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Is the global leadership of the US financial market over other financial markets shaken by 2007-2009 financial crisis? Evidence from Wavelet Analysis

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Abstract

The issue of market linkages (and price discovery) between stock indices and the lead-lag relationship are topics of interest to financial economists, financial managers and analysts. The lead-lag relationship analysis should take into account both the short and long-run investor. From a portfolio diversification perspective, the first type of investor is generally more interested in knowing the comovement of stock returns at higher frequencies, that is, short-run fluctuations, while the latter concentrates on the relationship at lower frequencies, that is, long-run fluctuations.

The study uses a technique known as the 'wavelet approach' which has been very recently imported to finance from engineering sciences. Daily return data covering the period from June 2005 to December 2011 for MSCI stock indices of East Asian countries (Japan, China, Korea, Taiwan and Hong Kong) are analyzed. We examine the following empirical question: Is the global leadership of the US financial market shaken by the 2007-2009 financial crisis in the short- and long run?

Our findings tend to, more or less, broadly suggest that regardless of the period considered, the US market is still the global leader in the exact time intervals. This is evidenced in the asymmetry of cross-correlation function of MSCI stock indices with the MSCI index of the US becoming more pronounced as the timescale increases. The evidence hitherto unexplored produced by the application of wavelet cross-correlation amongst the selected stock indices provides robust and very useful information to international financial analysts and short-term investors.

Key words: Lead-lag, Causality, Wavelet, Stock index, Financial crisis

1. Introduction

The lead-lag causal relationship between stock indices reflects how fast each index reacts to information and how well their comovement is. If one index reacts faster to the market information than the other index, there will be a lead-lag relationship that is expected to be observed in data. In other words, the lead-lag relationship between stock indices demonstrates how well two markets are connected, and how fast one market reacts to new information from the other (Floros and Vougas, 2007). In other words, we try to understand the information flow between the two stock indices and their causal direction.

Lo and MacKinlay (1990) argued that the lead-lag effect from large-firm portfolio returns to small firm portfolio returns may be the result in information flowing first to the prices of large market value securities and then to small market value securities. That is, lagged returns of large-firm portfolios are positively cross-correlated with the returns of small-firm portfolios. An important contribution derived from Lo and MacKinlay's findings is that the short-run predictability of portfolios returns, for example, returns of large-firm portfolios can be used to predict reliable returns of small-firm portfolios in the short-run. Other than that, Campbell (1997) found that "portfolios comprising large market capitalization stocks tend to lead the corresponding small market capitalization portfolios". Huth and Abergel (2014), by analyzing tick-by-tick data confirmed the intuition that "the most liquid assets (short inter-trade duration, narrow bid/ask spread, small volatility, high turnover) tend to lead smaller stocks". These lead/lag relationships become more and more pronounced as they zoom in on significant events.

Published articles examined the lead-lag relationship in the returns of the stock markets in the greater China region as well as relationships with the US and Japan. Huang et al (2008) found that there was no cointegration between the US, Japan, and markets in the greater China region. As Ghosh et al. (1999), Masih and Masih (2001) show that Japan is a regional market leader, yet other researchers (Yang et al., 2003) have found that Japan does not play a pivotal role in non-crisis periods. Masih and Masih (2001) examined the dynamic causal linkages among nine major international stock indices. One of the interesting statistical findings is the growing role of the Japanese market as a long-term leader in influencing the propagation mechanism driving international stock market linkages, including the emerging Asian stock markets. More recently, Eric (2008) found that the U.K. stock market returns appear to predict (lead) U.S. stock market returns.

More importantly, the lead-lag relationships have been analyzed between many financial markets in previous studies, in terms of methodology, these studies apply multivariate statistical approaches, for example, vector autoregressive (Lee, 1992; Gjerde and Saettem, 1999; Rapach, 2001) and vector error correction (Cheung and Ng, 1998; Nasseh and Strauss, 2000, Masih and Masih, 1997, 1999, 2001) models. These studies just examine the interactions between the stock market and aggregate economic activity, explore either their short-run or long-run relationships, as the time series methodologies employed (usually cointegration analysis with acknowledgment of the non-stationary property of stock prices) may separate out just two time periods in economic time series, i.e. the short-run and the long-run (Gallegati, 2010). However, we do not know how short is short and how long is long. Additionally, the stock market is an example of a market in which diverse investors are making decisions over different time periods, for example,

from minutes to years and operating at each moment on different time intervals (from hedging to investment activity).

Therefore, this lead-lag relationship analysis should take into account both the short and long-run investor (see, for example, Candelon et al., 2008, Gallegati, 2010). From a portfolio diversification perspective, the first type of investor is generally more interested in knowing the comovement of stock returns at higher frequencies, that is, short-run fluctuations, while the latter concentrates on the relationship at lower frequencies, that is, long-run fluctuations (Rua and Nunes, 2009). The lead-lag relationship between stock indices demonstrates how well two markets are connected, and how fast one market reacts to new information from the other (Floros and Vougas, 2007). If two markets are related and a feedback exists, then there is a probability that investors or traders may use past information to forecast prices (or returns) in the future. Hence, one has to rely on the frequency domain analysis to achieve insights about the comovement at the frequency level (see, for example, A'Hearn and Woitek, 2001 and Pakko, 2004). One should remember that, notwithstanding its recognized interest, analysis in the frequency domain is much less found in financial empirical literature (see, for example, Smith, 2001). By this logic, the nature of the relationships among stock markets may vary across time scales or frequencies according to the investment horizon of the traders and investors as small time scales may be associated with hedging activity and large time scales to investment activity. So we cannot ignore distinction between short and long-term investors at different time scales or frequencies.

No one can deny that this recent financial crisis was one of the most unpredicted economic events in the recent history, particularly the severity with which it melted markets and economies around the world. There were two waves of crises. Firstly, countrywide $11.5 billion drew from credit lines by commercial banks and Bank of America topped $2 billion of equity capital up into countrywide by August 2007 (Guo et al. 2011). Such events resulted in a widespread loss of confidence in the banking system in the mind of investors. A prediction from December 2007 stated that "subprime borrowers will probably default on 220 billion-450 billion of mortgages[1]". Consequently, another round of credit crisis resulted, due to tightened lending standards of banks. The crash reached a crucial point in September 2008 when the Federal Housing Finance Agency placed Fannie Mae and Freddie Mac in government conservatorship, Bank of America bought Merrill Lynch, Lehman Brothers filed for Chapter 11 protection, and the American International Group borrowed $85 billion from the Federal Reserve Board. Financial organizations and companies hastened to deleverage to minimize their risk exposures; therefore, selling massive assets at discounted rates.

Is the 2007-2009 financial crisis likely to diminish the status of the United States as the world's economic leader? Was the leadership of the US financial market over other financial markets shaken by this financial crisis?

We are going to look at the evolution of lead-lag relationship between East Asian stock indices and US stock index in pre-crisis and post-crisis periods at different time intervals. In other words, how the lead-lag causal relationship evolved before and after the 2007-2009 financial crisis.

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[1] See Economist, Dec 19 2007.

In such a context, we investigate the stock indices causality among the East Asian economies with the US economy through a novel approach known as wavelet analysis. This analysis is a very helpful technique since it represents a refinement in terms of analysis in both time and frequency domains (Rua and Nunes, 2009). Even though wavelets are very popular in some fields such as meteorology, physics, signal and image processing, etc, such a technique can also offer useful insights about several economic phenomena (see, for example, Ramsey and Zhang, 1996, 1997). According to literature, as a pioneer study Ramsey and Lampart (1998a, b) used wavelets to investigate the relationship between several macroeconomic variables. In particular, the wavelet approach provides a framework to measure comovement in the time–frequency space.

The main advantage of wavelet analysis is that it is able to decompose macroeconomic time series, and data in general, into their time scale or frequency components. Some applications of wavelet analysis in economics and finance have been supported by Ramsey and Lampart (1998a, b), Ramsey (2002) and Duchesne (2006), Gallegati (2008, 2010), Aguiar-Conraria and Soares (2008), Vacha and Barunik (2012), Madaleno and Pinho (2012) among others. However, less effort has been made to employ this technique in the analysis of the relationship between stock returns and overall economic activity. In their paper Kim and In (2003) analyzed the lead/lag relationship between financial variables and real economic activity using the Granger causality test on wavelet details and signals. Gallegati (2008) investigated the relationship between stock market returns and economic activity by employing signal decomposition techniques which were based on wavelet analysis. The wavelet cross-correlation employed to examine the lead/lag relationship between them at various time scales found that stock market returns tend to lead economic activity. In this study, we follow Gallegati's methodology (2008) to investigate the lead/lag relationship between stock returns by applying wavelet cross-correlation technique to wavelet coefficients.

