Eurasian Journal of Economics and Finance, 2(1), 2014, 13-27

EURASIAN JOURNAL OF ECONOMICS AND FINANCE

http://www.eurasianpublications.com

PALM OIL PRICE, EXCHANGE RATE, AND STOCK MARKET: A WAVELET ANALYSIS ON THE MALAYSIAN MARKET

Buerhan Saiti
Corresponding Author: Universiti Kuala Lumpur, Malaysia. Email: borhanseti@gmail.com

Azlan Ali
Universiti Kuala Lumpur, Malaysia. Email: azlanali@bis.unikl.edu.my

Naziruddin Abdullah
Universiti Kuala Lumpur, Malaysia. Email: naziruddin@bis.unikl.edu.my

Sulaiman Sajilan
Universiti Kuala Lumpur, Malaysia. Email: drsulaiman@bis.unikl.edu.my

Abstract

The study investigates causality between palm oil price, exchange rate and the Kuala Lumpur Composite Index (KLCI) based on the theory of wavelets on the basis of monthly data from the period January 1990 - December 2012. This methodology enables us to identify that the causality between these economic variables at different time intervals. This wavelet decomposition also provides additional evidence to the “reverse causality” theory. We found that the wavelet cross-correlations between stock price and exchange rate skewed to the right at all levels with negative significant correlations which implies that the exchange rate leads the stock price. In the case of stock and commodity prices, there is no significant wavelet-cross-correlation at first four levels. However, the wavelet cross-correlations skewed to the left at level 5 which implies that the stock price leads commodity price in the long-run. Finally, there is no significant wavelet cross-correlations at all levels as long as we concern between commodity price and exchange rate. It implies that there is no lead-lag relationship between commodity price and exchange rate.

Keywords: Stock Price, Commodity Price, Exchange Rate, Wavelet Cross-Correlation

1. Introduction

There are numerous articles devoted to the connections between fossil fuels and financial and economic variables. In most of them energy prices are represented by oil prices, and economic factors include, for example, inflation, exchange rates, and economic growth (Bahmani-Oskooee and Sohrabian, 1992; Ajayi and Mougoue, 1998). The analyses are conducted for single countries or using cross-sectional data. The researchers of this study addressed the relationships between palm oil price on the Malaysian market and the exchange rate of MYR/USD and the Kuala Lumpur Composite Index (KLCI), which is one of the leading indexes for Malaysian market. The analysis of dependencies has a dynamic nature and focuses on causality between the variables at different time scales. This allows us to verify the following research hypotheses:

1. Is the magnitude of this correlation different when the stock prices are the leading variable or when the exchange rates are the leading variable?
2. Are commodity and stock markets independent of each other in the case of Malaysian market?
3. Exchange rate drives commodity prices?

1.1. Why Study Stock Market and Exchange Rate?

Currency is more often being included as an asset in investment funds' portfolios. Knowledge about the link between currency rates and other assets in a portfolio is vital for the performance of the fund. The Mean-Variance approach to portfolio analysis suggests that the expected return is implied by the variance of the portfolio. Therefore, an accurate estimate of the variability of a given portfolio is needed. This requires an estimate of the correlation between stock prices and exchange rates. Is the magnitude of this correlation different when the stock prices are the leading variable or when the exchange rates are the leading variable?

Bahmani-Oskooee and Sohrabian (1992) analyzed the long run relationship between stock prices and exchange rates using the cointegration and Granger causality tests. From the results, they were unable to find any long run relationship between the two variables. Later, by using an error correction model (ECM), Ajayi and Mougoue (1998) show that an increase in aggregate domestic stock price has a negative short run effect on domestic currency value but in the long run increases in stock prices have a positive effect on domestic currency. Ibrahim (2000) and Ibrahim and Aziz (2003) analyzed the interaction between the two variables for Malaysia.

Ibrahim and Yusoff (2001) analyzed dynamic interactions among three macroeconomic variables (real output, price level, and money supply), exchange rate, and equity prices for the Malaysian case using time series techniques of cointegration and vector autoregression. They found that the inclusion of the macroeconomic variables and the exchange rate improve the predictability of the Malaysian equity prices. Conversely, the movements of the stock market also contain information on future variations of these variables particularly the consumer prices. They note specifically that movements in the Malaysian stock market are driven more by domestic factors, particularly the money supply, than by the external factor (i.e., the exchange rate).

The assumption of Dimitrova (2005) was, in the short run, an upward trend in the stock market may cause currency depreciation, whereas weak currency may cause decline in the stock market, in other words, this link is positive when stock prices are the lead variable and likely negative when exchange rates are the lead variable. They found that support for the hypothesis that a depreciation of the currency may depress the stock market - implies that an appreciating exchange rate boosts the stock market. But he did not support the assertion that a booming stock market would lead to currency depreciation.

1.2. Commodity Price and Stock Price

At first, there is an investigation as to whether or not there are information spillovers between the commodity and the stock market. The primary question is whether the stock market leads the commodity market or vice versa. The temporal relationship between the commodities market and the stock market has a lot of implications for not only the participants of the markets but also for the policy makers, the producers of the commodities, and, in the case of developing nations, the economy as a whole. This relationship may be studied using various methods and by identifying the lead-lag relationship between the values of representative indices of the markets. The hypothesis is: "Are Commodity and Stock Markets Independent of Each Other?"

Most casual stock market investors do not pay too much attention to the current price of the various different commodities such as oil, gold and copper, for example. However these current prices can have a major bearing on the value of the main stock market indices.

