross-wavelet power spectrum, wavelet coherency and phase difference concepts are also presented. Data overview and descriptive statistics are provided in Section 4, in conjunction with the identification of the most important financial crisis historical dates to analyze markets comovements. In Section 5 empirical results, applying the tools described in Section 2, for the four stock market indices are discussed. Finally, Section 6 concludes pointing out directions for future research.

2. LITERATURE REVIEW

Previous studies discuss the issue of international linkages and cointegration of stock exchanges (Da Costa *et al.*, 2005; Floros, 2005; Kizys and Pierdzioch, 2009; Taylor and Tonks, 1989; Wu and Su, 1998), but they are based on the estimation of a correlation matrix of stock market index returns and/or on multivariate

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analysis techniques, such as cointegration theory and principal component analysis. Taylor and Tonks (1989) find evidence of cointegration between stock prices in the UK, Germany, the Netherlands and Japan but not the USA. Wu and Su (1998) find that there is a significant dynamic relation among the US, Japan, UK and Hong Kong stock markets.

Floros (2005) use a vector error correction model and the Granger-causality approach to re-examine the evidence of market linkages and cointegration between S&P500, Nikkei225 and FTSE-100 stock indices from 1988 until 2003, suggesting that mature markets are cointegrated. Eun and Shim (1989) use the same method for the 1979–1985 periods among the US and nine other stock markets, concluding that USA had a dominant influence. Berument *et al.* (2006) put forward that effects of the S&P500 on emerging market returns has got to do with the geographical location of the markets and that these effects die out in a quick manner. Furthermore, Eun and Shim (1989) and Bessler and Yang (2003) give a detailed review of the earlier and the more recent literature on the relationship between major stock markets. Ozdemir and Cakan (2007) examine the dynamic relationships between the stock market indices of the US, Japan, France and the UK using non-linear causality tests, finding a strong bidirectional nonlinear causal relationship between the US and the other countries.

However, these studies do not concentrate their analysis in the frequency and scale domains. Non-popularity of wavelets may be due to the fact that it has been applied either to analyze individual time series (Gallegati and Gallegati, 2007) or to individually analyze several time series, but one at each time. Decompositions are then studied using traditional time-domain methods (Ramsey and Lampart, 1998a,b).

For economic issues, Aguiar-Conraria *et al.* (2008) use cross-wavelet coherency and phase-difference to directly study interactions between time-series at different frequencies and how they evolve over time. Wavelet analysis is a comparatively new and powerful mathematical tool for signal processing being an important addition to time-series methods with practical applications in Economics and Finance, allowing to decompose relationships in the time-frequency domain. Their main advantage is the ability to decompose financial time series into their time scale components and given their translation and scale properties, non-stationarity in the data is not a problem.

Applications of wavelet analysis in economics and finance have been recently provided by Ramsey and Lampart (1998a,b) and In and Kim (2006). Wavelet theory for international comovement of stock indices has been applied by Lee (2004), Sharkasi *et al.* (2005) and Rua and Nunes (2009). Lee (2004) studied international transmission effects between US, Germany and Japan and two emerging markets in the Middle East and North Africa (MENA) region, namely Egypt and Turkey. He reports that movements from the developed markets affected the developing markets but not vice versa. Sharkasi *et al.* (2005) investigated the price interdependence between seven international stock markets, finding evidence of intra-European market comovement with the US market, while US markets impact Asian markets, which in turn influence European markets. They also find an increase in the importance of international spillover effects since the mid 1990s, having this importance decreased since the beginning of this century. Rua and Nunes (2009) also tested the stylized fact that comovement has changed over time using monthly data from Germany, Japan, UK and US. The analysis is done both at the aggregate and sector levels. The degree of comovement of Germany with the US and UK markets are characterized by some permanent changes over time: a gradual but steady increase of comovement at lower frequencies and also a sudden increase after the end of the nineties for other frequencies. They also conclude that Japan presents a low comovement with all other countries considered.

However, the previously three mentioned authors use discrete wavelet transform versions. The present work differs from these by using the continuous Morlet Wavelet transform (CWT) technique instead. This expands a time series into a time frequency space where oscillations can be seen in a highly intuitive way, exposing regions with high common power and further reveals information about the phase relationship, which improves conclusions quality.

3. THE USE OF WAVELETS TO DYNAMICALLY DECOMPOSE TIME

Wavelets take their roots from filtering methods[2] and Fourier analysis,[3] but overcome most of the limitations of these two methods. Combining information from both time-frequency domains, they are very

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flexible turning unnecessary to make strong assumptions concerning the data generating process for the series under investigation.

What makes wavelets interesting and useful is the fact that its window can be continuously resized. By looking at a signal with a small window only fine features can be viewed, whereas by looking at the same signal with a large window, the coarse features will be viewed. Thus, by using wavelets we could see both fine details and approximations. The temporal analysis by wavelets is performed with a contracted, high-frequency version of the wavelet, while frequency analysis is performed with a dilated, low-frequency version of the same wavelet.

3.1. Continuous Morlet wavelet

There are two classes of wavelet[4] transforms; the continuous wavelet transform (CWT) and its discrete counterpart (DWT). The DWT is a compact representation of the data and is particularly useful for noise reduction and data compression, whereas the CWT is better for feature extraction purposes.