2. Literature Review

Causal linkages among stock markets have crucial implications in security pricing, hedging and trading strategies, and financial market regulations (Ozdemir, et al., 2009). Furthermore, these linkages imply that stock prices of a country contain the information to estimate the stock prices of another country. In this context, casualty between the stock market of US, being the leading economy of the world, and those of other countries such as Far East, is of significance in that it has the information to forecast the stock prices of other countries.

Stock markets which are cointegrated display stable long-term behavior, and sudden shocks to the stock prices are short-lived rather than permanent. In the short-term, stock prices across markets may deviate from each other; however, the stock prices, due to market forces, investors' tastes and preferences, and government regulations will return to their long-run equilibrium.

While most studies examine changes in cross-market interdependencies, there are a few studies that investigate changes in the existence and direction of causality. Some previous researchers have found that international stock markets have causalities. Hamao and Masulis (1990), King and Wadhwani (1990), Kasa (1992), and Arshanapalli and Doukas (1993) have reached a conclusion that the stock markets of the developed countries are integrated and also the US

market dominates other developed markets such as Japanese and European markets. Kasa (1992) found evidence of a single stochastic trend underlying the equity markets of the selected countries, and point estimates of factor loadings which indicate this trend is most important in the Japanese market and least important in the Canadian market. By the same token, developed markets lead emerging markets (e.g. Najand, 1996), and there are causal linkages among emerging markets (e.g. Chen et al., 2002). Additionally, Cheung and Mak (1992), Liu and Pan (1997) and Wu and Su (1998) have found that both the US and Japanese stock markets lead the stock markets of the Asian countries. Masih and Masih (1997) have investigated long-run relationships and short-term dynamic causal linkages among major developed markets and the NIC stock markets, and arrived at a conclusion that all established markets drive the fluctuations of the NIC stock markets. As Ghosh et al. (1999), Masih and Masih (2001) have investigated that Japan is a market leader, other researches (Yang et al., 2003) found that Japan does not play a pivotal role in non-crisis periods. A few other studies have shown that Hong Kong particularly is the most dominant stock market in Asia (e.g., Masih and Masih, 1999; Dekker et al., 2001). Similarly, Cha and Oh (2000) have concluded that the US and Japanese markets have important effects on the stock markets of Hong Kong, Korea, Singapore and Taiwan. Berument and Ince (2005) and Berument et al. (2006) have traced the pattern of the effects of the S&P 500 on 15 emerging markets based on the geographical location of these markets.

In yet other studies, it is, however, shown that there are no linkages between or among some markets. Masih and Masih (1997, 1999) have provided the cointegration relation among the stock markets of Thailand, Malaysia, the US, the UK, Japan, Hong Kong and Singapore for the pre-financial crisis period of October 1987. However, they did not find any long-term relationships between these markets for the after-financial crisis period of October 1987. By the same token, Felix et al. (1998) have found no long-run comovement between the US and a number of emerging markets. In the same way, Byers and Peel (1993) have concluded that there is no linkage between the markets of US and Europe. Similarly, Ghosh et al. (1999) did not find any evidence of Japan and the US, on the stock markets of Taiwan and Thailand. Phylaktis and Ravazzolo (2005) too, did not find any support for dynamic interconnections among the equity markets of Pacific-Basin countries (Hong Kong, South Korea, Malaysia, Singapore, Taiwan, and Thailand) and the industrialized countries of Japan and US for the 1980–1998 periods.

Even though lead-lag relationships have been analyzed between many financial markets in previous studies, this analysis should distinguish between the short and long-run investor (see, for example, Candelon et al., 2008, Gallegati, 2008). From a portfolio diversification perspective, the first type of investor is generally more interested in knowing the comovement of stock returns at higher frequencies, that is, short-run fluctuations, while the latter concentrates on the relationship at lower frequencies, that is, long-run fluctuations. The lead-lag relationship between stock indices demonstrates how well two markets are connected, and how fast one market transmits new information from the other (Floros and Vougas, 2007). If two markets are related and a feedback exists, then there is the probability that investors or traders may use past information to forecast prices (or returns) in the future. Hence, one has to rely on frequency domain analysis to achieve insights about the comovement at the frequency level (see, for example, A'Hearn and Woitek, 2001 and Pakko, 2004). One should remember that, notwithstanding its recognized interest, analysis of the frequency domain is much less found in financial empirical literature (see, for example, Smith, 2001).

These earlier empirical studies employ multivariate statistical approaches such as vector autoregressive (Lee, 1992; Gjerde and Saettem, 1999; Rapach, 2001) and vector error correction (Cheung and Ng, 1998; Nasseh and Strauss, 2000, Masih and Masih, 1997, 1999, 2001) models. In many cases, the time series methodologies employed (usually cointegration analysis) may separate out just two time periods in economic time series, i.e. the short-run and the long-run (Gallegati, 2008). However, the stock market is an example of a market which involves diverse investors making decisions over different time periods, for example, from minutes to years and operating at each moment on different time scales (from hedging to investment activity). By this logic, the nature of the relationship among the stock markets may vary across time scales according to the investment horizon of the traders and investors as lower time scales may be associated with hedging activity and higher time scales with investment activity. So we cannot ignore the distinction between short and long-term investors.

3. Methodology

In this section, we propose the techniques which identifies the dynamic linkages (in terms of lead-lag relationships) of a basket of stock indices representing MSCI stock indices in order to assess what effect the 2007-2009 subprime crisis had on the transmission mechanism. The issue of market linkages (and price discovery) between stock indices and the lead-lag relationship are topics of interest to financial economists, financial managers and analysts. The speed of information processing as well as the lead-lag relationship between price movements of stock indices illustrates how well stock markets are linked together.

Several applications of wavelet analysis in economics and finance have been provided by Ramsey and Lampart (1998a, b), Ramsey (2002) and Duchesne (2006), Gallegati (2008, 2010), Aguiar-Conraria and Soares (2011), Vacha and Barunik (2012), Madaleno and Pinho (2012), among others, but only one study has been made to employ this methodology to the examination of the relationship between stock returns and overall economic activity (Kim and In, 2003). They analyzed the causality between financial variables and real economic activity by utilizing the Granger causality test on wavelet details and signals.

In this research, in order to identify the lead-lag relationship between the stock indices, we have applied a methodology called the wavelet-cross-correlation. In doing this, we follow Gallegati's (2008) methodology and analyze the lead/lag relationship between stock returns.

3.1 Wavelet-cross-correlation

One of the most important properties of wavelet analysis of economic and financial data that, this method can decompose the time series data into several components associated with different scales of resolution (Gallegati, 2010). Any function $f(t)$ in $L^2(R)$ can be symbolized by the following wavelet series expansion:

$$f\ t = \ \ \ \ \ \upsilon_{J,k}\,\phi_{J,k}\ t + \ \ \ \ \ \omega_{J,k}\,\psi_{J,k}\ t + \ \ \ \ \ \omega_{j,k}\,\psi_{j,k}\ t + \cdots + \ \ \ \ \ \omega_{1,k}\,\psi_{1,k}\ t \qquad (1)$$

$k \qquad k \qquad k \qquad k$

Where the coefficients $\upsilon_{J,k} = {}_{k}\phi_{J,k} f\ \ t$ and $\omega_{j,k} = {}_{k}\psi_{j,k} f\ \ t$ denote the underlying smooth behavior of the economic or financial data at the coarsest scale (the scaling coefficients) and the coarse-scale deviations from it (the wavelet coefficients), correspondingly, and where$\phi_{J,k}$,$\psi_{j,k}$ are the so-called scaling and according to Gallegati (2010), the wavelet functions must fulfill the following conditions:

$$\phi_{J,k}\ \ t\ \ \phi_{J,k^*}\ \ t\ \ dt = \delta_{k,k^*},$$

$$\psi_{j,k}\ \ t\ \ \psi_{j^*,k^*}\ \ t\ \ dt = \delta_{j,j^*}\delta_{k,k^*},$$

$$\psi_{j,k}\ \ t\ \ \phi_{j,k^*}\ \ t\ \ dt = 0,\ \ \forall j,k,$$

Where$\delta_{j,k}$ is the Kronecker delta. The scaling function is known as the "father wavelet", it can be defined as:

$$\phi_{J,k}\ \ t\ \ = 2^{-\frac{J}{2}}\phi(\frac{t-2^J k}{2^J})$$

and the wavelet function is known as the "mother wavelet", which can be represent as:

$$\psi_{j,k}\ \ t\ \ = 2^{-\frac{j}{2}}\psi(\frac{t-2^j k}{2^j})$$

The wavelet function in Eq. (1) depends on two parameters such as scale (or frequency) and time: the scale factor *j* controls the length of the wavelet (window), while parameter *k* refers to the location and indicates the non-zero portion of each wavelet basis vector. Based on the scale parameter the wavelet function is stretched (or compressed) to obtain frequency information (a wide window yields information on low-frequency movements, while a narrow window yields information on high-frequency movements), and in order to get time information from the signal in question, it moves on the time line (from the beginning to the end).

