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# **Comovement of Selected International Stock Market Indices:A Continuous Wavelet Transformation and Cross Wavelet Transformation Analysis**

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## **ABSTRACT**

This study accounts for the time-varying pattern of price shock transmission, exploring stock market co-movements using continuous wavelet coherency methodology to find the correlation analysis between stock market indices of Malaysia, Thailand (Asian), Greece (Europe) and United States, in the time-frequency domain of time-series data. We employ the Wavelet Coherence method with the consideration of the financial crisis episodes of 1997 Asian Financial Crisis, 1998 Russian Sovereign Debt Default, 9/11 Attack on World Trade Centre US, 2008 US Sub-Prime Mortgage Crisis and the recent 2010-2011 Greece Debt Crisis. Results tend to indicate that the relations among indices are strong but not homogeneous across time scales, that local phenomena are more evident than others in these markets and that there seems to be no quick transmission through markets around the world, but a significant time delay. The relations among these indices have changed and evolved through time, mostly due to the financial crises that occurred at different time periods. Results also favour the view that regionally and economically closer markets exhibit higher correlation and more short run co-movements among them. The high correlation between the two regional indices of Malaysia and Thailand, indicates that for the international investors, it is little gain to include both in their portfolio diversification. Strong co-movement is mostly confined to long-run fluctuations favouring contagion analysis. This indicates that shocks in the high frequency but low period are short term but shocks in the low frequency but high period are long term with the trend elements affecting the co-movements of the indices. The study of market correlations on the frequency-time scale domain using continuous wavelet coherency is appealing and can be an important tool in decision making for different types of investors.

**KEY WORDS:** stock market comovement; continuous wavelet transform; cross-wavelet; wavelet coherency; frequency-time scale domain

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## 1. INTRODUCTION – THE MOTIVATION OF THE STUDY

The globalization of trade and liberalization of financial markets around the world is growing since studies have found recent integration of international stock markets across borders has further enhanced the recent trend of market integration. As a consequence, business cycles synchronization and stock correlations are expected to rise over time and across countries. The recent developments in the global financial markets have shown the importance of risk measurements and co-movements for the decision of market players. In fact, it was pointed out that in the integrated capital markets, assets are priced according to a common set of risk and by contrast, prices reflect country-specific factors in the segmented markets (Boyle,2009).

However, although investors are said to be risk averse, different types of investors have different motivation and level in terms of the expectation of risk and return to their investment portfolio. The short term investors would be interested in the high frequency shocks (low time scale) as opposed to the long term investors who are more interested in the low frequency shocks (high time scale) to the market. Thus, our co-movement analysis must consider the different expectations of the 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. It can be argued that from a portfolio diversification point of view, the short-term investor is naturally more interested in the co-movement 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 investors also depend on the nature and magnitude of the existing relationships between different stock markets. Understanding the interrelations among the various markets is therefore important to diversify risk and to derive high returns.

This study investigates this relationship, comparing the weekly dynamics of four stock market indices around the world, namely stock market indices of Malaysia, Thailand, Greece and United States. Together, they represent the financial crisis episodes of 1997 Asian Financial Crisis, 1998 Russian devaluation of rouble and its subsequent sovereign debt default, 2008 US Sub-Prime Credit Crunch Crisis and the recent 2010-2011 Greece Debt Crisis.

As such interestingly, our study will address the following questions:

- (1) Do co-movements between the stock markets under study exist and if so, are they strengthening or weakening during the period studied?**
- (2) Are the co-movements (correlations) between them time-varying and scale dependent?**
- (3) Finally, is there short-term or long-term interdependence and contagion (i.e. short term fluctuations of say, US index prices spill over to Malaysian index prices) and is such co-movement unstable over high volatility periods?**

In analysing the co-movements, what effect did the financial crises during the period 1992 to 2011 have on the co-movements between these markets and how did the international investors react. It is worth noting that it will be significant to determine who (which market) is leading (lagging) who (which market), precisely when, and the strength of the relationship (indicated by the energy of the spectrum).

This non-parametric study analysis should reveal whether there is a dominant economy, thus influencing the 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; Did the international (cross border and cross continent) financial crises stimulate stronger co-movements (correlations) among world markets? Which major stock market dominated? Again, we would expect the US market to be the exogenous 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).