The CWT, with respect to the 'mother wavelet' ϕ, is a function $W_x(s,\tau)$ that provides wavelet coefficients, defined as:

$$W_x(s,\tau) = \int_{-\infty}^{+\infty} x(t)\frac{1}{\sqrt{s}}\phi^*\left(\frac{t-\tau}{s}\right)\mathrm{d}t \tag{1}$$

where * denotes the complex conjugate form. The mother wavelet $\phi(.)$ serves as a prototype for generating other window functions. The term translation, τ, refers to the location of the window (indicating where it is centered). As the window shifts through the signal, the time information in the transform domain is obtained. The term scaling, s, refers to dilating (if $|s|>1$) or compressing (if $|s|<1$) the wavelet (controls the length of the wavelet by extracting frequency information from the time series). The mother wavelet is dilated or compressed to correspond to cycles of different frequencies. In this way an entire set of wavelets can be generated from a single mother wavelet function and this set can then be used to analyze the time series. If the wavelet function $\phi(t)$ is complex, the wavelet transform W_x will also be complex, meaning that the transform can be divided into the real part ($\mathbb{R}\{W_x\}$) and imaginary part ($I\{W_x\}$), or amplitude, $|W_x|$, and phase,[5] $\tan^{-1}\left(I\{W_x\}/\mathbb{R}\{W_x\}\right)$.

Wavelets constructed over short time scales will tend to isolate sharp, high frequency volatility in the time series. Because of the short time scales, this information will have good time resolution but poor scale (frequency) resolution. Relatively, long-scale wavelets will tend to capture low frequency volatility and will have relatively poor time resolution but good scale (frequency) resolution.

The wavelet transform can thus be used to analyze time series that contain nonstationary power at many different frequencies. This study uses the Morlet wavelet as the basis function for wavelet transform (Percival and Walden, 2000).

The Morlet wavelet allows good identification and isolation of periodic signals, as it provides a balance between localization of time and frequency (Grinsted *et al*., 2004). This is a complex wavelet, as it yields a complex transform, with information on both amplitude and phase, essential for studying synchronisms between different time series. The Morlet wavelet[6] in its simplified version is defined as:

$$\phi_\eta(t) = \pi^{-\frac{1}{4}}\mathrm{e}^{i\eta t}\mathrm{e}^{-\frac{t^2}{2}} \tag{2}$$

The relationship between scale (s) and frequency (f) is simply $f = \mu_f/s \approx 1/s$ meaning that the wavelet scale is inversely related to the frequency, simplifying the interpretation of wavelet analysis. Here μ_f is the frequency center of the Fourier transform of ϕ, $\Phi(f)$. The central frequency of a wavelet determines the waveforms, where for the Morlet wavelet the central frequency was chosen to be equal to six ($\eta = 6$), providing a good balance between time and frequency localization. For this central frequency the Fourier frequency period ($1/f$) is almost equal to scale.

Wavelet transforms perform what is called time-frequency analysis of signals, being able to estimate the spectral characteristics of signals as a function of time. Therefore, it can provide not only the time-varying power spectrum but also the phase spectrum needed for computation of coherence.

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3.2. Wavelet power spectrum, coherency and phase difference

Coherence is very important when dealing with fluctuating quantities, indicating how closely X and Y are related by a linear transformation. This happens if and only if their degree of coherence is close to its maximum value of unity. In time-series, the degree of coherence of two time series $x(t)$ and $y(t)$ with zero time-average values is the magnitude of their temporal correlation coefficient.

Coherence is like a correlation measure that indicates how strongly the two variables are related at business cycle frequencies. It ranges from 0 (no correlation; completely incoherent) to 1 (perfect correlation; completely coherent). The caveat is that this correlation may not be contemporaneous, but may involve a lead or a lag, being the magnitude measured by the phase lead.

Dealing with discrete time series $\{x_n, n = 0, \ldots, N-1\}$ of N observations with a uniform time step δt, the integral in (1) has to be discretized, and the CWT of the time series $\{x_n\}$ becomes

$$W_m^x(s) = \frac{\delta t}{\sqrt{s}} \sum_{n=0}^{N-1} x_n \phi^* \left((n-m) \frac{\delta t}{s} \right), \quad m = 0, 1, \ldots, N-1 \tag{3}$$

It is possible to calculate the wavelet transform using this formula for each value of s and m but we can also identify the computation for all the values of m simultaneously as a simple convolution of two sequences (Aguiar-Conraria *et al.*, 2008; Torrence and Compo, 1998). When applying the CWT to a finite length time series we inevitably suffer from border distortions, due to the fact that the values of the transform at the beginning and at the end of the series are always incorrectly computed, involving missing values of the series, which are then artificially prescribed. The region in which the transform suffers from these edge effects is called the cone of influence and results must be interpreted carefully there. Similar to Torrence and Compo (1998) and Aguiar-Conraria *et al.* (2008), the cone of influence will be defined here as the e-folding time of the wavelet at scale s, that is, so that the wavelet power of a Dirac δ at the edges decreases by a factor of e^{-2}. For the Morlet wavelet under analysis, this is given by $\sqrt{2s}$.

The wavelet power spectrum is just $|W_n^x|^2$. It characterizes the distribution of the energy (spectral density) of a time series across the two-dimensional time-scale plane, leading to a time-scale (or time-frequency) representation. The theoretical distribution of the local wavelet power spectrum is given in Torrence and Compo (1998) by

$$D\left(\frac{|W_n^x(s)|^2}{\sigma_x^2} < p \right) = \frac{1}{2} P_f \chi_v^2 \tag{4}$$

at each time n and scale s, where the value of P_f is the mean spectrum at the Fourier frequency f that corresponds to the wavelet scales $s\left(\approx 1/f\right)$ and v is equal to 1 or 2, for real or complex wavelets respectively.