Companies like Sime Darby, whose share price is determined to a large extent by the price of the palm oil. As a result the share prices of the major palm oil companies have been driven higher because they obviously make more money selling palm oil when the price is higher.

Wassmer *et al.* (2011) by analyzing the S&P 500 Total Return index and the DJ-UBSCI are taken as representatives for the US stock and the commodity market, found that there is an interconnection between the Commodity and the Stock Market. There is evidence for various information spillovers across the markets from returns as well as from news sentiments. Together with the findings of the growing correlations between the two markets it supports the theory that the commodity and the stock market are converging. Based on the analysis results presented herein one cannot conclude whether one market primarily leads the other. The cross relations over various interdependences made it difficult to define clear lead-lag relations between the commodity and the stock market.

Therefore, we would like to examine the lead-lag relationship between the stock price and commodity like palm oil in Malaysian case by using of a noble approach – wavelet analysis.

1.3. Commodity Price and Exchange Rate

There are a few studies on the relationship between currency and commodity prices. It is clear that the early 1970's witnessed a significant run-up in prices while the same is true for the 2007/2008 period. The important local question is: What is the cause of this episodic volatility, and the "big picture" question is exactly the title of this talk namely: "What drives commodity prices?"

Tse *et al.* (2010) examined the relationships among currency and commodity futures markets based on four commodity- the Australian dollar, Canadian dollar, New Zealand dollar, and South African rand. They found that commodity/currency relationships exist contemporaneously, but fail to exhibit Granger-causality in either direction. Their study examined short-horizon commodity/currency relationships using two types of restriction-based causality tests as well as a rolling, out- of-sample forecasting methodology. They find no evidence of cross-asset causality or predictive ability in either direction. These results suggest that commodity returns information is rapidly incorporated into currency returns (and vice versa) on a daily level. Their results also suggest that economic expectations embedded in currency returns are rapidly incorporated into a country's terms-of-trade, which are embedded in commodity returns (and vice versa).

Even though, lead-lag relationships have been analyzed between these economic variables such as commodity price, stock market and exchange rate, in terms of methodology, these studies apply multivariate statistical approaches, for example, vector autoregressive (Ibrahim and Yusoff, 2001) and vector error correction (Ajayi and Mougoue, 1998) models and cointegration and Granger causality tests (Bahmani-Oskooee and Sohrabian, 1992; Tse *et al.* 2010). 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, 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 economic variables how well two different markets are connected, and how fast one market reacts 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 co-movement at the frequency level (see, for example, A'Hearn and Woitek, 2001; 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 different economic variables 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.

In such a context, we investigate the causality among the stock price, commodity price and exchange rate 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 are considered (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; 1998b) use wavelets to investigate the relationship between several macroeconomic variables. In particular, the wavelet approach provides a framework to measure co-movement in the time–frequency space.

The main advantage of wavelet analysis that it is able to decompose macroeconomic time series, and data in general, into their time scale components. Some applications of wavelet analysis in economics and finance have been supported by Ramsey and Lampart (1998; 1998b), 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 was 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 price, commodity price and exchange rate by applying wavelet cross-correlation technique to wavelet coefficients.

2. Methodology

Though, some researchers (e.g. Cheung and Ng, 1998; Nasseh and Strauss, 2000, Masih and Masih, 1997; 1999; 2001) have examined either the short-run or long-run relationships, the time series methodologies employed (usually co-integration analysis) may separate out just two time periods in economic time series, i.e. the short-run and the long-run. The vector error-correction modelling (VECM) cannot tell us the lead-lag relationship at different time intervals; it only tells us short-term and long-term relationship among the financial/economic variables. However, the financial market provides an example of a market in which the agents involved comprise of diverse investors making decisions over different time horizons such as, from minutes to years and operating at each moment on different time scales (from hedging to investment activity).

The substantial progress in computation and visualization tools that characterize the various mathematical and statistical packages implementing wavelet analysis algorithms has made extended graphic and signal processing capabilities available to researchers (Gallegati, 2008). Wavelet analysis is able to decompose a time series into its time scale (or frequency) components; therefore, it reveals a structure of different time horizons which may be useful in analyzing situations in which the degree of association between two time series is likely to change with the time horizon. Particularly, wavelet cross-correlation analysis, the analogue of the standard time domain measure of association in the time-scale domain, may be used to determine the lead/lag relationship between two time series on a scale-by-scale basis.

We propose the techniques which identifies the dynamic linkages (in terms of lead-lag relationships) of three different economic variables, namely, stock price, commodity price and exchange rate. The issue of market linkages (and price discovery) between these variables 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 two different variables illustrates how well these markets are linked together.

Several applications of wavelet analysis in economics and finance have been provided by Ramsey and Lampart (1998a; 1998b), Ramsey (2002) and Duchesne (2006), Gallegati (2008; 2010), Aguiar-Conraria and Soares (2008), 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 these proposed economic variables, we have applied wavelet-cross-correlation which under maximal overlap discrete wavelet transform (MODWT) by following Gallegati's methodology (2008; 2010).

2.1. Wavelet Series Expansion

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:

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

where the coefficients $\upsilon_{J,k} = \sum_k \phi_{J,k} f\,(t)$ and $\omega_{j,k} = \sum_k \Psi_{j,k}\, f(t)$ 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:

$$\int \phi_{J,k}(t)\phi_{J,k^*}(t)dt = \delta_{k,k^*},$$
$$\int \Psi_{j,k}(t)\Psi_{j^*,k^*}(t)dt = \delta_{j,j^*}\delta_{k,k^*},$$
$$\int \Psi_{j,k}(t)\phi_{j,k^*}(t)dt = 0, \ \ \forall j,k,$$

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

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

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

$$\Psi_{j,k}(t) = 2^{-\frac{j}{2}}\Psi\left(\frac{t-2^j k}{2^j}\right)$$

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.