This work extends previous literature in the following important aspects. First, we explore the potential time-varying behaviour of long run stock market relationships. For the 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.

Financial crisis is conceivably a potential source of structural break in the 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 (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 which may carry certain implications for the portfolio investment and stock trading.

By applying the continuous time wavelet methodology, we can overcome the problems of non-stationarity of the time-series signals and the technique can be used to analyse the financial relations in the short and long run relations (low frequency but high (long) period and high frequency but low period). Also, by applying the wavelet analysis technique over the Vector Error Correction Model (VECM), we can look further into the frequency and timescale domain which the VECM is unable to accommodate.

The main advantage of the cross-wavelet coherency-phase analysis is its ability to analyse 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 co-movement during the crisis periods compared with the periods of stability. If cross-market co-movements 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 the financial crisis in order to analyse the co-movement of stock market indices during these periods of time, if any correlation existed.

We organized this paper as follows. In Section 2 we present a brief **literature review** about stock market linkages. Section 3 discusses the **methodology** used, which explains the main advantages of wavelet analysis and presents the continuous wavelet transform (CWT) and cross-wavelet transform (XWT). Wavelet power spectrum, the cross-wavelet power spectrum, wavelet coherency and phase difference concepts are also presented. In Section 4, we provide **data** overview in conjunction with the identification of the most important financial crisis historical dates to analyse markets co-movements. In Section 5 we produce the **empirical results**, for the four conventional stock market indices and the four Islamic indices are discussed. Finally, in Section 6 we provide our **conclusions**, including the limitations of the study that future research could enhance the border of knowledge further.

## 2. LITERATURE REVIEW

Previous studies discuss the issue of international linkages and cointegration of stock exchanges (Idier,2008), but they are based on the estimation of a correlation matrix of stock market index returns and/or on multivariate analysis techniques, such as cointegration theory. Wu and Su (1998) find that there is a significant dynamic relation among the US, Japan, UK and Hong Kong stock markets. Eun and Shim (1989) use the same method concluding that USA had a dominant influence over nine other stock markets. Idier uses the fractal properties of asset returns and present estimation of Markov switching multi-fractal model (MSM) to give insights about short run and long run dependencies in stock returns. However, these studies do not concentrate their analysis in the **frequency and time-scale domains**. For economic issues, Aguiar-Conraria et al. (2008) use cross-wavelet coherency to study interactions between time-series at different frequencies and how they evolve over time.

Wavelet analysis has been used extensively. However, for financial and economics, it is a comparatively new and powerful mathematical tool for signal processing, being an important addition to time-series methods with practical applications, **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.

Wavelet theory for international co-movement of stock indices has been applied by Rua and Nunes (2009) and Lee (2004). Lee (2004) studied international transmission effects between US, Germany and Japan and two emerging markets, namely Egypt and Turkey. He reports that movements from the developed markets affected the developing markets but not vice versa. Rua and Nunes (2009) tested the changing of co-movement over time using monthly data from Germany, Japan, UK and US. The degree of co-movement of Germany with the US and UK markets are characterized by some permanent changes over time: a gradual but steady increase of co-movement 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 co-movement with all other countries considered.

However, the previously mentioned authors use **discrete wavelet transform** versions. The present work differs from these by using the **Continuous 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.

### 3. THE METHODOLOGY

#### Use of Wavelet to Dynamically Decompose Time to Time-Frequency Domain

Wavelet is a signal decomposition technique. It is used to decompose (separate) the original time series into different timescales and by doing that and then studied them separately, we can show that the causal relationship differs depending on the timescale.

Wavelets take their roots from filtering methods and Fourier analysis. Unfortunately, this technique was unable to deal adequately with changes in small period of time. Wavelet transform could overcome these limitations as it is define over general space. Wavelet transform can deal with abrupt changes in a time-series and enable us to characterize signals by frequency, position in time and the duration. It maps a function ( $t$ ), from time domain to the timescale domain through  $w(t,j)=\psi(\cdot)(t)$ . Here  $t$  is a time index,  $j$  a scale and  $\psi(\cdot)$  is the wavelet filter used to transform the original signal. The two basis wavelet filters used are the father function and the mother function. Father wavelet represents the smooth (low frequency) part of the signal, while the mother wavelet represents the volatile (high frequency) – low scale, i.e where the ‘noise’ are. Combining information from both time-frequency domains, they are very 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.