The cross wavelet transform (XWT) of two time series x_n and y_n is defined as $W_n^{xy} = W_n^x W_n^{y*}$, where * denotes complex conjugation and W_n^x and W_y^n are the wavelet transforms of x and y respectively. Let us define the cross wavelet power as $|W^{xy}|$. The complex argument $\arg(W^{xy})$ can be interpreted as the local relative phase between x_n and y_n in time frequency space. The theoretical distribution of the cross wavelet power of two time series with background power spectra is given in Torrence and Compo (1998). Therefore, the wavelet power spectrum can be interpreted as depicting the local variance of a time series, while cross-wavelet power of two times series depicts the local covariance between these series at each scale or frequency.

The phase for wavelets shows any lag or lead relationships between components, and is defined as

$$\phi_{x,y} = \tan^{-1} \frac{I\{W_n^{xy}\}}{\mathbb{R}\{W_n^{xy}\}}, \quad \phi_{x,y} \in [-\pi, \pi] \tag{5}$$

where I and $\mathbb{R}$ are the imaginary and real parts, respectively, of the smooth power spectrum. Phase differences are useful to characterize phase relationships between two time series. A phase difference of zero indicates that the time series move together (analogous to positive covariance) at the specified frequency. If $\phi_{x,y} \in \left(0, \frac{\pi}{2}\right)$, then the series move in-phase, with the time-series y leading x. On the other hand, if

$\phi_{x,y} \in \left(-\frac{\pi}{2}, 0\right)$ then it is x that is leading. We have an anti-phase relation (analogous to negative covariance) if we have a phase difference of π (or $-\pi$), meaning $\phi_{x,y} \in \left(-\frac{\pi}{2}, \pi\right] \cup \left(-\pi, \frac{\pi}{2}\right]$. If $\phi_{x,y} \in \left(\frac{\pi}{2}, \pi\right)$ then x is leading, and the time series y is leading if $\phi_{x,y} \in \left(-\pi, -\frac{\pi}{2}\right)$.

Cross-wavelet power reveals areas with high common power. Another useful measure is how coherent the cross wavelet transform is in the time frequency space. Following Torrence and Compo (1998), we define the wavelet coherency of two time series as

$$R_n^2(s) = \frac{|S(s^{-1} W_n^{xy}(s))|^2}{S(s^{-1}|W_n^x(s)|^2).S(s^{-1}|W_n^y(s)|^2)} \tag{6}$$

where S is a smoothing operator in both time and scale, which can be written as a convolution in time and scale $S(W) = S_{\text{scale}}(S_{\text{time}}(W_n(s)))$ where S_{scale} denotes smoothing along the wavelet scale axis and S_{time} smoothing in time (Torrence and Compo, 1998). For the Morlet wavelet a suitable smoothing operator is given by $S_{\text{time}}(W)|_s = (W_n(s)^* c_1^{(-t^2/2s^2)})|_s$ and $S_{\text{scale}}(W)|_n = (W_n(s)^* c_2 \Pi(0, 6s))|_n$, where c_1 and c_2 are normalization constants and Π is the rectangle function. The factor of 0.6 is the empirically determined scale decorrelation length for the Morlet wavelet (Torrence and Compo, 1998). In practice both convolutions are done discretely and therefore the normalization coefficients are determined numerically.[7] The cross-wavelet coherence gives an indication of the correlation between rotary components that are rotating in the same direction as a function of time and periodicity. It can be defined as the ratio of the cross-spectrum to the product of the spectrum of each series, and can be thought of as the local correlation between two CWTs.

4. DATA DESCRIPTION AND IDENTIFICATION OF CRISIS

Daily prices of stock market indices, namely the FTSE100 of United Kingdom, the Bovespa of Brazil, the Nikkei225 of Japan and from the United States the Dow Jones Industrial Average30 (DJIA30), measured in domestic currencies,[8] are used. Stock price data were taken from Bloomberg, covering the period 1 October 1997 to 6 March 2009 that has been adjusted given data availability.

Time series plots of the stock indices under analysis[9] appear to display similar long-swing movements. The exception is the Bovespa index, which shows the most erratic behavior. These stock market indices are analyzed in levels, although there are several reasons to justify the use of returns instead of levels.[10] However, daily prices instead of returns are used since the main advantage of wavelet analysis is its ability to decompose time series, and data in general, into their time scale components. Due to the translation and scale properties, non-stationarity in the data is not a problem when using wavelets, and pre-filtering is not needed. Like the present work, Floros (2005) and Charles and Darné (2006) also use prices instead of returns.

Summary statistics for daily prices are presented in Table 1. In all cases, the excess kurtosis and skewness measures are indicative of evidence against the normal distribution, and time series plot also show the

Table 1. Descriptive statistics of daily prices for the stock market indices under analysis

Variable	FTSE100	DJIA30	Nikkei225	Bovespa
Obs.	2976	2976	2976	2976
Max	6930.20	14 164.50	20 833.20	73 517.00
Min	3287.00	6594.44	7162.90	4761.00
Mean	5413.32	10 358.61	13 575.05	24 771.26
Std.	845.15	1457.12	3145.27	16 631.80
Variance	714 285.10	2 123 185.21	9 892 746.33	276 616 738.33
Skewness	−0.3727	0.2319	−0.0420	1.0985
Kurtosis	0.1299	2.8237	1.9116	3.1074

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typical phenomena of volatility clustering in stock prices. We can also see that the Brazilian market shows the highest variability as measured by the standard deviation of prices. On the other hand, the FTSE100 market index (UK) displays less volatility than other markets, while it also exhibits less average daily prices. Such features are in accordance with the conventional wisdom of low risk and low return. Moreover, sample means of prices for all indices are positive. The negative (positive) values for skewness indicate that the series distributions are skewed to the left (right). Kurtosis values are smaller than three, except for Bovespa.

