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Comovement of East and West Stock Market Indexes

Yuzlizawati Yusoff[1] and Mansur Masih[2]

ABSTRACT

Determination of diversification strategies by investors depends on the nature and magnitude of the relationships existing between different stock markets. Therefore, it is important for international investors to understand the relationship among various markets in order to diversify risk and derive high return. In a co-movement analysis a consideration that is being looked upon is the distinction between the short and the long term investor, who have different term objectives. Wavelets were used to assess the co-movement and interactions of East and West stock index, namely; FBKLCI (Malaysia), FSSTI (Singapore), INDU (Indonesia), HIS (Hong Kong) and JCI (New York). The findings suggest that most of the indexes investigated in this study through the wavelet coherency shows that high coherency exists among them on the daily time scale of 32 to 512 days band. A negative correlation between them was also found among the markets, which shows a tendency in the correlation coefficients to move downwards with the timescale, except for the very long-run. In addition, it is also observed that there exists a linear relationship between the wavelet variance and wavelet timescale. The variance for most of the indexes decreases as the wavelet timescale increases. The cross correlation analysis showed that the short and medium term fluctuations for the indexes are more closely related compared to those over the long term.

Keywords: comovement of international stocks, wavelet analysis (CWT and MODWT)

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INTRODUCTION

In a co-movement analysis a consideration that is being looked upon is the distinction between the short and the long term investor, who have different term objectives. This is in particular when they are dealing with the international investor who has an intention to diversify risk and also derive returns from an international portfolio. International investor also depends on the nature and magnitude of relationship that exists between different stock markets in order to determine their diversification strategies. Therefore, as an investor, it is very important to understand the relationship among various markets to diversify risk and to derive high return.

In this study, wavelets were used to assess the co-movement and interactions of East and West stock index, namely; FBKLCI (Malaysia), FSSTI (Singapore), INDU (Indonesia), HIS (Hong Kong) and JCI (New York). According to Madeleno and Pinho (2010), in their paper, they highlighted the importance of wavelets as an important addition to time-series methods which allows researcher how to decompose relationship in the time-frequency scale. Therefore, inspired by the above paper, this study is trying to apply the continuous Wavelet Transform analysis and MODWT analysis to show the relationship among indexes investigated. The objectives of this study is to investigate whether those five markets above changed and evolved with time which investors shall consider in their portfolio diversification.

This paper is discussed as follows. In section 2, the discussion will be on the literature review on the co-movement issues and also wavelet history. In section 3, discuss the data description and the methodology. In section 4, the empirical results will be discussed. Finally, section 5 will be the conclusion for the whole paper.

LITERATURE REVIEW

Previous research had looks into many angle on the co-movement analysis. Empirical studies also had shown that there are an investigation being made on the interdependence and co-movement between international stock market which are based on the estimation of correlation matrix of stock market index returns, and also on the multivariate analysis techniques such as co-integration theory and principle component theory. Studies done by Kizys and Pierdzioch (2009) and also Karolyi and Stulz (1996) concluded that co-movement of stock returns is not constant over time.

Consideration on the distinction between short and long term investor in regards to the co-movement analysis had been given attention also. According to Candelon et al (2008), they give arguments that from a portfolio diversification point of view, short term investor is naturally more interested in the co-movement of stock returns at higher frequencies, known as short term fluctuations. Meanwhile, long term investor will focus on the long term fluctuations; looking on the relationship at lower frequencies.

Later, Ramsey and Lampart (1998) had studied the decomposition using traditional time-domain methods. While, Gallegati and Gallegati (2007) mentioned that wavelet was not popular because it applied either to analyze individual time series or several time series. Aguiar-Conraria et al (2008) applied cross-wavelet coherency and phase-difference and showed that the method can be used in order to study interactions between series at different frequencies and also to see how they evolve over time.

Several studies also had applied the wavelet analysis, especially studies that are being done in economics and finance; Ramsay and Lampart (1998) and also Kim and In (2003), Lee (2004), Rua and Nunes (2009) and also Madaleno and Pinho (2010). Lee (2004) applies Wavelet transform technique to study the international transmission effects and reported that movements from the developed markets affected the developing markets. Rua and Nunes (2009) found that the degree of co-movement has changed over time using Wavelet techniques. They applied the techniques to four major markets; Germany, Japan, UK and US. Madeleno and Pinho (2009) use a continuous Wavelet Transform analysis and cross-wavelet analysis to show the relationship among indexes investigated have changed and evolved overtime. Vacha and Barunik (2012) in their studies found that wavelet coherence uncovered long cycles (64 to 128 days) in heating oil-crude oil pair that were also present in the recession period.