There are two classes of wavelet 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.

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.

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.

## WAVELET COHERENCE

In this paper we have use the wavelet coherence method to analyse the stock indices. Wavelet coherence measures the local correlation of two time series in the frequency domain. We define the wavelet coherence (Torrence and Compo (1998)), of two time series, as follows:

$$Rn^2(s) = \frac{|S(s^{-1}W_{xy}(u, s))|^2}{S(s^{-1}|W_x(u, s)|^2) S(s^{-1}|W_y(u, s)|^2)}$$

where S is a smoothing operator in both time and scale, which can be written as a convolution in time and scale  $S(W)=S_{scale}(S_{time}(Wn(s)))$  where  $S_{scale}$  denotes smoothing along the wavelet scale axis and  $S_{time}$  smoothing in time (Torrence and Compo, 1998). Thus this will provide a useful tool for analysis of comovement across the stock markets. The phase difference, indicated by arrows, gives us details about delays of oscillation of the two examined time series. Arrows pointing to the **right** when the time series are **in-phase** are **positively correlated**. While arrows pointing to the **left** when time series are **anti-phase** are **negatively correlated**. Arrow pointing **up** means that the first time series leads the second one, arrow pointing **down** indicates that the second time series leads the first one.

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.

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.

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. 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.

#### 4. DATA DESCRIPTION AND IDENTIFICATION OF CRISIS

We obtained the weekly prices of stock market indices, namely the Dow Jones (DJ) of Malaysia, Thailand, Greece and United States from 1992 to 2011. Stock price data were taken from Datastream (Reuters-Thompson), that has been adjusted given data availability.

However, weekly prices instead of returns are used since the main advantage of wavelet analysis is its ability to decompose time-series data into their frequency and 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. As such, like the works of Floros (2005) and Charles and Darne´ (2006), our study also uses prices instead of returns.

**Table 1.** Estimated Unconditional Volatility Matrix of the weekly return of stock market indices under study

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Estimated Unconditional Volatility Matrix
1026 observations used for estimation from 30-Jun-92 to 21-Feb-12
Unconditional Volatilities (Standard Errors) on the Diagonal Elements
Unconditional Correlations on the Off-Diagonal Elements
*****
RDJGREC      RDJGREC      RDJMALY      RDJTHAI      RDTUSAM
RDJGREC      .047993      .22998      .23845      .41067
RDJMALY      .22998      .040940     .52570      .27203
RDJTHAI      .23845      .52570      .048584     .30523
RDTUSAM      .41067      .27203      .30523      .024405

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\*\*\*\*\*  
For the time-varying conditional volatilities and correlations see the  
Post Estimation Menu.

Table 1 presents the volatilities and correlation matrix between all four stock market indices under analysis. It can be seen that the European index is more correlated with the US index than the Asian stock markets, and that the latter has the highest correlation among them. This is shown by the Malaysian index having the highest correlation of 0.5257 with the Thailand index.