Table 2 presents the correlation matrix between all four stock market indices under analysis. As we can see, the European index is more correlated with the Japanese index and with the American one, having the smallest correlation with the Latin American index (Bovespa).

The DJIA index shows the lowest correlation with the Japanese index, and the Bovespa index shows the highest correlation with the other American index, the DJIA30. In summary, less developed markets show lowest correlation values with the most distant indices in geographical terms. Results for the simple cross-correlation analysis of stock index prices indicate that these stock markets do exhibit a significant degree of integration with each other in accordance with Sharkasi *et al.* (2005) and Rua and Nunes (2009).

As argued before, financial crisis also play an important role in stock market integration. The problem presented by periods of financial crisis is that the fundamental relationship linking asset returns appear to break down, both across national boundaries and across asset classes. This presents serious problems for portfolio management as existing diversification strategies can be undermined by changes in the correlation between assets, leaving portfolios exposed to international shocks. Typical examples of financial crisis where the crisis has spread across national boundaries and across asset classes are the East Asian crisis of 1997–1998; the Russian bond default of August 1998 and the Brazilian collapse; the American 2001 (terrorist attack) and 2002 (accounting scandals associated with the Enron bankruptcies and WorldCom fraud) crisis; the Dot-Com Bubble from 2000 to 2003; and the 2004 and 2055 terrorist attacks in Madrid and London, respectively. Our analysis ends with the 2007–2009 financial crises ('subprime crisis') that has been spread out to the world, resulting in bank collapses, and that together with high oil prices and high interest rates at the beginning of that period lead to stock market crashes worldwide, especially in Europe and Japan.[11]

The non-American crises are significant with respect to their extent. The indices in crisis markets in each case fell more than 40% during the turmoil. The two American crashes in 2001 and 2002 are included in line with Mishkin and White (2003) who found that the 2001–2002 crises was among the 15 biggest crashes in the US during the last century.

Charles and Darné (2006) investigate the effects of the terrorist attacks in US on September 11, 2001, on international stock markets. They examine 10 daily stock market indices using the outlier detection methodology, showing that international stock markets experienced large (permanent and temporary) shocks in response to the terrorist attacks and its aftermath. They found that US macroeconomic news announcements can have a great impact on the US and European stock markets by detecting large shocks. In a similar fashion, Awokuse *et al.* (2009) investigate the interdependence of Asian, Japan, US and UK markets using cointegration methods, finding evidence for an increase in international stock market integration as a result of the 1997 Asian Financial crisis.

The dates for the financial collapses in Russia and Brazil are based on Rigobon (2003). The initial shock to the Russian financial markets took place on August 6, 1998, and persisted till the end of September.

Table 2. Cross-correlation analysis among the stock market index prices under analysis

Variable	FTSE100	DJIA30	Nikkei225	Bovespa
FTSE100	1	0.666	0.891	0.286
DJIA30	0.666	1	0.517	0.741
Nikkei225	0.891	0.517	1	0.180
Bovespa	0.286	0.741	0.180	1

The Brazilian collapse, which has been often associated with contagion from the Russian crisis, lasted from October 1998 till March 1999, but the capital market suffered mostly during the period from the end of November 1998 to January 1999. These were preceded by the Kyoto Protocol.

The terrorist acts in New York and Washington took place on September 11, 2001 and WorldCom revealed its great accounting fraud on June 25, 2002. Nevertheless, the prolonged downturn of the US stock market was also heavily influenced by a slowdown of the American economy. Other crises episodes affecting stock markets, with more or less intensity, were the Iraq Invasion, the terrorist attacks of Madrid (2004) and London (2005), the Militant attacks in Nigeria, and the OPEC Cut Agreement.

The collapse of the housing market led to bank collapses in the US and Europe, causing the amount of available credit to be sharply curtailed, resulting in massive liquidity and solvency crises. In addition to high oil prices, stock markets crashed worldwide and a banking collapse took place in the United States.

5. EMPIRICAL RESULTS

As far as we know, until the present moment when wavelets were applied to the analysis of stock market indices, the use of the discrete wavelet transform or one of its variants dominated (Lee, 2004; Rua and Nunes, 2009; Sharkasi *et al*., 2005). Sometimes, the same type of analysis can be done more easily and in a straightforward manner using the continuous wavelet transform. Looking at Figure 1 one can immediately