METHODOLOGY

The data in this paper consists of the daily stock index of five countries, namely Malaysia (FBMKLCI), Singapore (FSSTI), Indonesia (INDU), Hong Kong (HSI) and United States (JCI). The index were taken from the Bloomberg which cover a period between 3 January 2003 until 31 October 2013.

In this writing we apply two techniques from the Wavelet family analysis; the continuous Wavelet technique (CWT) and also the maximal overlap discrete wavelet transform (MODWT). The term wavelet refers to a small wave because the wavelet function is non-zero over a finite length of time and wave because the function oscillates.

The continuous wavelet transform (CWT) is defined as the integral over all over time of the signal multiplied by scaled, shifted versions of the wavelet function Ψ (scale, position, time), In and Kim (2012).

$$\text{C (scale, position)} = \int_{\infty}^{\infty} xt\varphi(scale, position, t)dt$$

$$\text{W}x(\text{s},\tau) = \int_{-\infty}^{\infty} x\tau \frac{1}{\sqrt{s}} \emptyset * \left(\frac{t-\tau}{s}\right) dt$$

Expected results from CWT are many wavelets coefficients C, which are the function of scale and position. According to In and Kim (2012), the scale and position can take on any values compatible with the region of the time series xt.

Wavelet Variance, Covariance and Correlation

Variance, covariance and correlation are used to provide useful statistical information to researchers, and they are applied to many financial theories.

Wavelet variance

When the wavelet coefficient being derived using MODWT, the coefficient indicate the changes at a particular scale. According to Percival and Walden (2000), the basic idea of the wavelet variance is to substitute the notion of variability over certain scales for the global measure of variability estimated by the sample variance. It can be expressed as below:

$$\sigma_y^2 = {}^{1}/_{2} \sum_{i=1}^{N} [yi - \bar{y}]^2$$

$$= {}^{1}/_{2} \sum_{i=1}^{N} [yi]^2 - [\bar{y}]^2$$

Where, $\bar{y}$ is the sample mean. Using orthogonality of the wavelet basis vectors, the sum of the series can be expressed as the sum of the squares of the wavelet coefficients.

Wavelet covariance and correlation

As in the standard statistics, wavelet covariance can be defined as the covariance between the wavelet coefficients of Xt and Yt at scale λj.

The sample covariance between Xt and Yt is:

$$\sigma XY = \frac{1}{N} \sum_{i=1}^{N} (Xi, t - \overline{X)}\ (Yi, t - \bar{Y})$$

$$= \frac{1}{N} \sum_{i=1}^{N} Xi, t\, Yi, t - \bar{X}\, \bar{Y})$$

$$= \frac{<XY>}{N} - \overline{XY}$$

MODWT wavelet covariance can also be expressed in terms of MODWT wavelet coefficients:

$$\tilde{\sigma}\ XY, j = {}^{1}/_{2j\ \widetilde{Nj}} \sum_{k=Lj}^{Nj} \tilde{d}_{j,k}^{X}\ \tilde{d}_{j,k}^{Y}$$

EMPIRICAL FINDINGS

The correlation and the co-movement between the market indexes is very well documented facts as previously analyzed in the brief literature review. Thus, to perform cross-wavelet analysis, in this writing, it will focus on the wavelet coherency.

In the appendixes A, Figures 1.1, 1.2, 1.3, 1.4, 1.5, 1.6, 1.7, 1.8, 1.9 and 1.10 were the estimated wavelet coherency and the phase difference between the four indexes. By using the Monte Carlo simulation, the values for significance was produced and obtained.

Contours denote the wavelet-squared coherency. Meanwhile the thick black contour is the 5 percent level of significance and outside the thin line is the boundary affected zone. The vectors indicate the phase difference between the two series.

The colour code for the power ranges from the low power (blue) to high power (red). The phase difference between the two series is indicated by arrows. Those pointing to the right means that the variables are in the phase. To the right and up with the first series lagging. To the right and down with the first series leading. Arrows pointing to the left mean that the variables are out of phase. To the left and up with the first series leading. To the left and down, with the first series lagging.

The wavelet coherence is used to identify both frequency bands and time intervals within which pairs of index are co-varying.