The scaling function integrates to 1 and reconstructs the smooth and low-frequency parts of a signal. However, the wavelet function integrates to 0 and describes the detailed and high-frequency parts of a signal (Gallegati, 2010). In this way, it can be provided a complete reconstruction of the signal partitioned into a set of *J* frequency components by applying a *J-level* multi-resolution decomposition analysis so that each component relates to a particular range of frequencies.

On the top of multi-resolution decomposition analysis, wavelet methods also can offer a different or an alternative illustration of the variability and association structure of certain stochastic processes on a scale-by-scale basis (Gallegati, 2008). Given a stationary stochastic process {X}

with variance σ_X^2 and the wavelet variance definition at scale j as $\sigma_{X,j}^2$, the following relationship can be hold:

$$\sigma_{X,j}^2 = \sigma_X^2$$

Thus, as $\sigma_{X,j}^2$ denotes the contribution of the changes at scale j to the overall variability of the process, this relationship means that wavelet variance can provide a precise decomposition of the variance of an economic or financial time series data into components that associate with different time scales. The wavelet variance decomposes the variance of a stationary process with respect to the scale at *jth* level just as the spectral density decomposes the variance of the original series with respect to frequency *f,* that is

$$\sigma_{X,j}^2 = \sigma_X^2 = S_X \; f \; df,$$

where S(.) is the spectral density function (Gallegati, 2008).

By definition the (time independent) wavelet variance at scale j , $\sigma_{X,j}^2$, is given by the variance of *j-level* wavelet coefficients:

$$\sigma_{X,j}^2 = var \;\; \omega_{j,t} \; .$$

A time-independent wavelet variance may be defined not only for stationary processes, but also for non-stationary processes but with stationary *dth* order differences, and for non-stationary processes but with local stationarity (see Percival and Walden, 2000 and Gellagati, 2008). Indeed, as the wavelet filter $\{h_l\}$denotes the difference between two generalized averages and is related to a difference operator (Whitcher et al., 1999), wavelet variance is also time-independent in case of non-stationary processes, but with stationary *dth* order differences, provided that the length L of the wavelet filter is large enough. Percival and Walden (2000) and Gallegati (2008) show that L≥d is an adequate condition to create the wavelet coefficients $\omega_{j,t}$ of a stochastic process whose *dth* order backward difference is stationary a sample of stationary wavelet coefficients.

As MODWT need to employ circular convolution, the coefficients generated by both the beginning and ending data could be spurious (Gallagati, 2008). Thus, if the length of the filter is L, there are $(2^j - 1)(L-1)$ coefficients affected for 2^{j-1}scale wavelet and scaling coefficients (Percival and Walden, 2000 and Gallagati, 2008). As shown in Percival (1995), provided that $N - L_j \geq 0$, an unbiased estimator of the wavelet variance based on the MODWT may be obtained after removing all coefficients affected by the periodic boundary conditions using

$$\sigma_{X,j}^2 = \frac{1}{N_j} \sum_{t=L_J}^{N} \omega_{j,t}^2$$

Where N_j = N − L_j +1 is the number of maximal overlap coefficients at scale j and L_j = (2_j −1)(L−1) +1 is the length of the wavelet filter for level j. Thus, the *jth* scale wavelet variance is simply the variance of the non-boundary or interior wavelet coefficients at that level (Percival, 1995; Serroukh et al., 2000). Both DWT and MODWT can decompose the sample variance of a time series on a scale-by-scale basis via its squared wavelet coefficients, but the MODWT-based estimator has been shown to be superior to the DWT-based estimator (Percival, 1995 and Gallegati, 2008).

Whitcher et al. (1999, 2000) extended the notion of wavelet variance for the maximal overlap DWT (MODWT) and introduced the definition of wavelet covariance and wavelet correlation between the two processes, along with their estimators and approximate confidence intervals. To determine the magnitude of the association between two series of observations X and Y on a scale-by-scale basis the notion of wavelet covariance has to be used. Following Gençay et al. (2001) and Gallegati (2008) the wavelet covariance at wavelet scale j may be defined as the covariance between scale j wavelet coefficients of X and Y, that is $\gamma_{XY,j} = Cov[\omega_{j,t}^X \omega_{j,t}^Y]$.

An unbiased estimator of the wavelet covariance using maximal overlap discrete wavelet transform (MODWT) may be given by in the following equation after removing all wavelet coefficients affected by boundary conditions (Gallagati, 2008),

$$\gamma_{XY,j} = \frac{1}{N_j} N - 1 \sum_{t=L_{J-1}}^{N-1} \omega_{j,t}^X \omega_{j,t}^Y$$

Then, the MODWT estimator of the wavelet cross-correlation coefficients for scale j and lag τ may be achieved by making use of the wavelet cross-covariance, $\gamma_{\tau,XY,j}$, and the square root of their wavelet variances $\sigma_{X,j}$and $\sigma_{Y,j}$ as follows:

$$\rho_{\tau,XY,j} = \frac{\gamma_{\tau,XY,j}}{\sigma_{X,j}\sigma_{Y,j}}$$

The wavelet cross-correlation coefficients $\rho_{\tau,XY,j}$, similar to other usual unconditional cross-correlation coefficients, are between 0 and 1 and offers the lead/lag relationships between the two processes on a scale-by-scale basis.

Starting from spectrum $S_{\omega\, X,j}$ of scale j wavelet coefficients, it is possible that to determine the asymptotic variance V_j of the MODWT-based estimator of the wavelet variance (covariance). After that, we construct a random interval which forms a 100(1 − 2p)% confidence interval. The formulas for an approximate 100(1 − 2p)% confidence intervals MODWT estimator robust to non-Gaussianity for $\upsilon_{X,j}^2$ are provided in Gençay et al. (2002) and Gallegati (2008). According to empirical evidence from the wavelet variance, it suggests that N_j = 128 is a large enough number

of wavelet coefficients for the large sample theory to be a good approximation (Whitcher et al., 2000 and Gallegati, 2008).

4. Data and Empirical Results

We use close-to-close daily return data in USD currency for MSCI stock indices in East Asian countries (Japan, China, Korea, Hong Kong, Taiwan), plus the MSCI index of US. Data are sourced from Datastream and cover the period, June 2005 to December 2011. These stock indices are transformed to compounded stock market returns by calculating the natural logarithmic differences of the daily stock prices, that is, rt = $\ln(\frac{p_t}{p_{t-1}})$, where P_t and P_{t-1} represent the stock price index at time t and $t-1$, respectively. Consistent with other researchers (Kasa, 1992; King et al., 1997, Masih and Masih, 2001), the raw index values and returns have been transformed to reflect real US dollars in order to adopt the perspective of the US investor.

We have split the data into three periods such as before the first wave of subprime crisis [sample: 1 July 2006 – 31 July 2007], after the first wave of crisis and before the second wave of crisis [sample: 1 June 2007 – 12 September 2008] and after the second wave of crisis [sample: 15 September 2008 – 31 December 2009]. Since we need to have roughly the same number of observations in each of the sub-samples to be able to compare the same wavelet timescales, the second sample is overlapped with the first sample by two months and we take the third sample only until 31 December 2009. We examine the lead-lag relationship for all periods of MSCI stock indices ;

Table 1: Number of observations for each data period

Periods	No. of Observations
Before the first wave of crisis	282
After the first wave of crisis and before the second wave of crisis	336
After the second wave of crisis	339

Note: The empirical evidence from the wavelet variance suggests that $N_j = 128$ is a large enough number of wavelet coefficients for the large sample theory to be a good approximation (Whitcher et al., 2000).

First wave of crisis: In many crises, key financial or economic events can be associated with the outbreak of a crisis (e.g., the stock market crash in October 1987, the collapse of LTCM in 1998, or the bankruptcy of Lehman Brothers in 2008). In contrast, the end of a crisis period is generally not marked by a specific event. First wave of crisis refers to the occurrence of the US mortgage bubble which was dated 1 August 2007.