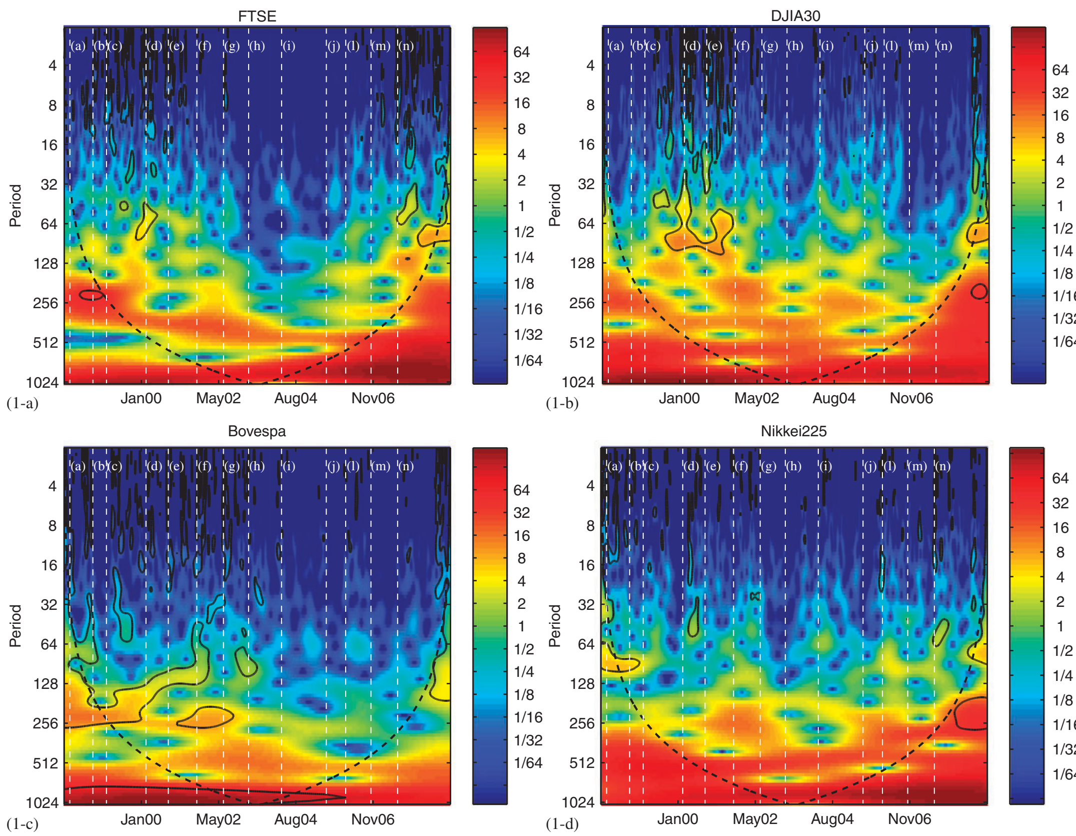

Figure 1. Wavelet power spectrum of stock market indices: (a) FTSE100, (b) DJIA30, (c) Bovespa and (d) Nikkei225, respectively, for the period October 1997 to March 2009. (a) Kyoto Protocol; (b) Russian Financial crisis; (c) Brazilian Currency Crises/Collapse; (d) Climax of the 'dot-com-bubble'; (e) US Elections; (f) Terrorist Attacks in the USA; (g) WorldCom Accounting Fraud; (h) Iraq Invasion; (i) Terrorist Attacks of Madrid; (j) Terrorist Attack in London; (l) Militant Attacks in Nigeria; (m) OPEC Cut Agreement; (n) Financial (Sub-prime) Crisis.

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infer the evolution of the variance for the four stock market indices under analysis at several time scales along the period 1997–2009 and extract most of the conclusions taken by the previously mentioned researchers.

Figure 1 shows the continuous wavelet power spectrum for the FTSE100, DJIA30, Bovespa and Nikkei225 stock market indices. In the wavelet power spectrum, the black contour in regions with energy indices designates the 5% significance level (95% confidence level) estimated from Monte Carlo simulations using phase randomized surrogate series, assuming the bottom red noise defined by the variance and the number of points of the original time series. The cone of influence, indicating the region affected by edge effects, is shown with a dotted line. The periods outside the cone of influence must be neglected since they do not possess statistical confidence. Finally, color code for power ranges from blue (low power) to red (high power).

Looking at the time scale decomposition of these variables, some interesting facts are revealed. Most of the actions in the indices occurred at high scales (low frequencies). There are no clear and general structural changes occurring for all the series at once in the years under analysis, since the red power is spread through all of them.

The wavelet power spectrum (WPS) of DJIA30 shows a small significant power event in the period from September 1999 to August 2001 in the daily time scale of 64–128 days. The WPS of the Bovespa index (1-c) shows an highly significant power event from the starting period through June 2005 in the 512–1024 days time-scale band. Given that this black contour relies outside the cone of influence results must be interpreted carefully. The WPS of Nikkei225 shows no significant high power event. However, once again, most of the actions in this index occurred at high scales (almost 3 years). Finally, the WPS for the FTSE100 index shows the action mostly occurred at high scales, but some happened also at the 128–256 days band in the period October 1997–September 1999 and May 2007–March 2009 that increased the index volatility.

It is clear that different time series have different characteristics in the time-frequency domain, but volatility for all of them is quite high at low frequencies and low at higher frequencies (mostly at periodicity until half an year). In the period of 2006–2009, probably as a consequence of the major financial crisis, the variance of the stock market indices became higher, where the effect is clearer at medium and high scales, suggesting we were facing medium to long-term shocks in stock market indices.

Figure 2 presents the estimated wavelet coherency and phase difference between the four indices. Values for significance were obtained from Monte Carlo simulations. Contours denote wavelet-squared coherency, the thick black contour is the 5% significance level and outside of the thin line is the boundary affected zone. In the cross-wavelet power pictures, color code for power ranges from blue (low coherency) to red (high coherency). Vectors indicate the phase difference between the two series.[12]

All pictures show the cross-coherency between two indices. The name of the index presented first is the first series, the other one being the second,[13] given that we need to know their order for the scheme to be valid.