2.2. Multi-scale Analysis of Correlation

The wavelet decomposition enables us for a different representation of the variability and association structure of certain stochastic processes on a scale-by-scale basis (Gallegati, 2010). The wavelet coefficients can be manipulated in a straight forward manner to achieve recognizable statistical quantities such as wavelet variance, wavelet covariance, and wavelet correlation.

Whitcher *et al.* (1999; 2000) extended the notion of wavelet variance for the maximal overlap discrete wavelet transform (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. In order to achieve the wavelet covariance, we followed Gencay *et al.* (2001) and Gallegati (2010).

The wavelet variance decomposes the variance of a time series into components associated with different scales (Percival, 1995; Gallegati, 2010), where the wavelet variance at scale *j*, $\sigma_X^2(\lambda_j)$, of a stationary stochastic process {X} with variance is given by the variance of *j-level* wavelet coefficients:

$$\sigma_X^2(\lambda j) = \mathrm{Var}(\omega_{j,t}^{X})$$

Just as their classical counterparts, the wavelet covariance can be defined as between two processes X and Y at wavelet scale *j* as the covariance between *scale-j* wavelet coefficients of X and Y, that is, $\gamma_{XY}(\lambda_j) = \mathrm{Cov}(\omega_{j,t}^{X}\omega_{j,t}^{Y})$). In the similar way, the wavelet correlation between two time series $\rho_{XY}(\lambda_j)$ as the ratio of the wavelet covariance, $\gamma_{XY}(\lambda_j)$, and the square root of their wavelet variances $\sigma_X(\lambda_j)$ and $\sigma_Y(\lambda_j)$ (see Whitcher *et al.* 1999 and 2000; Gallegati, 2010). A standardized measure of the relationship between the two processes X and Y on a scale-by-scale basis can obtained by wavelet correlation coefficient $\rho_{XY}(\lambda_j)$ and, similarly the correlation coefficient between two random variables, $|\tilde{\rho}_{XY}(\lambda_j)| \leq 1$. In detail, given the unbiased estimators of the wavelet variances, $\tilde{\sigma}_X(\lambda_j)$ and $\tilde{\sigma}_Y(\lambda_j)$, and covariance, $\tilde{\gamma}_{XY}(\lambda_j)$, the unbiased estimator of the wavelet correlation for scale *j*, $\tilde{\rho}_{XY}(\lambda_j)$, may be achieved by:

$$\tilde{\rho}_{XY}(\lambda_j) = \frac{\tilde{\gamma}_{XY}(\lambda_j)}{\tilde{\sigma}_X(\lambda_j)\tilde{\sigma}_Y(\lambda_j)}$$

2.3. Wavelet-cross-correlation

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).

$$\tilde{\gamma}_{XY,j} = \frac{1}{\tilde{N}_j} N - 1 \sum_{t=L_{J-1}}^{N-1} \tilde{\omega}_{j,t}^{X} \tilde{\omega}_{j,t}^{Y}$$

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, $\tilde{\gamma}_{\tau,XY,j}$, and the square root of their wavelet variances $\tilde{\sigma}_{X,j}$and $\tilde{\sigma}_{Y,j}$ as follows:

$$\tilde{\rho}_{\tau,XY,j} = \frac{\tilde{\gamma}_{\tau,XY,j}}{\tilde{\sigma}_{X,j}\tilde{\sigma}_{Y,j}}$$

The wavelet cross-correlation co-efficients $\tilde{\rho}_{\tau,XY,j}$, 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 $\tilde{\upsilon}_{X,j}^2$ are provided in Gencay *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; Gallegati, 2008).

3. Data

We use close-to-close monthly data in local currencies for the stock price (KLCI), commodity price and exchange rate (MYR/USD). Data are taken from the Datastream and cover the period from January 1990 to December 2012. These variables are analyzed in levels, although there are several reasons to justify the use of returns instead of levels. But, due to the main advantage of wavelet analysis which is its ability to decompose time series into their time scale components (Madaleno and Pinho, 2012), we use monthly prices instead of returns. Furthermore, the translation and scale properties, non-stationarity in the data are not a problem when using wavelets, and pre-filtering is not necessary. Madaleno and Pinho (2012) also use prices instead of returns.

4. Empirical Analysis

4.1. Wavelet Variance and Correlations

By help of MODWT variance analysis, with an LA (8) wavelet and 5 levels of decomposition, we get the variance of decomposition of our three variables shown in from Figures 1 to 3.

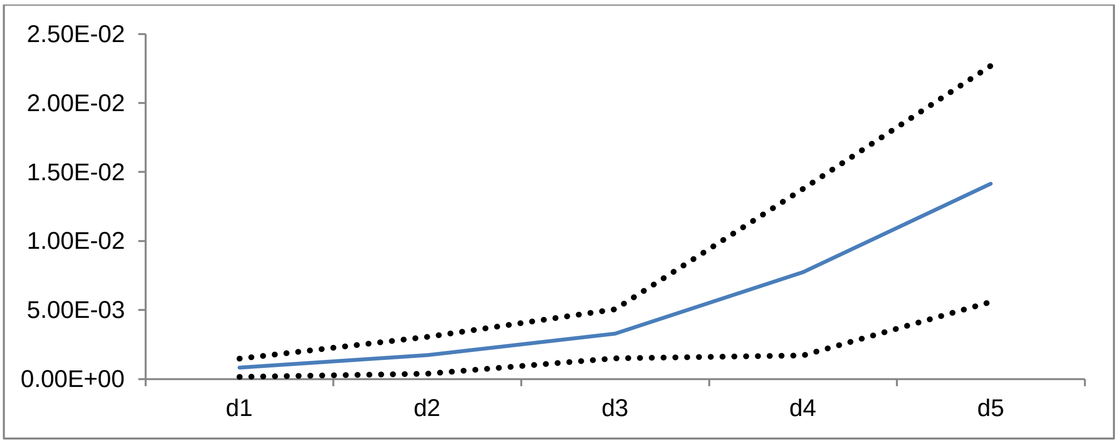

Figure 1. Wavelet variance of the stock price, at all 5 levels, with a 95% confidence interval