Second wave of crisis: This crisis refers to 15 September 2008 which had a more severe impact on the global economy. This crisis is associated with the collapse of Lehman Brothers.

4.1 The Wavelet Cross-Correlations between the MSCI indices with the US MSCI Index

In Figures 1-5, we report the MODWT-based wavelet cross-correlation between the other MSCI stock indices and the MSCI stock index of the US at all periods - on the three sub-samples, with the corresponding approximate confidence intervals, against time leads and lags for all scales, where each scale is associated with a particular time period. The individual cross-correlation functions correspond to – from bottom to top - wavelet scales $\lambda_1, \dots, \lambda_5$ which are associated with changes of 1-2, 2-4, 4-8, 8-16, 16-32 days. The red lines bound approximately 95% confidence interval for the wavelet cross-correlation. Breakpoints have occurred due to the outbreak of the US mortgage bubble and the collapse of Lehman Brothers; therefore, we have separated the original sample into these periods: (a) during the period [1 July 2006 – 31 July 2007], (b) during the period [1 June 2007 – 12 September 2008] and (c) during the period [15 September 2008 – 31 December 2009]. If the curve is significant on the right side of the graph, it means that the US MSCI index is leading other MSCI indices. If the curve is significant on the left side of the graph, it is the opposite. In other words, the wavelet cross-correlation skewed to the right means the US MSCI index is leading other MSCI indices ; skewed to the left, it is the opposite. If both the 95% confidence levels are above the horizontal axes, it is considered as significant positive wavelet cross-correlation; if the both 95% confidence levels are below the horizontal axes, it is considered as significant negative wavelet cross-correlation.

Figures 1 and 2 present the wavelet cross-correlations of the China and Japan MSCI stock indices with the US MSCI stock index in the three sub-samples, respectively. From these Figures, we can observe the following:

i) At the first wavelet level, we can observe some clear differences between the three periods: periods (a) and (b) show only one significant correlation on the right side of the graph. However, period (c) displays lower correlations, and many significant events on the right side of the graph. It implies that the US MSCI index leads both China and Japan MSCI indices.

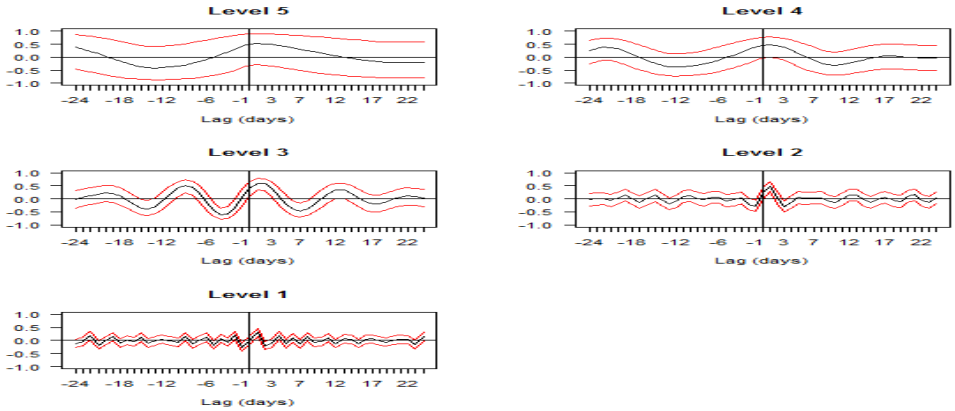
ii) At the second and third wavelet levels, the lead-lag relationships are very clear. The wavelet cross-correlations skewed to the right, means that the US MSCI index leads both China and Japan MSCI indices.

iii) At the fourth and fifth wavelet levels, a clear difference emerges from the three periods. Periods (b) and (c) show a significant positive correlation on the right side of the graph of both countries. In other words, the wavelet cross-correlations skewed to the right, implies that the US MSCI index leads both China and Japan MSCI indices. However, period (a) shows almost no significant event on both sides of the graph, hence we cannot find any evidence for the lead-lag role of the US MSCI index in period (a) in the case of both countries.

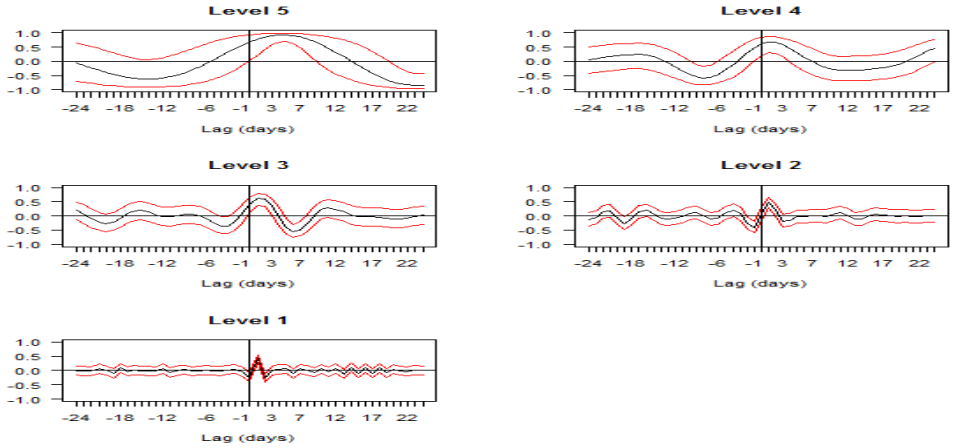
Based on the study of Naccache (2011), the magnitude of the cross-correlation between MSCI stock price and oil price increases with the wavelet level. They observe many significant events in the first three levels, where the correlation is either positive or negative on both sides of the graph. However, at the fourth and fifth levels, they found that the oil price is not leading the stock price anymore. The only significant events that they found happen on the right side of the graph, which implies that only the stock price is leading the oil price. Moreover, the correlation of these significant events is positive.

Figure 1: Wavelet cross-correlation between the China MSCI stock index and the US MSCI stock index.

a)



b)



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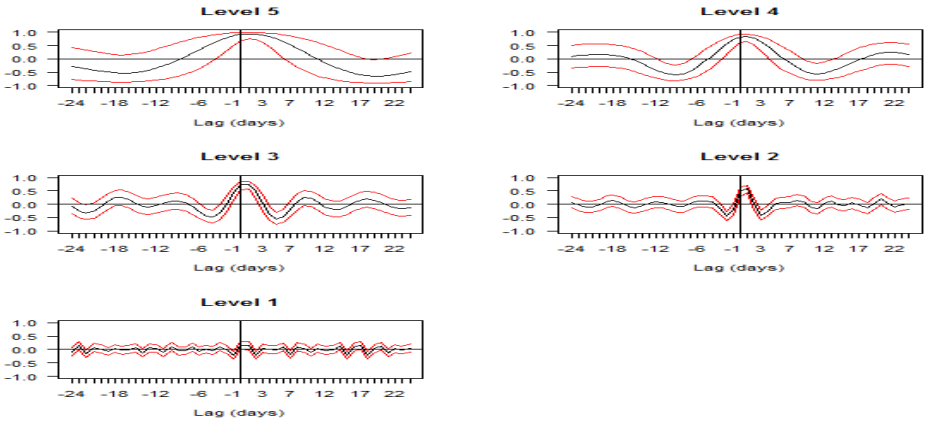
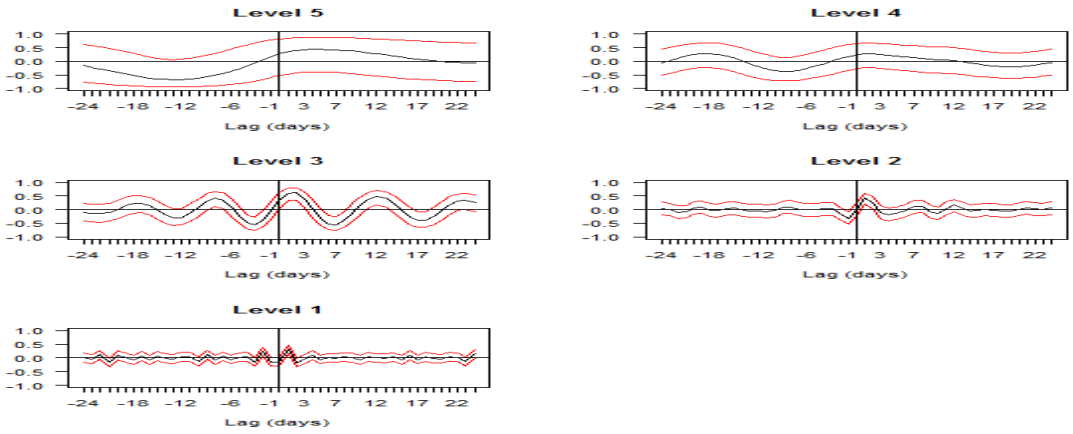
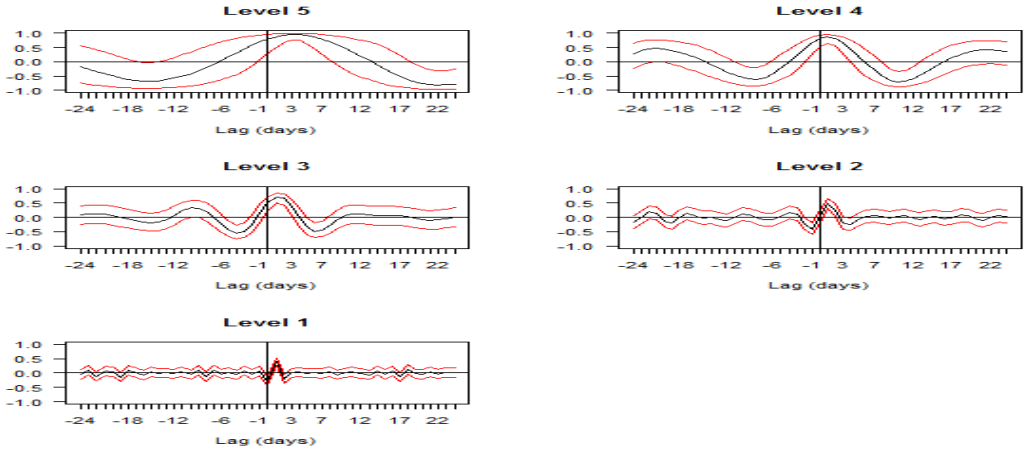