Information on the phases shows us that the relationship among stock market indices was not homogeneous across scales, since arrows point right and left, down and up constantly. Moreover, the cross-wavelet coherency is high at low frequencies, but in the highest scale of all, most of the coherence results are not statistically significant since they rely below the cone of influence.

The wavelet cross-coherency shows low–to-medium statistically significant coherence, but we are still able to observe some islands of medium power, mostly during the 11th September 2001 terrorist attack and the 2007–2009 current financial crisis for most of the indices. For example, in the cross-coherency and phase plot between FTSE and Bovespa we are able to observe an island of high statistically significant power for the period October 1997 until January 2000. This suggests that both series were strongly correlated and in phase during the period of the Asian and Russian crisis, with the FTSE index leading Bovespa in the 128–260 days band, during about 1/8 of the period. During the terrorist attacks of Madrid (March 2004) and London (July 2005), FTSE still leads but at lower day frequencies (high scales). In higher frequencies (low scales), from 4 to 64 days, during the London terrorist attack FTSE and Bovespa were completely in phase (with arrows being straight lines and pointing right). We should also notice that during the 11th September terrorist attack at frequencies 32–128 days, FTSE and Bovespa were in phase with FTSE

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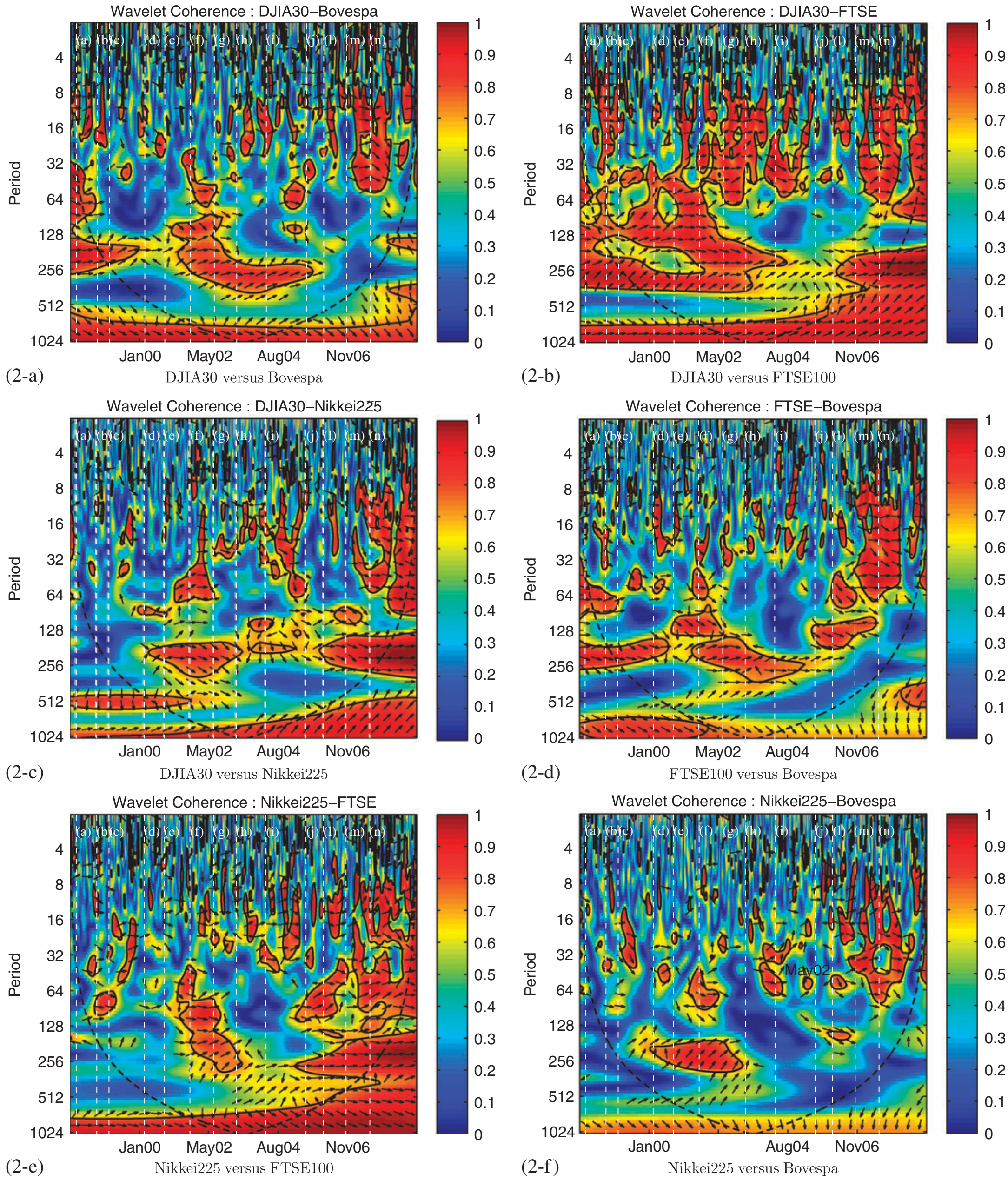

(2-a) DJIA30 versus Bovespa
(2-b) DJIA30 versus FTSE100
(2-c) DJIA30 versus Nikkei225
(2-d) FTSE100 versus Bovespa
(2-e) Nikkei225 versus FTSE100
(2-f) Nikkei225 versus Bovespa