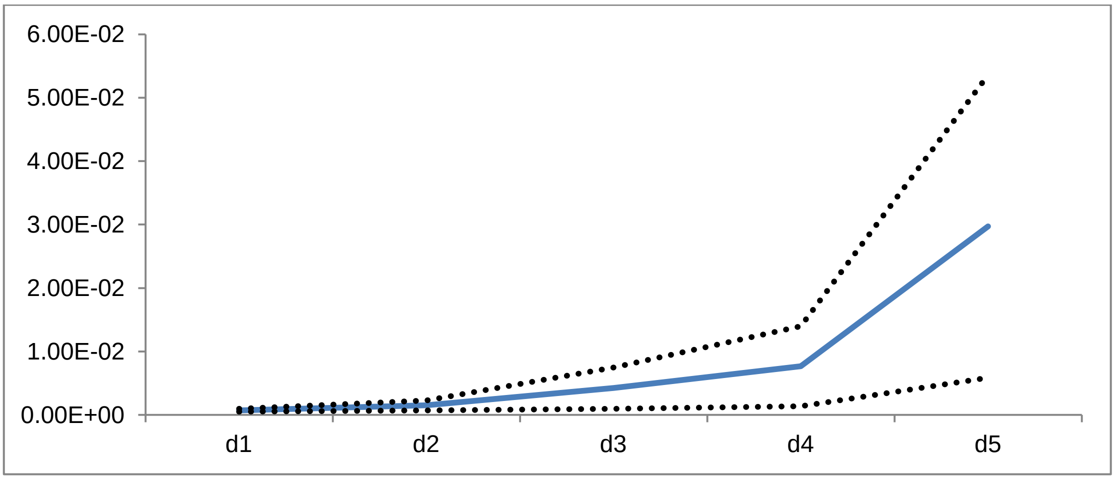

Figure 2. Wavelet variance of the commodity price, at all 5 levels, with a 95% confidence interval

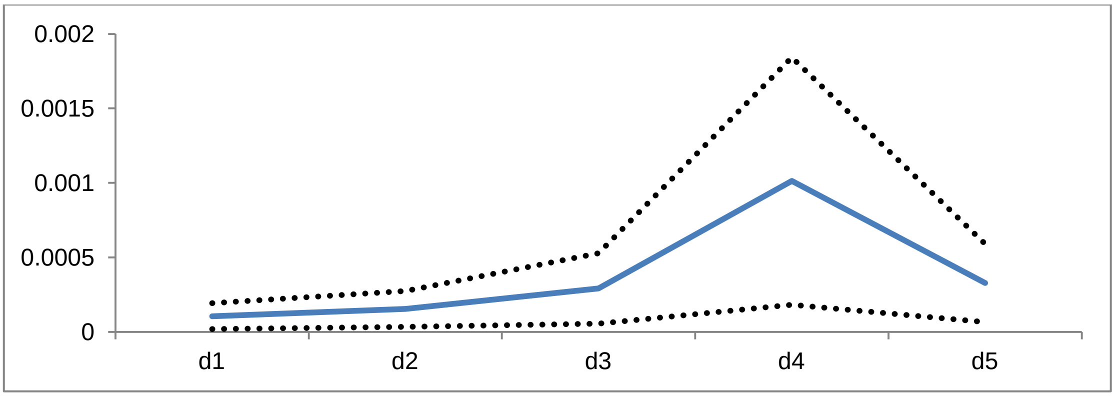

Figure 3. Wavelet variance of the exchange rate, at all 5 levels, with a 95% confidence interval

From Figures 1 and 2, we can see that the variance of both variables, namely, stock price and commodity price, their volatilities rise when the level increases; however, as far as the exchange rate concern, the variance rises until level 4 which associated with 8-16 months, then it declines at level 5 which associated with 16-32 months;

When analyzing the relationship between stock price, commodity price and exchange rate; our major concern is whether one is leading the other one or not. To investigate this issue, from Figures 4 to 6 shows the wavelet correlation between these three variables at all five levels.