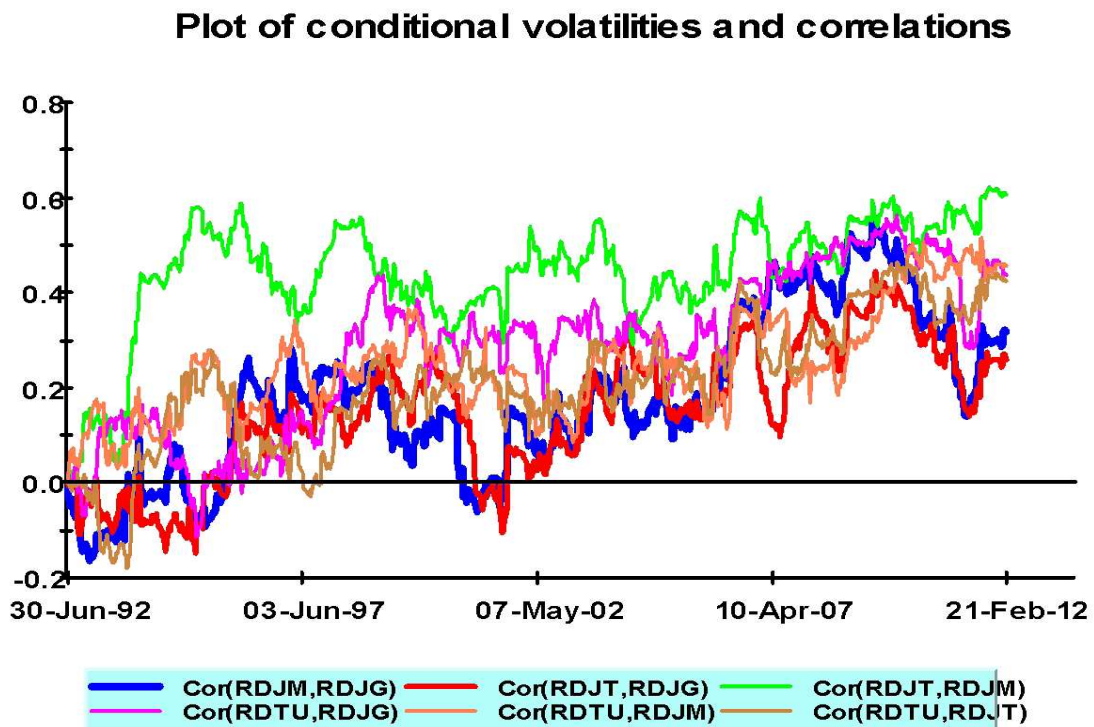
In summary, less developed markets show lowest correlation values with the most distant indices in geographical terms. Results for the simple cross correlation analysis of stock index prices indicate that these stock markets do exhibit a significant degree of integration with each other in accordance with 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 Asian financial crisis of 1997–1998; the US 2001 (9/11 terrorist attack) and 2002 (Enron accounting scandals and WorldCom fraud) crisis; the Dot-Com Bubble (2000 – 2003); the Euro zone crisis (20002); the terrorist bombings in Madrid and London (2003-2004); the 2007–2009 US financial crises (‘subprime crisis’) that has been spread out to the world and finally the recent Greece debt crisis of 2011. Charles and Darne´ (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. 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. 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 2003 Iraq Invasion, the terrorist attacks of Madrid (2004) and London (2005). The US mortgage crisis and ‘toxic’ loans crisis 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 was imminent.

## 5. EMPIRICAL RESULTS

Until recently when wavelets were applied to the analysis of stock market indices, the use of the discrete wavelet transform (DWT) or one of its variants dominated (Rua and Nunes, 2009). It was only recently, that the same type of analysis can be done more easily and in a using the continuous wavelet transform (CWT).

In **Figure 1** we can see the correlation between the market indices return for the period 1992 to 2012. We noticed an upward trend for correlations between all indices. The correlations between the index return of Malaysia and Thailand is higher as compared to the correlations between Malaysia with Greece and with USA. The correlation of the index return of Malaysia and Greece is the lowest of the three. Secondly, the fluctuation in the correlation is the greatest between Malaysia and Thailand, from zero in 2002 to a highest of 0.6 in 1997 and 2007. The correlation between Malaysia-Greece and Malaysia-USA was less volatile throughout the period. This confirmed our expectation that index return of market within a common trade region as Malaysia and Thailand is highly correlated due to the similar characteristics of the regional market.

**Figure 1 – Plot of Conditional Volatilities and Correlations using Microfit 5**



In **Figure 2**, Wavelet power spectrum of stock market indices: Malaysia (DJMALY), Thailand (DJTHAI), Greece (DJGREC) and US (DTUSAM) respectively, for the period from 1 January 1992 to 31 December 2011. The scales with its respective dates are;

- a. 200 (corresponding to 31/10/1995),

- b. 400 (corresponding to 31/8/1999),
- c. 600 (corresponding to 1/7/2003),
- d. 800 (corresponding to 1/5/2007) and
- e. 1000 (corresponding to 1/3/2011).

In these timescale, we are looking into the major crisis of 1997 Asian financial crisis, 2001 9/11 US Terrorist attack, 2008 US Sub-prime crisis and 2011 Greece debt crisis. Looking at Figure 2 one can immediately infer the evolution of the variance for the four stock market indices under analysis at several time scales along the period 1992–2011 and extract most of the conclusions taken by the previously mentioned researchers. Figure 2 shows the **continuous wavelet power spectrum** for the four stock market indices mentioned.