Figure 2. Cross-wavelet coherency and phase plots between the DJIA30, Nikkei225, FTSE100 and Bovespa stock market indices for the period October 1997 to March 2009. (a) Kyoto Protocol; (b) Russian Financial crisis; (c) Brazilian Currency Crises/Collapse; (d) Climax of the 'dot-com-bubble'; (e) US Elections; (f) Terrorist Attacks in the USA; (g) WorldCom Accounting Fraud; (h) Iraq Invasion; (i) Terrorist Attacks of Madrid; (j) Terrorist Attack in London; (l) Militant Attacks in Nigeria; (m) OPEC Cut Agreement; (n) Financial (Sub-prime) Crisis.

leading, but during the several US scandals and the Dot-Com bubble at medium frequencies, FTSE was lagging.

On the daily time scales of 4–64 days band, the 5% significance regions indicate that stock market indices under analysis do not show long periods of high coherency until May 2007. The exception is given by DJIA30 and FTSE100 in the 8–64 period bands with both series in phase, but with DJIA30 leading and

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lagging in different time periods. Still, in most of the cases there is high coherency among the stock indices on the daily time scales bands of 128–1024 days.

Between August 2001 and June 2005 the relationship between DJIA and Bovespa was very strong. Phase information shows a phase relation with the DJIA30 index leading in the 32–64 bands, but lagging in the 128–256 bands in 1/8 of the period. Near May 2007, a quite different behavior with high correlation at the 8–64 period bands is observed, showing a quicker transmission of innovations through both markets. In April 2008 there was a statistically significant relation between Bovespa and DJIA in the 16–32 days band with indications of a perfect anti-phase relation, which matches with the US month declaration of recession. During the OPEC cut agreement period, we see the DJIA index lagging at low scales, but right after that, we see it leading Bovespa, FTSE and Nikkei, during the period of the ongoing financial (subprime) crises. In fact, looking at all the plots at once almost all series show cycles of high coherence during the terrorist attacks of USA and the World Com Accounting fraud (at medium and high scales), and during the OPEC Cut Agreement and the subprime crises period (at lower scales).

The cross-wavelet coherency for the other indices under analysis also shows some interesting behaviors, especially in the period May 2007 until March 2009. This is evidenced by the DJIA-Nikkei and DJIA-FTSE indices, where we see a phase relationship with DJIA leading in that period in the bands 8–64 and 128–256. The wavelet coherence plot between DJIA and FTSE reveals that both indices are strongly correlated and that both series commove a lot at either lower and higher scales with special periods of strong comovement.

During the cycles of November 2000 and September 2001, DJIA and FTSE show high coherency. During the collapse of the Dot-Com bubble and the accounting scandals in the US, who contributed to a relatively mild contraction in the North American Economy, we see DJIA lagging in the 16–32 days band, but leading on 1/16 of the period in the 32–64 days band. On the contrary, on those previously identified cycles corresponding to crisis periods, DJIA30 and Nikkei225 show a complete phase relationship, meaning that both markets move in the same direction at different time scales or frequencies.

FTSE and Nikkei and Nikkei and Bovespa show smaller cycles of high coherence, consistent with the results of Rua e Nunes (2009). Between August 2001 and July 2003, in the time frequency bands of 64–128 and 128–256 bands (medium scales) we see FTSE leading the Nikkei stock market. The highest coherent cycle between Nikkei and Bovespa occurred for the period January 2000 till January 2003, with Nikkei and Bovespa showing an anti-phase relationship, in the 128–256 band, with FTSE leading in 3/8 of the period in the beginning of the year 2000, but showing a phase relationship for both from that date until the end of the cycle.

During the Russian financial crisis that took place and the Brazilian collapse, a statistically significant contour is observed, for all pictures related to Bovespa, in the 16–32 period bands, with the greatest indices showing a phase leading relationship with Bovespa. The exception is for Dow Jones that for the 8–16 days period band shows a lagging behavior relative to Bovespa in 1/8 and 1/4 of the period.

From the above exposition there is a clear indication of a stronger coherence between the American, the European and Japanese markets, than with Japanese and European markets, which possess an even lower coherence with the Latin American market. So, geographically and economically closer countries exhibit higher levels of market linkages as suggested by Janakiramanan and Lamba (1998) and Ozdemir (2009).

Still, if long run adjustments were taken out, short-run movements would be little correlated. From this we can infer that country-specific phenomenons are not rapidly transmitted to other markets, where some show a clear delay in transmissions, as measured by the frequency bands. This was especially noted in the September 11, 2001 and Dot-Com Bubble events and since results indicate that most of the action in the indices occurred at high scales.

Empirical results obtained in this work are not completely in line with those previous empirical findings that innovations in US and UK stock markets are rapidly transmitted to other markets (Eun and Shim, 1989; Harju and Hussain, 2008). For this let us analyze carefully the relationships between the finest components in stock markets. Since these finest scales capture movements in 2–8 days (because the next finest scale has a fairly large portion of energy in stock price movements as evidenced by the cross-wavelet power and coherency), we may argue that only with a considerable time span (the lowest frequencies)

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spillovers are transmitted to other markets. These results contradict those obtained by Lee (2004) where he argues that the most important impact in spillovers will be captured by higher frequencies. Moreover, if we really have a time delay in spillovers across countries, this may induce arbitrage opportunities that will be taken into account by international investors. Given our results the importance of historical transmissions is low for the period under analysis at small scales[14] (1997–2009),[15] which is in accordance with the findings of Sharkasi *et al.* (2005) and Janakiramanan and Lamba (1998), who pointed out the fact that the importance of historical transmissions has decreased since the beginning of this century, with the latter pointing this result for the US market over the nineties. Still, the US market seems to dominate all the others, especially the European and the Latin American one's, both in the short and in the long run. This is even more evidenced from May 2007 onwards, which favors the geographically closer view of the market coherence previously analyzed.