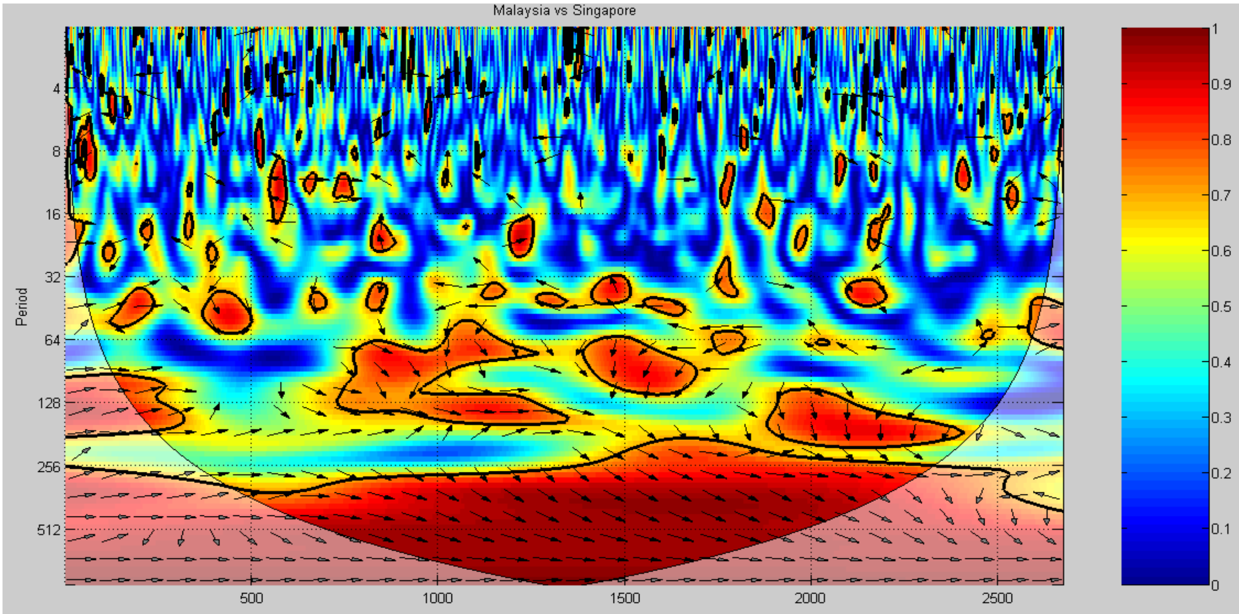


Figure 1.1 Wavelet coherence Malaysia vs Singapore

The wavelet coherency between Malaysia and Singapore is high at large scales, above the 64 days. It shows several statistically significant islands. On the daily time scales of 4 to 64 days band, the 5 percent significance regions indicate that the stock market indices under analysis do not show high coherency. The high coherency exists among them on the daily time scale of 256 to 512 band.