Figure 2: Wavelet cross-correlation between the Japan MSCI stock index and the US MSCI stock index.

a)



b)



c)

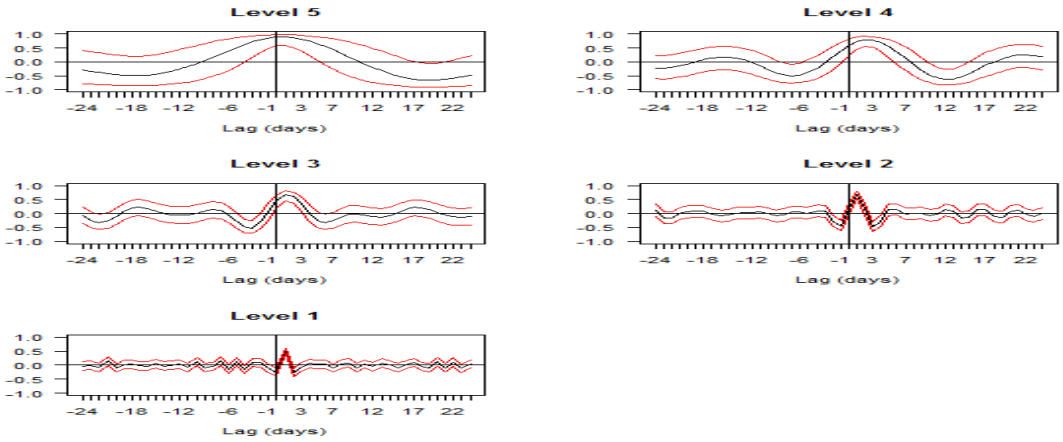


Figure 3 presents the wavelet cross-correlations between the Korea MSCI stock index and the US MSCI stock index in the three sub-samples.

i) At the first wavelet level, we can observe some differences between the three periods: period (a) show one significant positive correlation on the right side of the graph. Period (b) shows two significant correlations, one of them is positive and another one is negative; However, period (c) displays one significant events on the right side of the graph roughly at k = +15. All these results show that the US MSCI index leads the Korea MSCI index at first scale which is associated with 1-2 days.

ii) As far as the second and third wavelet levels are concerned, similar to Figures 1 and 2, the lead-lag relationship between these two stocks is very clear. The wavelet cross-correlation skewed to the right means that the US MSCI index leads the Korea MSCI index.

iii) At the fourth wavelet level, period (a) does not display any significant correlations on both sides of the graph. However, periods (b) and (c) display some significant events on right side of the graph, the wavelet cross-correlation is skewed to the right which implies that US MSCI index leads Korea MSCI index.

iv) At the fifth wavelet level, periods (a) and (b) show significant positive correlations on the right side of the graph. In other words, the wavelet cross-correlation skewed to the right means that the US MSCI index leads the Korea MSCI index. However, in the case of period (c), the situation is reversed; it shows the wavelet cross-correlation is slightly skewed to left, hence we cannot find any evidence for the leading role of the US MSCI index in period (c).

Figure 4 presents the wavelet cross-correlations between the Taiwan MSCI stock index and the US MSCI stock index in the three sub-samples.

i) At the first, second and third wavelet levels, we observe that the wavelet cross-correlations appear to be asymmetric about zero lag and there are some significant events on the right hand side of the graph. This means that the volatility of the US MSCI stock index is leading the volatility of the Taiwan MSCI stock index.

ii) At the fourth wavelet level, period (a) does not display any significant correlation on both sides of the graph. However, periods (b) and (c) display some significant events on right side of the graph; the wavelet cross-correlations skewed to right implies that the US MSCI index leads the Taiwan MSCI index.

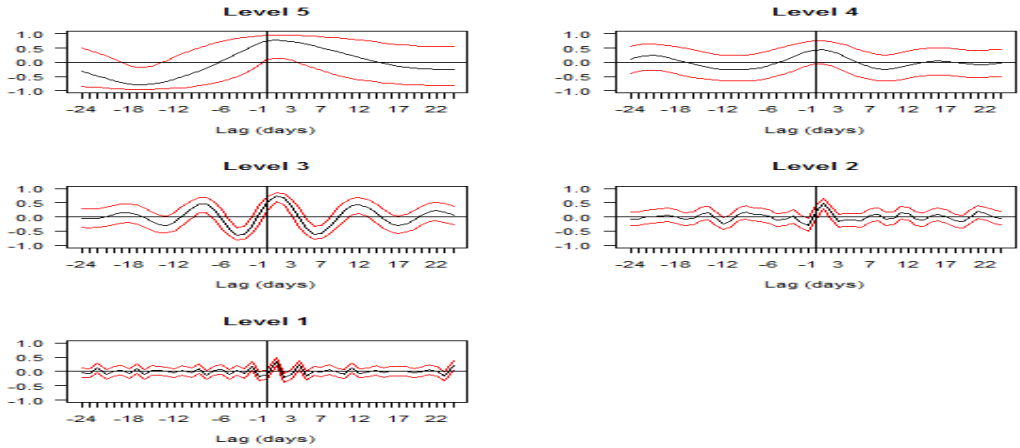
iii) At the fifth wavelet level, periods (a) and (c) do not display any significant correlations on both sides of the graph. In the case of period (b), the wavelet cross-correlations skewed to right implies that the US MSCI index leads the Taiwan MSCI index.

Figure 5 presents the wavelet cross-correlations between the Hong Kong MSCI stock index and the US MSCI stock index in the three sub-samples.

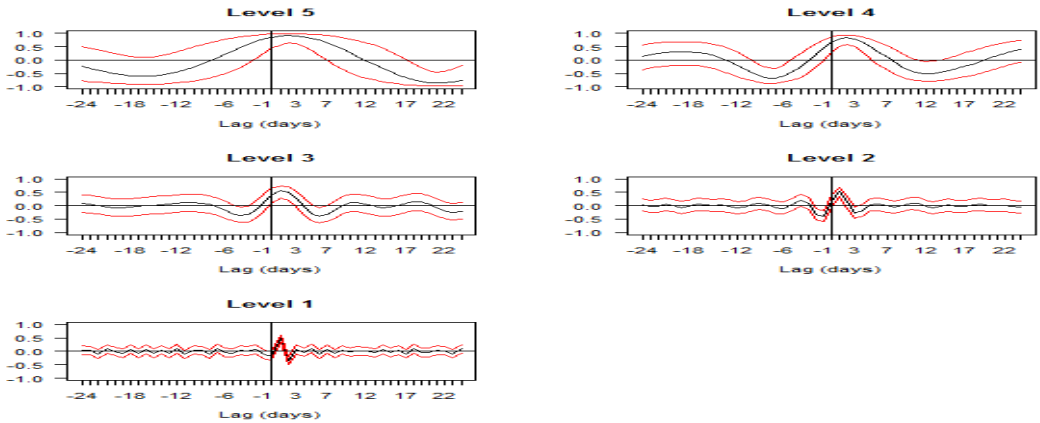
i) Interestingly, we observe that the wavelet cross-correlations appear to be asymmetric about zero lag from scale 1 up to scale 5 in all periods; In other words, the wavelet cross-correlations are skewed to the right at all wavelet levels; it implies that the US MSCI stock index tends to lead the Hong Kong MSCI stock index at all scales.