The time variation pattern documented in this study may carry some important implications for international investments. The instability in various aspects of market comovements may imply serious limitations to the investor's ability to exploit potential benefits of international diversification (Panton *et al.*, 1976). In this context, this study's finding could provide an alternative explanation to the 'home bias' phenomenon in portfolio holding. While many factors may contribute to this home bias, results suggest that well-informed investors might notice significant instability in the co-movement structure over time and, thus, may not fully trust observed low correlations across markets at a particular point of time. Hence, it is plausible to assume that a rational investor might have pessimistic expectations of long-run gains from international diversification. Much variation in the contemporaneous relationships among stock prices may also highlight inadequacy in assuming (short-term) relationships in international equity markets, which might account for the difficulty in achieving profitable active trading.

6. CONCLUSION

It is of considerable interest to investors and financial market regulators to examine how vulnerable stock markets are to different financial shocks. We provide additional evidence on breaks in linkages between crisis capital markets. Continuous wavelet analysis can be a very useful technique for analyzing financial relations and it is better suited dealing with index market prices than the Fourier transform. The usefulness of wavelet analysis to financial contagion and comovement is illustrated, considering that international investors distinguish between short and long run relations. Continuous wavelet and cross-wavelet analysis have the ability to analyze transient dynamics for single time series, or for their association, allowing, thus, for a multivariate (bivariate) analysis.

Strong coherence among stock market indices is found and at high scales index prices show a strong and significant relation. However, through the phase analysis arrows point in all directions, meaning that even if the series were mostly in phase, the relationship was not homogeneous across scales and time.

Results point out that innovations in the US and UK stock markets are not rapidly transmitted to other markets, which may induce arbitrage opportunities. Moreover, business cycle periods, corresponding to historical financial crisis periods, were identified, where the series show higher coherence, but mostly at low frequencies, favoring the contagion hypothesis during these periods. Also, geographically and economically closer countries exhibit higher levels of market linkages, as suggested by previous authors, and the Japanese market, in general, presents a low comovement with the other countries considered. Finally, the importance of historical transmissions has decreased in the last decade, with the exception given for the period 2007–2009.

This work may also be extended in several ways. First, by using other stock market indices. Second, results presented here for the different stock market indices indicate cases of breaks in linkages, which may induce that some stock markets are independent of certain crisis or even benefit from crises elsewhere. The explanation of this phenomenon could be the flow of capital from the crisis market to the non-crisis market and further studies in this direction are certainly needed. Finally, the delay in responses found maybe an indication of arbitrage opportunities, a statement that deserves a more careful attention.

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NOTES

1. When markets share a single common stochastic trend, then these markets are perfectly correlated over long horizons and there are no gains to international diversification (what Floros, 2005 founds for mature markets).
2. Filters permit to capture specific components (trends, cycles, seasonalities) of the original series.
3. Spectral analysis can be used to identify and to quantify the different frequency components of a data series, possessing two main drawbacks: they impose strong restrictions on the processes underlying the dynamics of the series (like stationarity), and they lead to a pure frequency-domain representation of the data (losing all the information from the time domain representation).
4. The term wavelet refers to a small wave: small because the wavelet function is non-zero over a finite length of time (compactly supported) and wave because the function oscillates.
5. The phase of a given time series $x(t)$ is parameterized in radians, ranging from $-\pi$ to π. Moreover, to separate the phase and amplitude information of a time series it is important to make use of complex wavelets. Just like the Fourier transform, under some regularity conditions, we can reconstruct $x(t)$ from its continuous wavelet transform (Aguiar-Conraria *et al*., 2008; Torrence and Compo, 1998).
6. For more details on the Morlet wavelet see Torrence and Compo (1998) and Aguiar-Conraria *et al*. (2008).
7. Since theoretical distributions for wavelet coherency have not been derived yet, to assess the statistical significance of the estimated wavelet coherency, one has to rely on Monte Carlo simulation methods.
8. We use three highly developed markets and one less developed one to be able to infer about market discrepancies.
9. Plots will be provided upon request.
10. As each market uses its local currency for presenting index values, daily returns may be a better choice. Also because these stock markets are operating in different time zones with different holidays and trading day schedules as well as different opening and closing times. The trading hour of the four stock exchanges are not perfectly synchronized, though there are several overlapping hours in each trading day for the developed markets. The differences in closing times could cause sequential price responses to common information that could be mistaken for causal linkages. Nevertheless, we are mainly interested in long-term relations, which turn this type of impacts softer.
11. The August 2007 sub-prime crises has spread out to the interest rate, currency and commodities markets.
12. For a complete interpretation of phase difference it is suggested to read the works of Barbosa and Blitzkow (2008, pp. 28–29).
13. For example, in the cross-coherency picture between DJIA30-Bovespa, DJIA30 is the first series and Bovespa the second.
14. The small periods of strong comovement among the series has decreased through time.
15. Being the exception the last 3 years in our sample period.

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