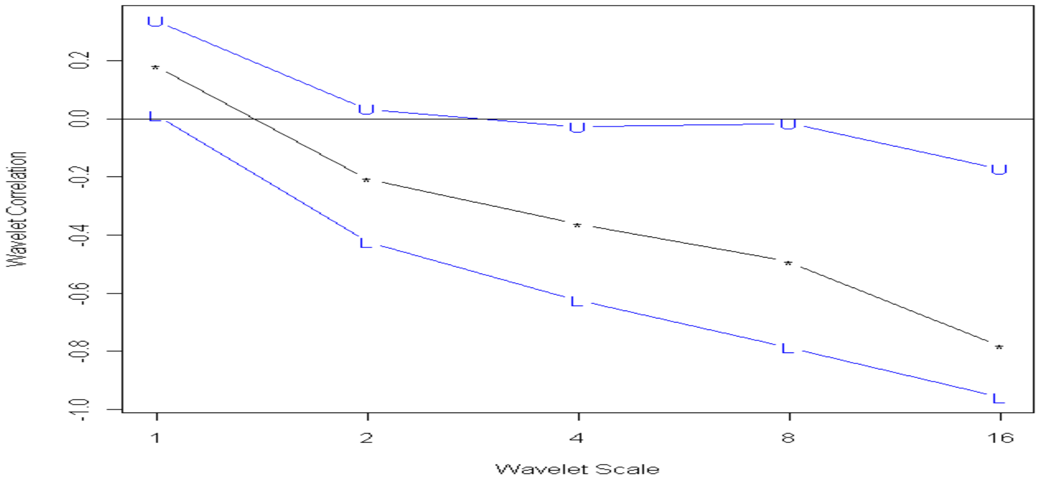

Figure 4. wavelet correlation between stock price and exchange rate, at all 5 levels, with a 95% confidence level

From Figure 4, we could see that, the correlations between the two variables only appear to be significant at levels 3, 4 and 5, with negative values. This is consistent with the assumption by Dimitrova (2005), if the relationship is negative when exchange rates are the lead variable. What we found is that the relevant time scales are levels 3, 4 and 5, which associated with 4 to 16 month cycles, which is of the same order of magnitude as the speed of reaction of stock price to exchange rate. At other levels, the correlation between the two variables is not significantly different from zero.

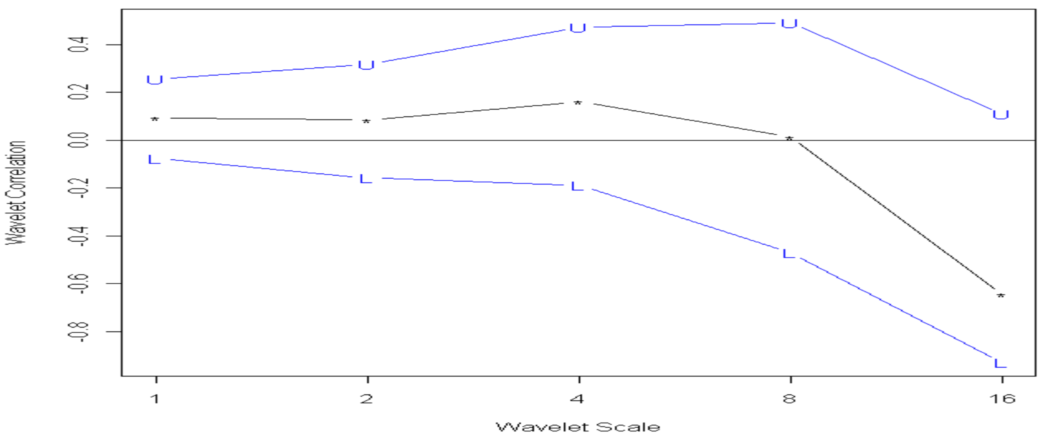

Figure 5. Wavelet correlation between stock price and commodity price, at all 5 levels, with a 95% confidence level

Figure 5 informs us that, the correlation between stock and commodity prices is not significant at all levels from level 1 to level 5. Our results are contradicted with findings of Wassmer *et al.* (2011). They found that there is an interconnection between the Commodity and the Stock Market in United States. There is evidence for various information spillovers across the markets from returns as well as from news sentiments. Our results support the hypothesis that stock and commodity prices are independent.

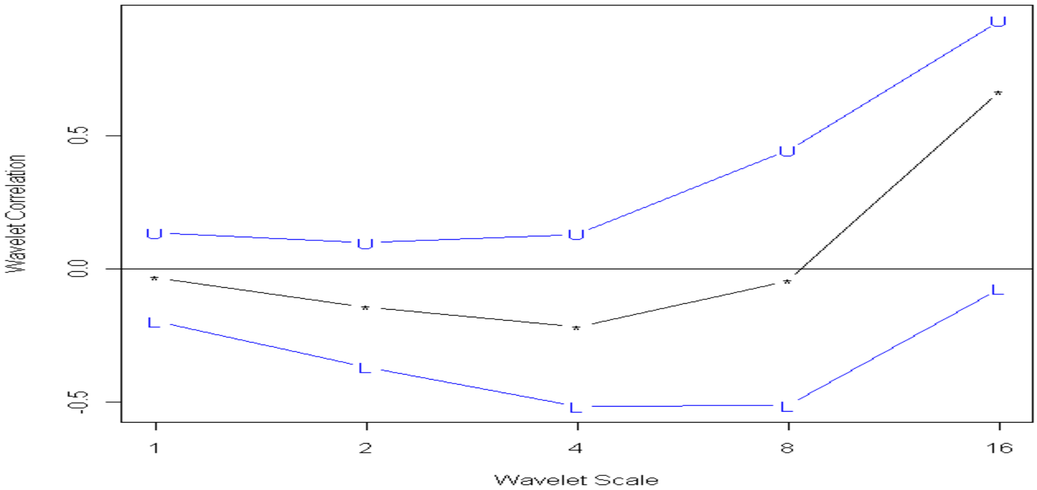

Figure 6. Wavelet correlation between commodity price and exchange rate, at all 5 levels, with a 95% confidence level

The results produced in Figure 6 are quite similar to Figure 5. We also fund that there is no significant correlation between commodity price and exchange rate at all levels. In other words, the correlation between the two variables is not significantly different from zero. Our results are similar to previous findings (Tse *et al.* 2010) that commodity price information is rapidly incorporated into exchange rates (and vice versa) on a monthly level.