In the wavelet power spectrum, the black contour in regions with energy indices designates the **5% significance level** (95% confidence level) 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, colour 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 DTUSAM shows a small significant power event in the period from 400-600 in the weekly time scale of exceeding 256 days. The WPS of the DJMALY index shows a highly significant power event from 128-256 days, time-scale band. The WPS of DJGREC shows no significant high power event. Most of the actions in this index occurred at high scales (more than six months). Finally, the WPS for the DJTHAI index also shows little the action and mostly occurred at high scales.

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 3 Cross-wavelet coherency** and phase plots between the Malaysia(DJMALY), Thailand (DJTHAI), Greece (DJGREC) and US (DTUSAM) stock market indices for the period 1992 to 2011.

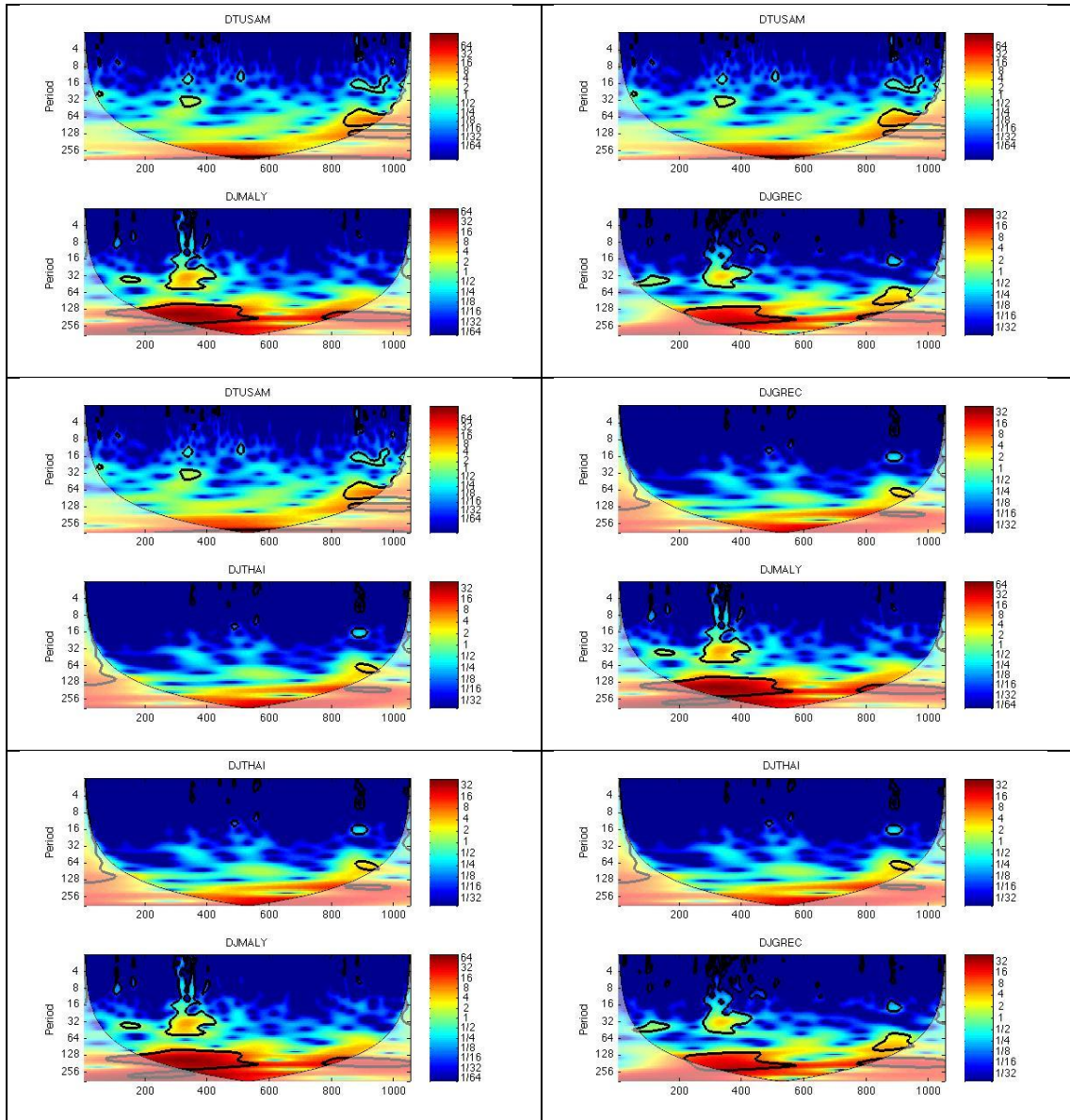
**Figure 4** presents the **estimated wavelet coherency** and phase difference between the four indices. Contours denote wavelet-squared coherency, the thick black contour is the 5% significance level and outside of the thin line is the boundary affected zone. In the cross-wavelet power pictures, colour code for power ranges from **blue (low coherency)** to **red (high coherency)**. Vectors indicate the phase difference between the two series.