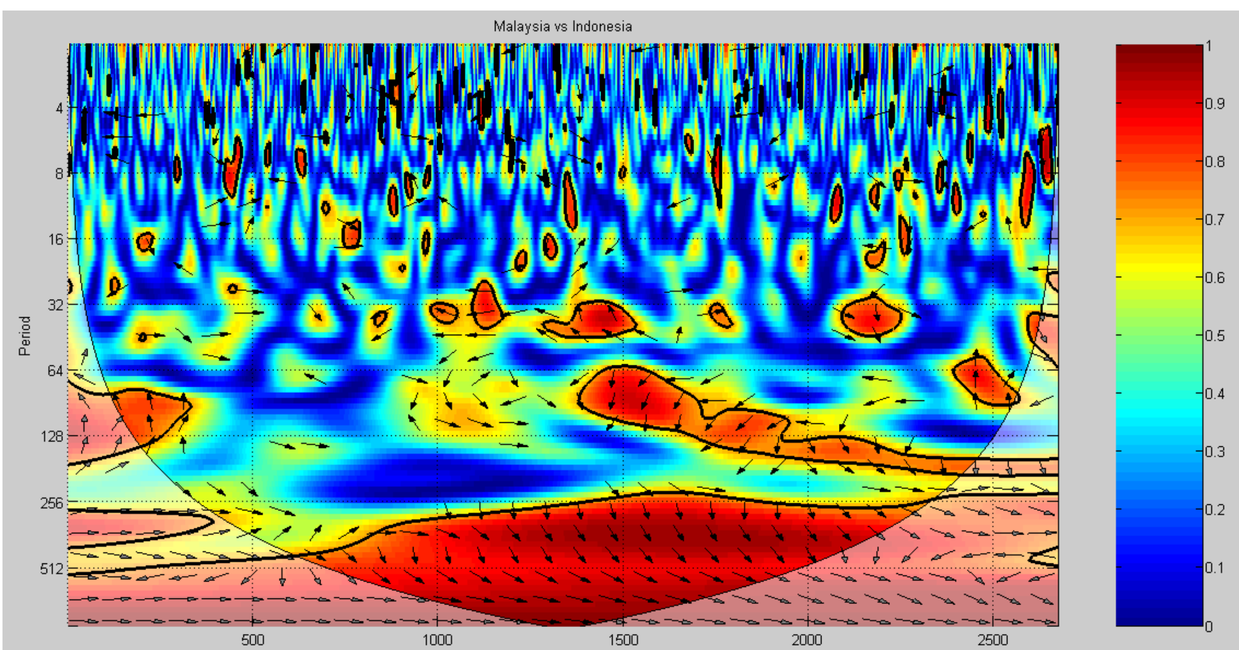


Figure 1.2 Malaysia vs Indonesia

The wavelet coherency between Malaysia and Indonesia is high at large scales, above the 64 days. It shows several statistically significant islands. On the daily time scales of 4 to 64 days band, the 5 percent significance regions indicate that the stock market indices under analysis do not show high coherency. The high coherency exist among them on the daily time scale of 256 to 512 band.

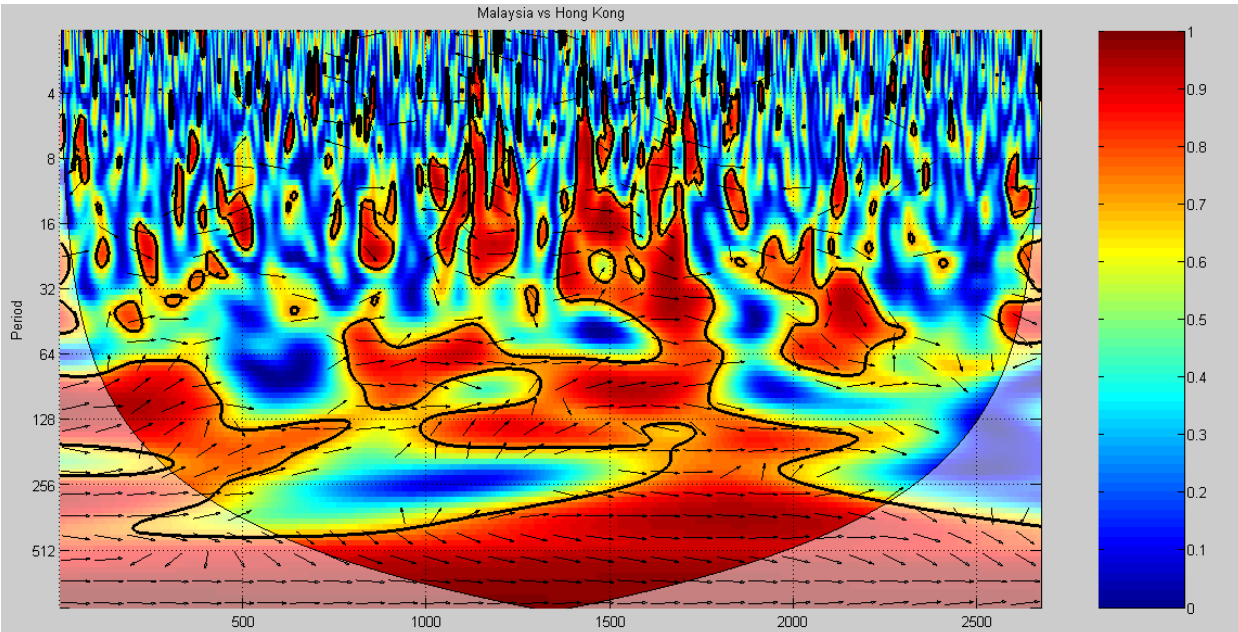


Figure 1.3 Malaysia vs Hong Kong

The wavelet coherency between Malaysia and Hong Kong quite different from the previous one. The wavelet coherency for both indexes started at scales, above the 16 days band. We can see several statistically significant islands exist. On the daily time scales of 4 to 32 days band, the 5 percent significance regions indicate that the stock market indices under analysis do not show high coherency. The high coherency exists among them on the daily time scale of 64 to 512 days band.