Figure 3: Wavelet cross-correlation between the Korea MSCI stock index and the US MSCI stock index.

a)



b)



c)

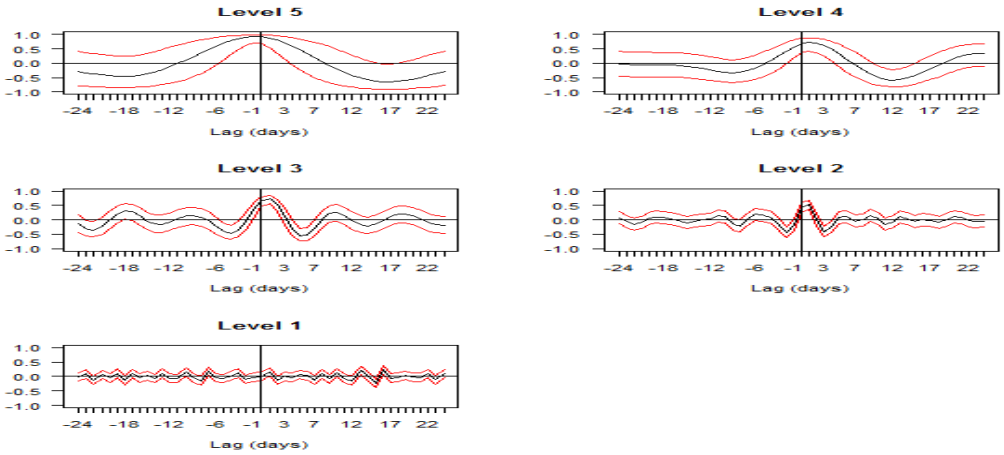
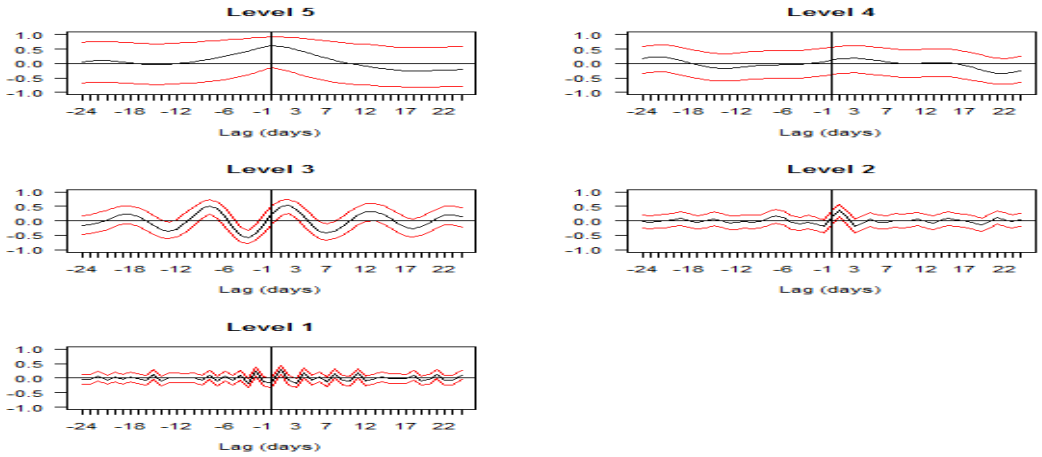
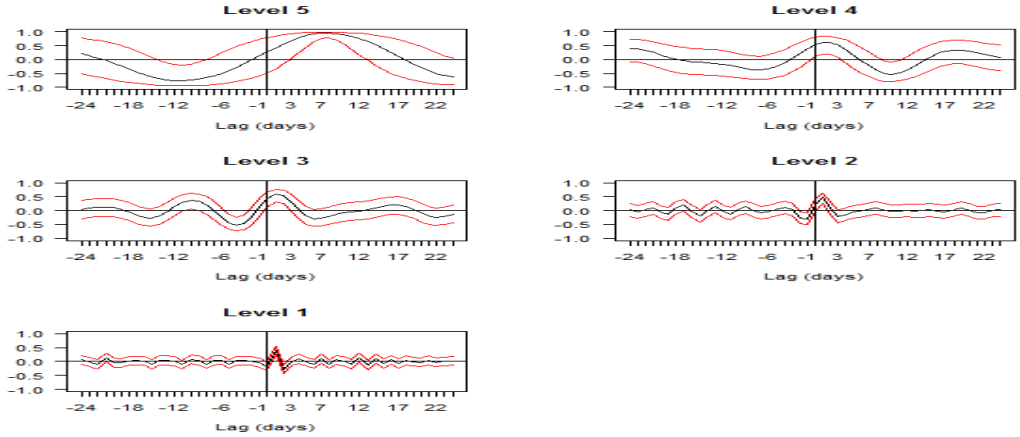


Figure 4: Wavelet cross-correlation between the Taiwan MSCI stock index and the US MSCI stock index.

a)



b)



c)

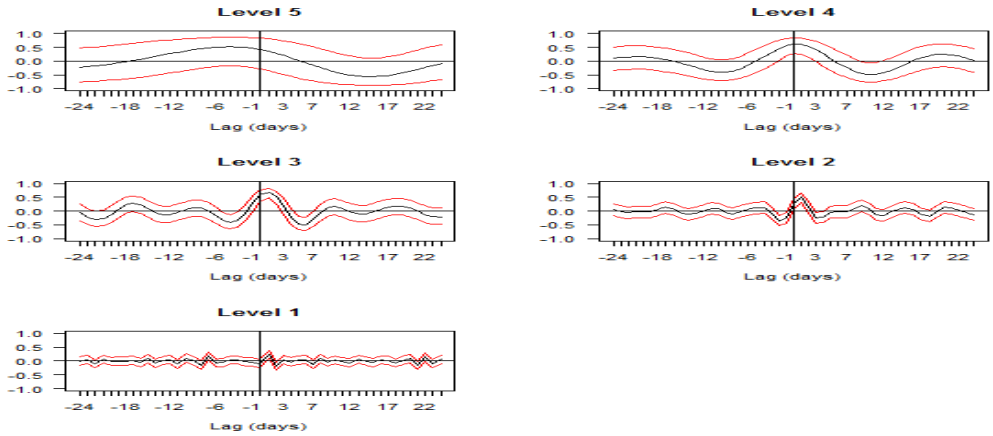
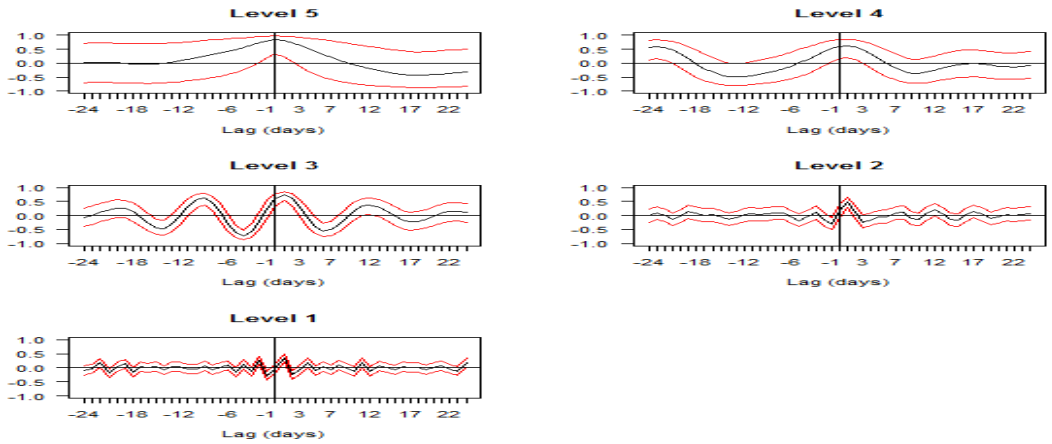
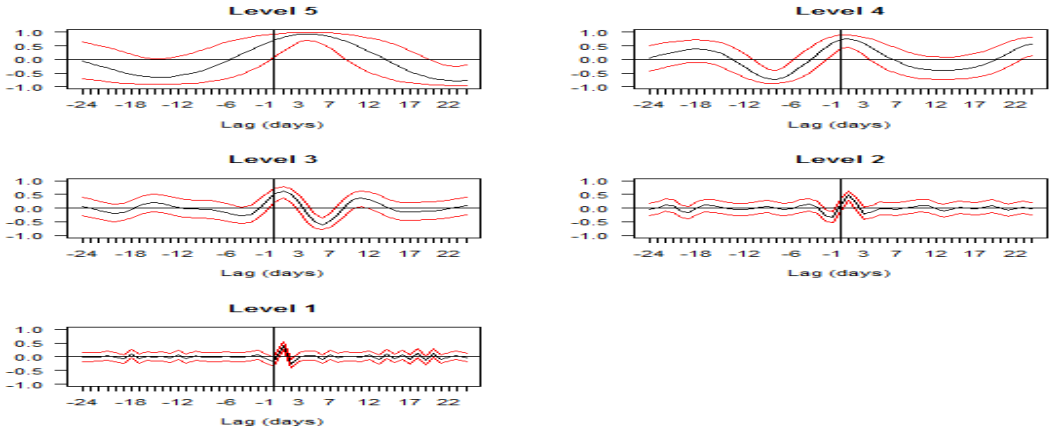