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**, given that we need to know their **order** for the scheme to be valid. Let us just assume that two indices, A and B represent the first and the second series respectively. When the arrow is pointing to east (right hand side), it is said to be **in-phase (positively correlated)**, that is both market moves together in the same direction. If the arrow is pointing west (left hand side), both indices is said to be **anti-phase (negatively correlated)**, that it both moves in the opposite direction. If the arrow is pointing east and downwards, A is leading B, but if the arrow is pointing upwards, A is lagging B. The opposite is true if, the arrow is pointing west and upwards, A is leading B in a negatively correlated situation, but A is lagging B if the arrow is pointing downwards.

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.

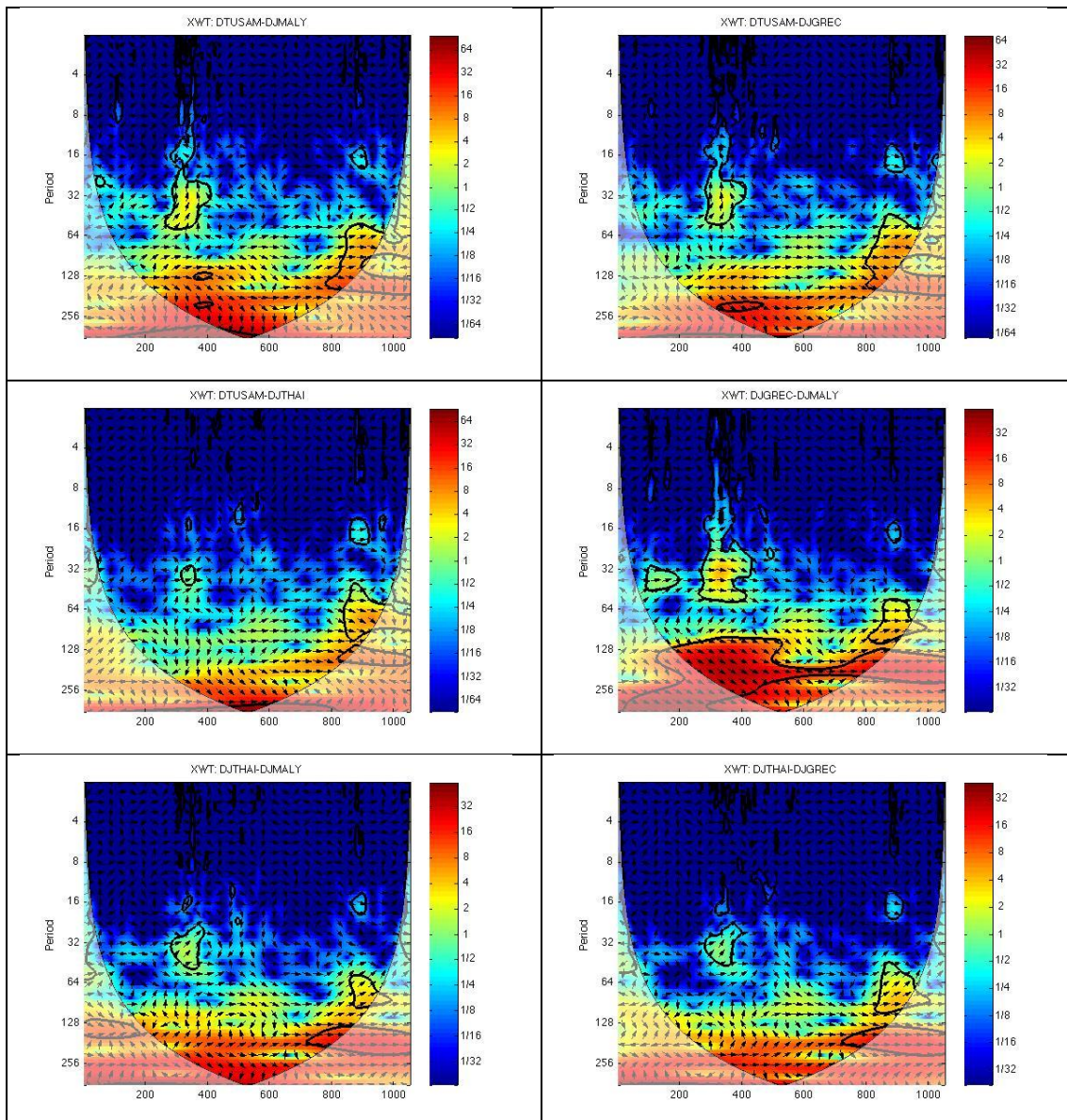
The wavelet cross-coherency shows low-to-medium statistically significant coherence, but we are still able to observe some islands of medium power, mostly during the 9/11 2001 terrorist attack and the 2007–2009 Asian financial crisis for most of the indices. For example, in the cross-coherency and phase plot between DJMALY and DTUSAM we are able to observe an island of high statistically significant power for the period 200 - 800. However, surprisingly, we see very high significant power between DJMALY and DJGREC, between 200-1000. This suggest that both series were strongly correlated and in phase during the period of the throughout all the major crisis mentioned, with the Malaysia index leading Greece in the 200–600 days band, and Greece leading in the 600-1000 days band. In between 400 – 800, (ref DTUSAM-DJGREC), US still leads but at lower day frequencies (high scales) of 64-128 days and both were completely in phase i.e. both first and second series moves together (with arrows being straight lines) and positively correlated (pointing right). We should also notice that during the 9/11 terrorist attack and 2003 Madrid bombing, at frequencies 32–128 days, US and Greece were in phase with US leading, but during the several US sub-prime crisis, at the same frequencies, US was lagging.