4.2. Wavelet Cross-Correlation Analysis (Lead - lag or Causality Analysis)

Simple correlations cannot capture the basic fact that lags often exist between variables, whatever their timescales. In order to grasp the lead-lag relationship between two variables, we have applied wavelet-cross-correlation. In Figures 7 -9, we report the MODWT-based wavelet cross-correlation between the stock price, commodity price and exchange rate, 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 months. The red lines bound approximately 95% confidence interval for the wavelet cross-correlation. If the curve is significant on the right side of the graph, it means that the second time series is leading the first time series; for example, in the case of stock price – exchange rate, If the curve is significant on the right side of the graph, it means that the exchange rate is leading the stock price; 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 second time series is leading the first time series; 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.

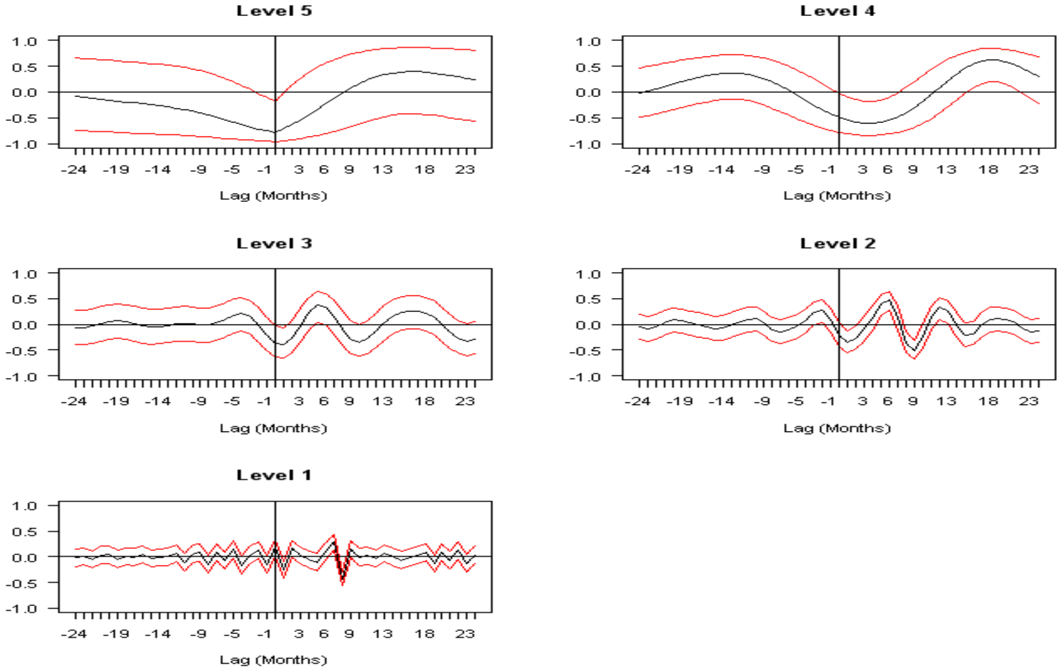

Figure 7. Wavelet cross-correlation between stock price and exchange rate at each level, with 95% confidence interval

Figure 7 presents the wavelet cross-correlations of the stock price and exchange rate at all 5 levels. From this Figure, we can observe the following:

At the first wavelet level, we can observe only one significant correlation on the right side of the graph. It implies that the exchange rate leads stock price.

At the second level, the lead-lag relationships are very clear. There are some significant correlations on the right side of the graph, two of them are negative correlations plus one positive correlation; the wavelet cross-correlations skewed to the right, means that the exchange rate, again, leads stock price.

The third, fourth and fifth wavelet levels are consistent with our previous finding which reveals that the correlations between the two variables only appear to be significant at levels 3, 4 and 5, with negative values (figure 4). The wavelet cross-correlations skewed to the right with negative significant correlations which implies that the exchange rate is exogenous variable. Our results are consistent with findings by assumption of Dimitrova (2005). They found that if this correlation is positive when stock prices are the lead variable and likely negative when exchange rates are the lead variable.