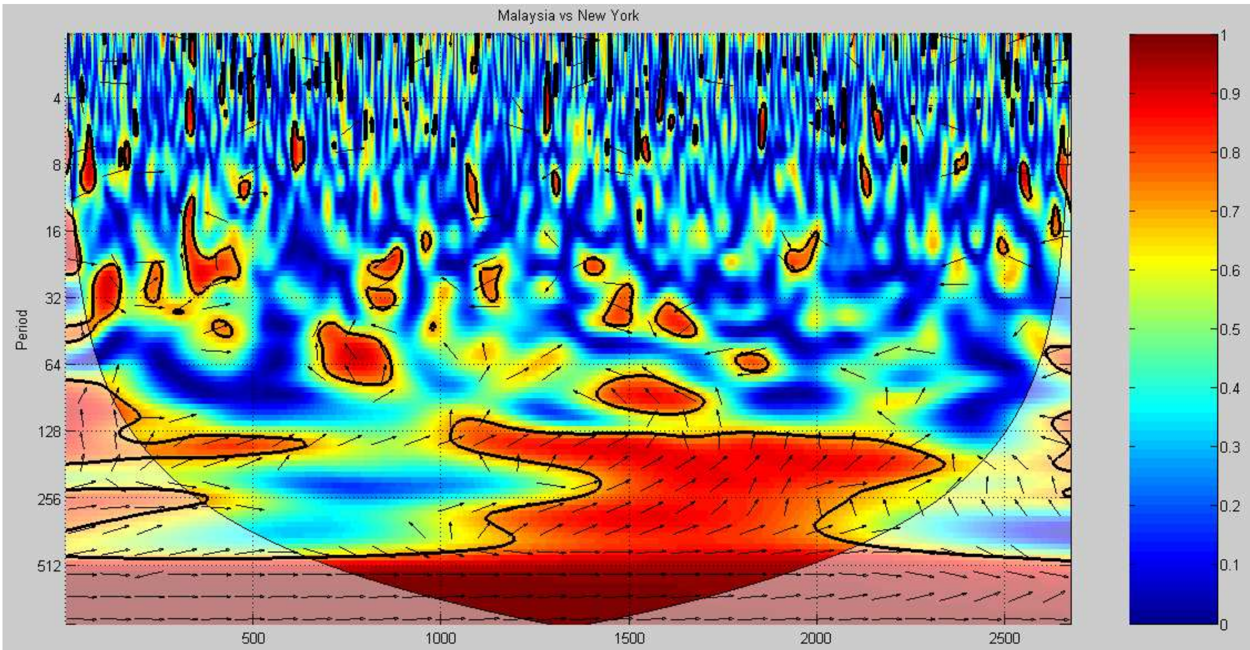


Figure 1.4 Malaysia vs New York

The wavelet coherency between Malaysia and New York, for both indexes started at scales, above the 128 days band. We can see several statistically significant islands exist. On the daily time scales of 4 to 64 days band, the 5 percent significance regions indicate that the stock market indices under analysis do not show high coherency. The high coherency exists among them on the daily time scale of 128 to 512 days band.