Figure 2 - DJWEEKLY Continuous wavelet transform (CWT)

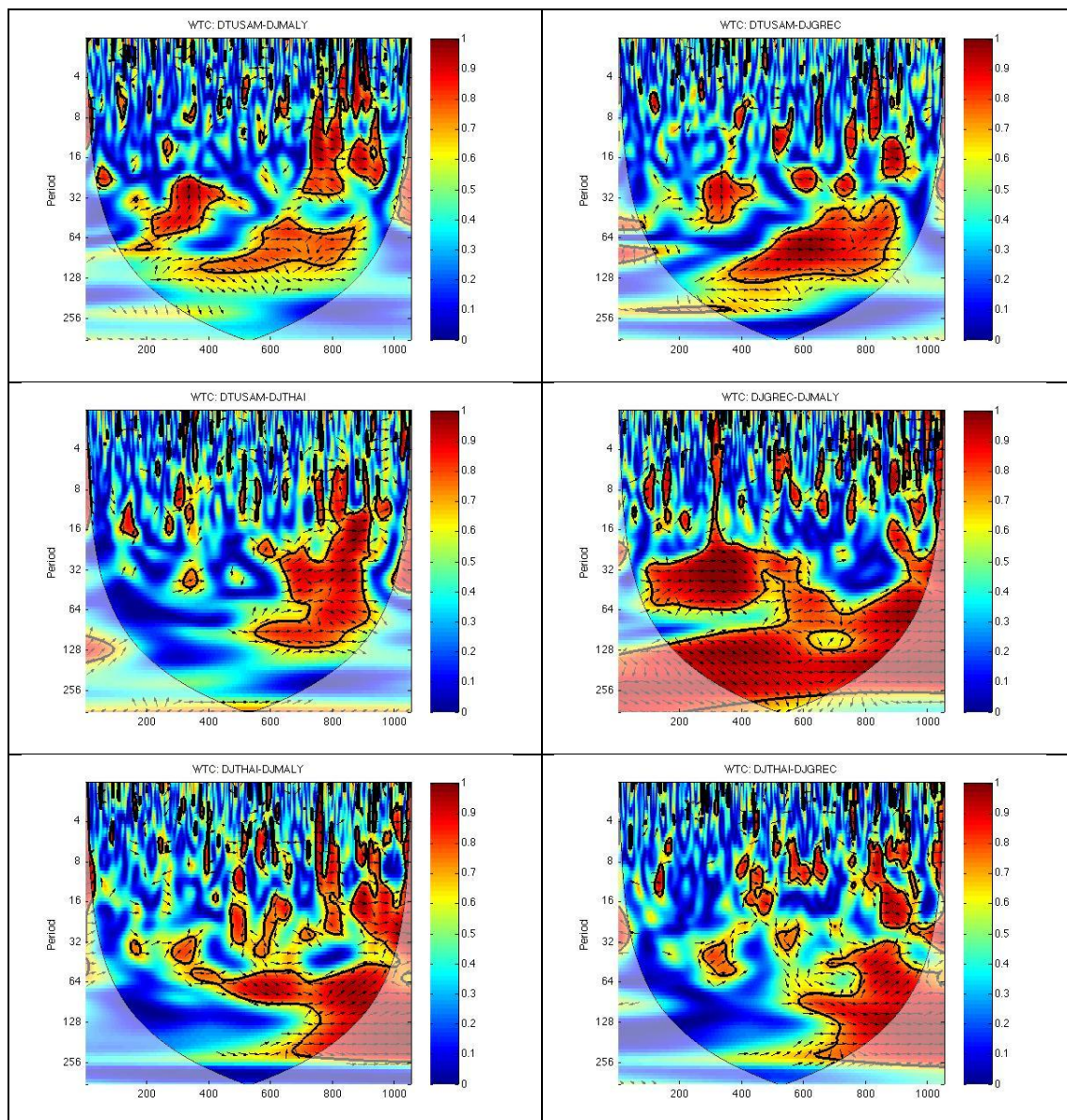




**Figure 3 - DJWEEKLY Cross wavelet transform (XWT)**



**Figure 4 - DJWEEKLY Wavelet coherence (WTC)**



## 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 co-movements (correlations) between capital markets during the financial crises. By employing continuous wavelet analysis, we could answer our research questions with index market prices and need not use the first difference of index return. We can see clearly that the market co-movements between the markets under study do exist and they are strengthening throughout the financial crises period of 1992 to early 2012. The usefulness of wavelet analysis to analyze financial contagion and co-movement is illustrated, considering that the international investors distinguish between short and long run relations. We have also demonstrated that the correlations (co-movements) show expected results when two time-series are further decomposed into frequency-timescale domain. Indices of Malaysia and Thailand showed no contagion effect but more of inter-dependence in nature. The high correlation between the two indices, indicates that for the international investors, it is unwise to include both in their portfolio diversification. Continuous wavelet and cross-wavelet analysis have the ability to analyze transient dynamics for single time series, or for their association, allowing thus a multivariate (bivariate) analysis. Strong coherence among stock market indices is found and at high scales the index prices show a strong and significant relation. However, through the phase analysis, arrows point to all directions, meaning that even if the series were mostly in phase, the relationship was not homogeneous across scales and time. As for the third research question, investors might be interested in knowing that the results point out that shocks in the US and Greece stock markets are not rapidly transmitted to other markets, which may induce arbitrage opportunities. This could be because the investors took the stand of 'wait and see' attitude, allowing more time to consolidate their holdings, rather than incurring unnecessary transaction cost in response to short term market volatilities. Moreover, business cycle periods, corresponding to historical financial crisis periods, were identified, where the series show higher coherence, but mostly at low frequencies, favouring the contagion hypothesis during these periods. However, it cannot be denied that possible market interdependence over contagion is noticeable between all the indices studied especially in the high frequency, low time scale period and the co-movements are unstable. Also, geographically and economically closer countries exhibit higher levels of market co-movements. Finally, the importance of shock 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, results presented here for the different stock market indices indicate cases of breaks in co-movements, 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 information and flow of capital from the crisis market to the non-crisis market. Further studies in this direction are certainly needed. Finally, the delay in responses found may be an indication of arbitrage opportunities, which deserves a more careful attention.



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