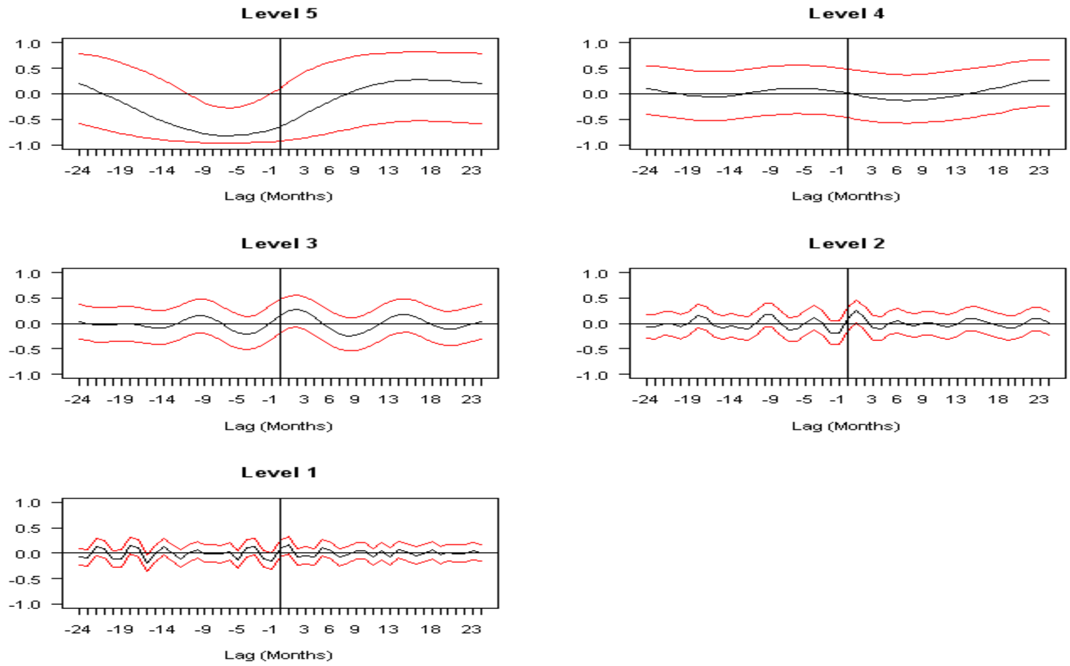

Figure 8. Wavelet cross-correlation between stock price and commodity price at each level, with 95% confidence interval

Figure 8 presents the wavelet cross-correlations of the stock price and commodity price at all 5 levels. This graph produces that there is no significant wavelet-cross-correlation at first four levels. However, we observe that there is negative and significant wavelet-cross-correlation at left hand side at level 5; in order words, the wavelet cross-correlations skewed to the left which implies that the stock price leads commodity price in the long-run – 16-32 months. Thus, the results from wavelet-cross-correlation analysis reveals that the stock price tend to lead commodity price, but only at scales corresponding to periods of 16 months and longer (lowest frequencies). These results are consistent with findings of Gallegati (2008). Their analysis indicates that stock returns are leading aggregate economic activity at scales corresponding to periods of 16 months and longer.

Last but not least, the Figure 9 shows that there are no significant wavelet cross-correlations at all levels. It implies that there is no lead-lag relationship between commodity price and exchange rate. Therefore, we support findings of Tse *et al.* (2010). They find no evidence of causality or predictive ability in either direction between commodity returns and currency returns. These results suggest that commodity returns information is rapidly incorporated into currency returns (and vice versa) on a daily level. Their results also suggest that economic expectations embedded in currency returns are rapidly incorporated into a country's terms-of-trade, which are embedded in commodity returns (and vice versa).

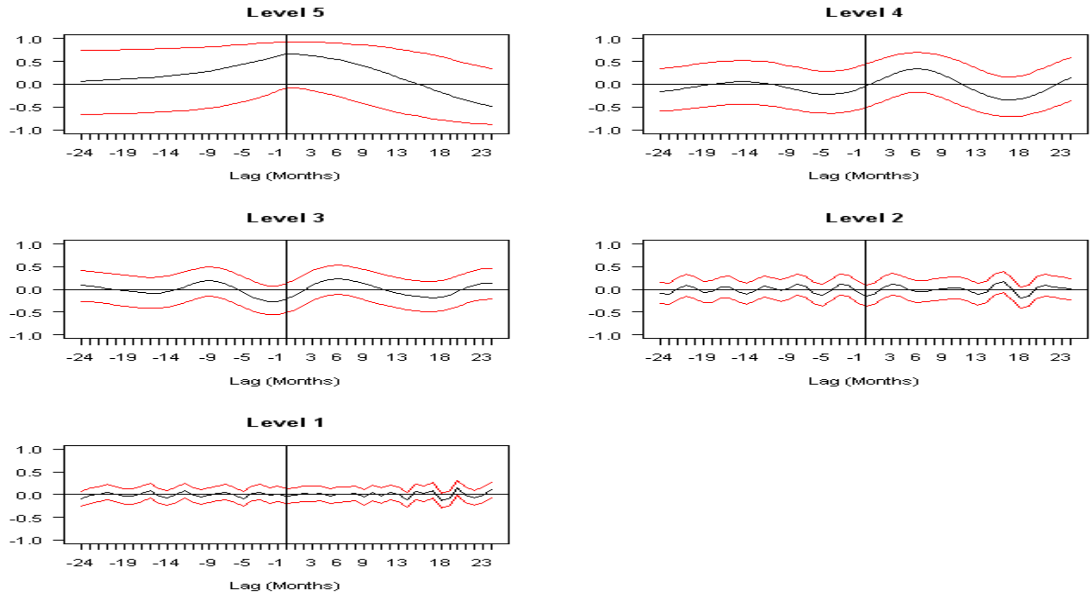

Figure 9. Wavelet cross-correlation between commodity price and exchange rate at each level, with 95% confidence interval

5. Conclusion

We examined the lead-lag relationships between the stock price, exchange rate and commodity price in the case of Malaysia through the application of wavelet analysis. Our main findings may be summarized as follows:

In term of volatility, the volatilities of stock price and commodity price rise when the level increases; in other words, they have lower volatility at high frequencies (lower scale) and higher volatility at lower frequencies (higher sales); however, as far as the exchange rate concern, the variance rises until level 4 which associated with 8-16 months, then it declines at level 5 which associated with 16-32 months;

As far as the wavelet correlations concern, the correlations between the stock price and exchange rate only appear to be significant at levels 3, 4 and 5 (4-8, 8-16, 16-32 months, respectively), with negative values. The correlations between stock and commodity prices as well as between commodity price and exchange rate are not significant at all levels from level 1 to level 5.

From the wavelet cross-correlations between stock price and exchange rate, we could see that the correlations skewed to the right with negative significant correlations which implies that the exchange rate is exogenous variable. In other words, the exchange rate leads the stock price.