Figure 5: Wavelet cross-correlation between the Hong Kong MSCI stock index and the US MSCI stock index.

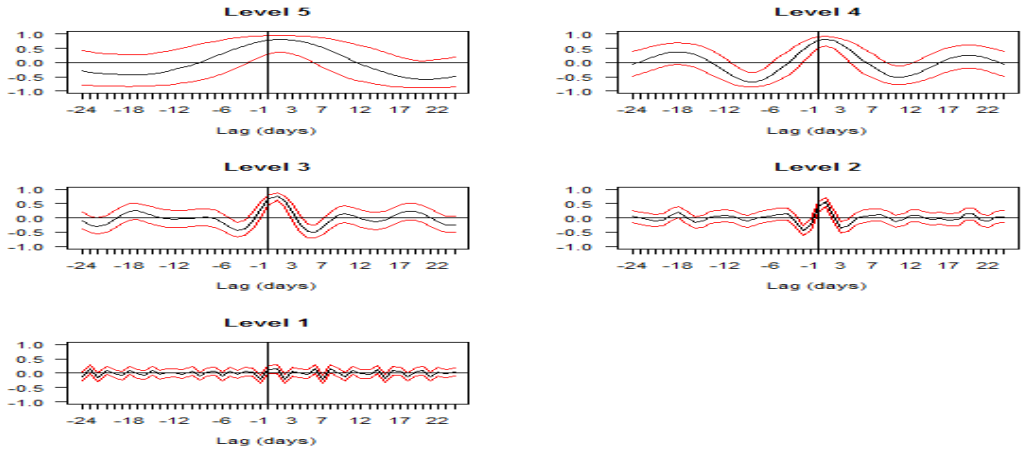
a)



b)



c)



5. Major findings and implications of the study

Although financial indices are widely studied, time-scale based analyses are rare. Previous researchers of financial indices have mainly focused on the study of temporal interrelations in time. With the introduction of wavelet methods, these interrelations can be studied in more detail. Understanding the dynamic behavior of financial indices is considered important because it has important practical implications on the implementation of investment and risk management strategies. Wavelet methods enhance the understanding of this dynamic behavior of financial indices at different time scales or frequencies.

Most previous researchers handled the issue of lead-lag relationship between the stock markets on the basis of the VAR-type methodologies, this study utilizes a more innovative method based on the wavelet approach. This wavelet analysis is able to decompose a signal into several time scales without losing time related information and to capture the various time scales at which the stock market leads other stock markets. Investors naturally have different time horizons in their investment plans. In this way, the wavelet methods are just the right solution for them because they can pick up the time-scale from the wavelet analysis that interests them most and make decisions according to this time-scale. Our main findings may be summarized as follows:

First, we find that in all sub-samples, the higher the correlation, the higher is the wavelet scale. In other words, wavelet cross-correlation values are low at the lower scales and high at the higher scales. Hence, short term fluctuations of stock indices are less correlated than longer periods. This implies that diversification benefits may only be available at the short intervals and not at long intervals. The cross-correlation structure between volatilities is different at shorter time scales than at longer time scales, suggesting nonlinear linkages between the markets. The wavelet cross-correlation analysis of Gallegati (2008) shows that stock market index tends to lead economic activity, but only at scales corresponding to periods of 16 months and longer.

Second, the wavelet cross-correlations appear to be very clear after the outbreak of the crisis which indicates the impact of the financial crisis of 2007-2009 on MSCI indices under review.

Third, the asymmetry of cross-correlation function of MSCI stock indices with the MSCI index of the US becomes more pronounced as the scale increases. The wavelet cross-correlations tend to, more or less, broadly suggest that regardless of the period considered, the US market is the leader in the exact time intervals. In other words, the US stock index is the initial receptor of exogenous shocks to its equilibrium relationship and the other stock markets make the short-run adjustment endogenously in different proportions in order to reestablish equilibrium. Our results are consistent with the findings of Aguiar-Conraria and Soares (2011); they also show that the US stock market leads the other stock markets based on wavelet coherency analysis. In another study, Madaleno & Pinho (2012) found a phase relationship with the DJIA leading the FTSE and the Nikkei 225 as far as the 2007-2009 financial crisis is concerned. The economic intuition arising from this finding is that the US stock index is the initial receptor of any exogenous shocks which disturbs the equilibrium. Therefore, it appears that the financial crisis of 2007-2009 did not affect the leading role played by the US stock index over other stock indices of the

Far East countries. At the global level, the findings based on wavelet cross-correlation confirm the widely-held view of the leadership of the US financial market over other financial markets. Naccache (2011), by investigating the relationship between the oil price and a global economic indicator proxied by the MCSI index, showed that at low wavelet levels (high frequency cycles), both the oil price and the MSCI index appear to have a feedback relationship, where they are both leading and lagging each other. However, at larger wavelet levels, only the MSCI world index happens to be leading the oil price with a positive correlation.

Finally, the lead-lag effect from the US MSCI stock index to the MSCI stock indices of the Far East countries may be the result of exogenous information being picked up first by the US MSCI index and then transmitted across to the other stock indices. In other words, the US market is the most influential producer of information. Hence, international investors usually overreact to the news from the US market and place less weight on information from other markets.

We can conclude that the US MSCI stock index appears to be the dominant market leader. This finding is in line with the findings by Diebold and Yilmaz (2011), where they found that the US market had a dominant volatility impact on other markets during the subprime mortgage crisis. We believe this requires a bit more explanation. First, in terms of the share of global equity capital, the greater liquidity of the market (the size of the trading volumes transacted) and the lower transaction costs, the US is ahead of other emerging markets. Therefore, the market leader is expected to be in the information context. Second, due to the technology explosion and the escalation of computerized trading systems, transfer of information from one market to another is almost seamless. Hence, it is no wonder that the US financial market is the global leader.

The implications of lead-lag relationship analysis are: i) International investors can predict one country's stock price by utilizing information of the US market's stock price; ii) The untapped evidence produced by the application of wavelet cross-correlation amongst the selected stock markets provides robust and very useful information to international financial analysts and short-term investors; iii) International investors usually overreact to news from the US market and place less weight on information from other markets.

Although financial indices are widely studied, time-scale based analyses are rare. Previous researchers of financial indices have mainly focused on the study of temporal interrelations in time. With the introduction of wavelet methods, these interrelations can be studied in more depth in terms of different time scales. Understanding the dynamic behavior of financial indices at different time scales is considered important because it has important practical implications on the implementation of investment and risk management strategies. Wavelet methods enhance the understanding of this dynamic behavior of financial indices.

References:

Aguiar-Conraria, L., Azevedo, N., & Soares MJ. (2008). Using wavelets to decompose the time-frequency effects of monetary policy. *Physica A: Statistical Mechanics and its Applications*, 387(12), 2863–2878.

A'Hearn, B., & Woitek, U. (2001). More international evidence on the historical properties of business cycles. *Journal of Monetary Economics,* 47, 321–346.

Arshanapalli, B., & Doukas, J. (1993). International stock market linkages: evidence from the pre- and post-October 1987 period. *Journal of Banking and Finance,* 17, 193-208.

Berument, H., & Ince, O. (2005). Effect of S&P 500's return on emerging markets: Turkish experience. *Applied Financial Economics Letters*, 1, 59–64.

Berument, H., Ceylan, N. B., & Gozpinar, E. (2006). Performance of soccer on the stock market: Evidence from Turkey. *The Social Science Journal, 43,* 695–699.

Campbell, B., & Dufour, J.-M. (1997). Exact nonparametric tests of orthogonality and random walk in the presence of a drift parameter. *International Economics Review*, 38, 151-173.

Candelon, B., Piplack, J., & Straetmans, S. (2008). On measuring synchronization of bulls and bears: the case of East Asia. *Journal of Banking and Finance*, 32, 1022–1035.

Cha, B., & Oh, S. (2000). The relationship between developed equity markets and the Pacific Basin's emerging equity markets. *International Review of Economics and Finance*, 9, 299–322.

Cheung, Y.W., & Ng, L.K. (1998). International evidence on the stock market and aggregate economic activity. *Journal of Empirical Finance*, 5, 281–296.

Dekker, A., Sen, K., & Young, M. (2001). Equity market in the Asia Pacific region: a comparison of the orthogonalized and generalized VAR approaches. *Global Finance Journal*, 12, 1–33.

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, *28*(1), 57-66.

Duchesne, P. (2006). Testing for multivariate autoregressive conditional hetroskedasticity using wavelets. *Computational Statistics & Data Analysis*, 50, 2142–2163.

Felix, A. O., Dufresne, U. B., & Chatterjee, A. (1998). Investment implications of the Korean financial market reform, *International Review of Financial Analysis*, 7, 83–95.

Floros, C., & Vougas, D.V. (2007). Lead-lag relationship between futures and spot markets in Greece: 1999-2001. *International Research Journal of Finance and Economics*, 7, 168-74.

Gallegati, M. (2008). Wavelet analysis of stock returns and aggregate economic activity. *Computational Statistics & Data Analysis,* 52, 3061 – 3074.

Gallegati, M. (2012). A wavelet-based approach to test for financial market contagion. *Computational Statistics & Data Analysis*, *56*(11), 3491-3497.

Gençay, R., Selçuk, F., & Whitcher, B. (2001). Scaling properties of exchange rate volatilities. *Physica A*, 289, 89–106.

Ghosh, A., Saidi, R., & Johnson, K. (1999). Who moves the Asia-Pacific stock markets – US or Japan? Empirical evidence based on the theory of cointegration. *Financial Review,* 34, 159–170.

Gjerde, O., & Saettem, F. (1999). Causal relations among stock returns and macroeconomic variables in a small open economy. *Journal of International Finance Markets Institutions & Money*, 9, 61–87.

Guo, F., Carl R. Chen, Ying Sophie Huang. (2011). Markets contagion during financial crisis: A regime-switching approach. *International Review of Economics and Finance*, 20, 95–109.

Hamao, Y., Masulis, R., & Ng, V. (1990). Correlations in price changes and volatility across international stock markets. *The Review of Financial Studies*, 3, 281-307.

Huang, L., (2008). Testing lead-lag effect and cointegration between FTSE 100 Index and its futures. A Dissertation presented in part consideration for MA Finance and Investment, University of Nottingham.

Huth, N., & Abergel, F. (2014). High frequency lead/lag relationships—Empirical facts. *Journal of Empirical Finance*, *26*, 41-58.

Kasa, K. (1992). Common stochastic trends in international stock markets. *Journal of Monetary Economics*, 29, 95-124.

Kim, S., & In, F. H. (2003). The relationship between financial variables and real economic activity: evidence from spectral and wavelet analyses. *Studies in Nonlinear Dynamics & Econometrics*, *7*(4).

King, M., & Wadhwani, S. (1990). Transmission of volatility between stock markets. *Review of Financial Studies,* 3, 5–33.

Lee, B.S. (1992). Causal relations among stock returns, interest rates, real activity and inflation. *Journal of Finance*, 47, 591–603.

Liu, Y. A., & Pan, M. (1997). Mean volatility spillover effects in the US and Pacific-Basin stock markets. *Multinational Finance Journal*, 1, 47–62.

Lo, A., & MacKinlay, C. (1990). When are contrarian profits due to stock market overreaction? *Review of Financial Studies*, 3, 175-206.

Madaleno, M., & Pinho, C. (2012). International Stock Market Indexes Comovements: A New Look. *International Journal of Finance and Economics*, 17, 89-102.

Masih A. M. M., & Masih R. (1997). A comparative analysis of the propagation of stock market fluctuations in alternative models of dynamic causal linkages. *Applied Financial Economics*, 7(1), 59-74.

Masih, A. M. M., & Masih, R. (2001). Long and short term dynamic causal transmission amongst international stock markets. *Journal of International Money and Finance*, 20(4), 563−587.

Masih, A.M.M., and Masih, R. (1999). Are Asian stock market fluctuations due mainly to intra-regional contagion effects? Evidence based on Asian emerging stock markets. *Pacific-Basin Finance Journal*, 7, 251-282.

Naccache, T. (2011). Oil price cycles and wavelets. *Energy Economics*, 33, 338-352.

Najand, M. (1996). A causality of the October crash of 1987: Evidence from Asian stock markets. *Journal of Business Finance and Accounting,* 23, 439–447.

Nasseh, A., & Strauss, J. (2000). Stock prices and domestic and international macroeconomic activity: a cointegration approach. *Quarterly Review of Economics & Finance*, 40, 229–245.

Ozdemir, Z. A., Olgun, H., & Saracoglu, B. (2009). Dynamic linkages between the center and periphery in international stock markets. *Research in International Business and Finance*, 23, 46–53

Pakko, M. (2004). A spectral analysis of the cross-country consumption correlation puzzle. *Economics Letters*, 84, 341–347.

Percival, D.B. (1995). On estimation of the wavelet variance. *Biometrika*, 82, 619–631.

Percival, D.B., & Walden, A.T. (2000). *Wavelet Methods for Time Series Analysis*. Cambridge University Press, Cambridge, UK, 2000.

Phylaktis, K., & Ravazzolo, F. (2005). Stock market linkages in emerging markets: implications for international portfolio diversification. *Journal of International Financial Markets, Institutions and Money*, 15, 91–106.

Ramsey, J., & Zhang, Z. (1996). The application of wave form dictionaries to stock market index data. In Y. Kratsov & J. Kadtke (Eds.), *Predictability of complex dynamical systems*. Springer.

Ramsey, J., & Lampart, C. (1998a). Decomposition of economic relationships by time scale using wavelets. *Macroeconomic dynamics*, 2 (1), 49–71.

Ramsey, J., & Lampart, C. (1998b). The decomposition of economic relationships by time scale using wavelets: expenditure and income. *Studies in Nonlinear Dynamics and Econometrics,* 3 (1), 23–42.

Ramsey, J., & Zhang, Z. (1997). The analysis of foreign exchange data using waveform dictionaries. *Journal of Empirical Finance*, 4, 341–372.

Rapach, D.E. (2001). Macro shocks and real stock prices. *Journal of Economics & Business*, 53, 5–26.

Rua, A., & Nunes, L.C. (2009), International Comovement of stock market returns: A wavelet analysis. *Journal of Empirical Finance*, 16, 632-639.

Smith, K. (2001). Pre- and post-1987 crash frequency domain analysis among Pacific Rim equity markets. *Journal of Multinational Financial Management*,11, 69–87.

Vacha, L., & Barunik, J. (2012). Co-movement of energy commodities revisited: Evidence from wavelet coherence analysis. *Energy Economics*, *34*(1), 241-247.

Whitcher, B., Guttorp, P., & Percival, D.B. (1999). Mathematical background for wavelet estimators for cross covariance and cross correlation. *Technical Report No. 38. National Research Centre for Statistics and the Environment*. Seattle.

Whitcher, B., Guttorp, P., & Percival, D. B. (2000). Wavelet analysis of covariance with application to atmospheric time series. *Journal of Geophysical Research: Atmospheres (1984–2012)*, *105*(D11), 14941-14962.

Wu, C., & Su, Y. (1998). Dynamic relations among international stock markets. *International Review of Economics and Finance*, 7, 63–84.

Yang, J., Kolari, J., & Min, I. (2003). Stock market integration and financial crises: the case of Asia. *Applied Financial Economics,* 13, 477–486.