In the case of stock and commodity prices, there is no significant wavelet-cross-correlation at first four levels. However, the wavelet cross-correlations skewed to the left at level 5 which implies that the stock price leads commodity price in the long-run – 16-32 months. Thus, the results reveals that the stock price tends to lead commodity price, but only at scales corresponding to periods of 16 months and longer (lowest frequencies).

Finally, there is no significant wavelet cross-correlations at all levels as long as we concern between commodity price and exchange rate. It implies that there is no lead-lag relationship between commodity price and exchange rate.

In conclusion, this study shows that wavelet analysis can provide a valuable alternative to the existing conventional methodologies in identifying lead-lag (causality) relationship between financial/economic variables, since wavelets considered heterogeneous agents who making decisions over different time horizons.

References

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

A'Hearn, B. and Woitek, U., 2001. More international evidence on the historical properties of business cycles. *Journal of Monetary Economics,* 47(2), pp.321-346.

Ajayi, R.A., Friedman J., and Mehdian S.M., 1998. On the relationship between stock returns and exchange rates: Tests of Granger Causality. *Global Finance Journal*, 9(2), pp. 241-251.

Bahmani-Oskooee, M. and Sohrabian, A., 1992. Stock prices and the effective exchange rate of the dollar. *Applied Economics*, 24(4), pp. 459-464.

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

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

Dimitrova, D., 2005. The relationship between exchange rates and stock prices: Studied in a multivariate model. *Issues in Political Economy*, 14, pp.1-25.

Duchesne, P., 2006. Testing for multivariate autoregressive conditional heteroskedasticity using wavelets. *Computational Statistics & Data Analysis*, 50, pp.2142-2163.

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

Gallegati, M., 2008. Wavelet analysis of stock returns and aggregate economic activity. *Computational Statistics & Data Analysis,* 52(6), pp.3061-3074.

Gallegati, M., 2010. A wavelet-based approach to test for financial market contagion. *Computational Statistics and Data Analysis,* 56(11), pp. 3491-3497.

Gencay, R., Selcuk, F., and Whitcher, B., 2001. Scaling properties of exchange rate volatilities. *Physica A: Statistical Mechanics and its Applications*, 289, pp.89-106.

Gencay, R., Selcuk, F., and Whitcher, B., 2002. *An introduction to wavelets and other filtering methods in finance and economics*. San Diego: San Diego Academic Press.

Ibrahim, MH., and Yusoff, W.S.W., 2001. Macroeconomic variables, exchange rate and stock price: A Malaysian perspective. *IIUM Journal of Economics and Management*, 9(2), pp.141-164.

Ibrahim, M., 2000. Cointegration and granger causality tests of stock price and exchange rates interactions in Malaysia. *ASEAN Economic Bulletin*, 17(1), pp.36-46.

Ibrahim, M.H., and Aziz, H., 2003. Macroeconomic variables and the Malaysian equity market: A view through rolling subsamples. *Journal of Economic Studies,* 30(1), pp.6-27.

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

Madaleno, M., and Pinho, C., 2012. International stock market indexes comovements: A new look. *International Journal of Finance and Economics*, 17(3), pp.89-102.

Masih, A.M.M. and 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), pp.59-74.

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(3), pp.251-282.

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

Nasseh, A. and Strauss, J., 2000. Stock prices and domestic and international macroeconomic activity: A cointegration approach. *Quarterly Review of Economics & Finance*, 40(2), pp.229-245.

Pakko, M., 2004. A spectral analysis of the cross-country consumption correlation puzzle. *Economics Letters*, 84(3), pp.341-347.

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

Ramsey, J. and Lampart, C., 1998a. Decomposition of economic relationships by time scale using wavelets. *Macroeconomic Dynamics*, 2(1), pp.49-71.

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

Ramsey, J. and Zhang, Z., 1996. The application of wave form dictionaries to stock market index data. In: Y. Kratsov and J. Kadtke eds. *Predictability of complex dynamical systems*. Berlin: Springer.

Ramsey, J. and Zhang, Z., 1997. The analysis of foreign exchange data using waveform dictionaries. *Journal of Empirical Finance*, 4, pp.341-372.

Ramsey, J.B., 2002.Wavelets in economics and finance: Past and future. *C.V. Starr Center for Applied Economics,* 11, 2002-02.

Rua, A. and Nunes, L.C., 2009. International Comovement of stock market returns: A wavelet analysis. *Journal of Empirical Finance*, 16(4), pp.632-639.

Smith, K., 2001. Pre- and post-1987 crash frequency domain analysis among Pacific Rim equity markets. *Journal of Multinational Financial Management*, 11(1), pp.69-87.

Tse, Y., Williams, M., and Chan, K., 2010. The relationship between commodity prices and currency exchange rates: Evidence from the futures markets. *College of Business, University of Texas at San Antonio Working Paper,* 0005FIN-257-2010.

Vacha, L. and Barunik, J., 2012. Co-movement of energy commodities revisited: Evidence from wavelet coherence analysis. *Preprint submitted to Elsevier* - January 24, 2012.

Wassmer, T., Steude, S.C., and Hens, T., 2011. Information spillover effects between the commodity and the stock markets. *Swiss Banking Institute University of Zurich Master Thesis.*

Whitcher, B., Guttorp, P., and Percival, D.B., 1999. Mathematical background for wavelet estimators for cross covariance and cross correlation*. National Research Centre for Statistics and the Environment*, Seattle. *Technical Report,* 38.

Whitcher, B., Guttorp, P., and Percival, D.B., 2000. Wavelet analysis of covariance with application to atmospheric series. *Journal of Geophysical Research: Atmosphere*, 105(D11), pp.14941-14962.