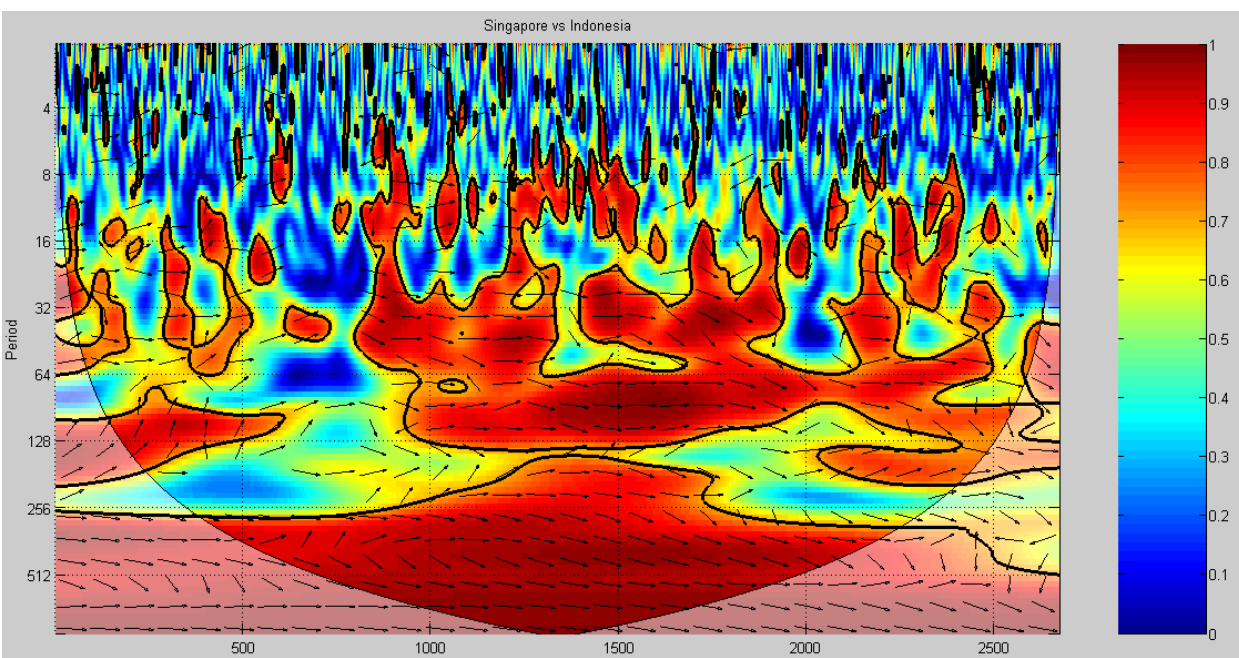


Figure 1.5 Singapore vs Indonesia

The wavelet coherency between Singapore and Indonesia, for both indexes started at scales, above the 32 days band. There are several statistically significant islands exist. On the daily time scales of 4 to 16 days band, the 5 percent significance regions indicate that the stock market indices under analysis do not show high coherency. The high coherency exists among them on the daily time scale of 32 to 512 days band.

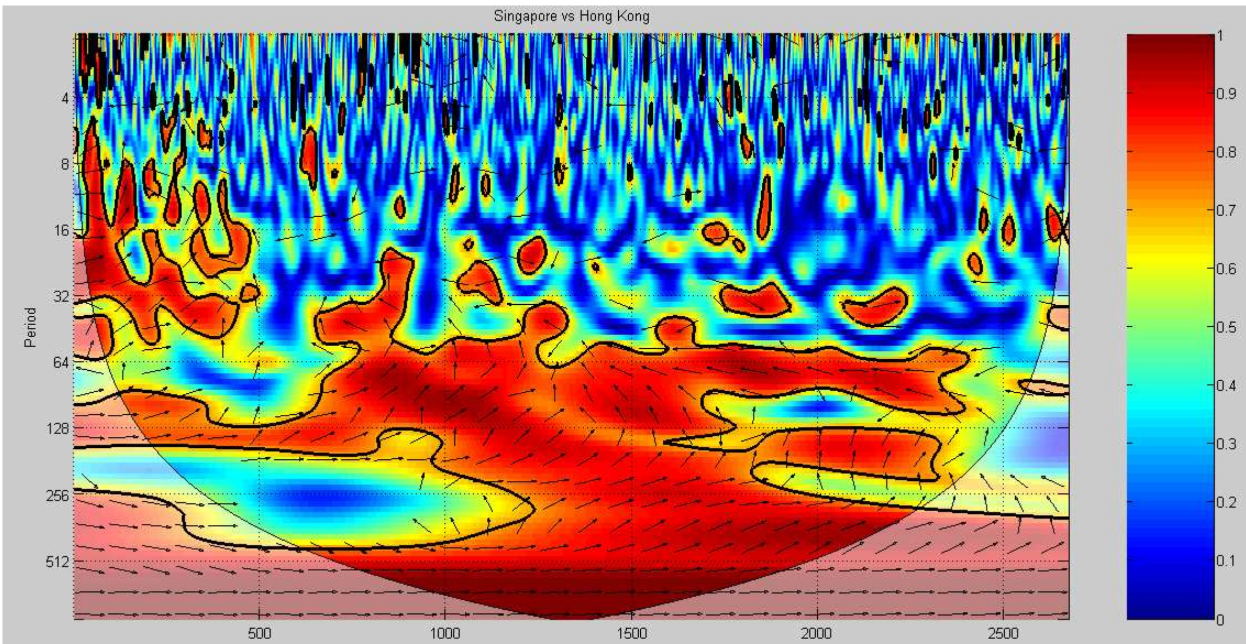


Figure 1.6 Singapore vs Hong Kong

The wavelet coherency between Singapore and Hong Kong, for both indexes started at scales, above the 64 days band. There are several statistically significant islands exist. On the daily time scales of 4 to 16 days band, the 5 percent significance regions indicate that the stock market indices under analysis do not show high coherency. The high coherency exists among them on the daily time scale of 64 to 512 days band.

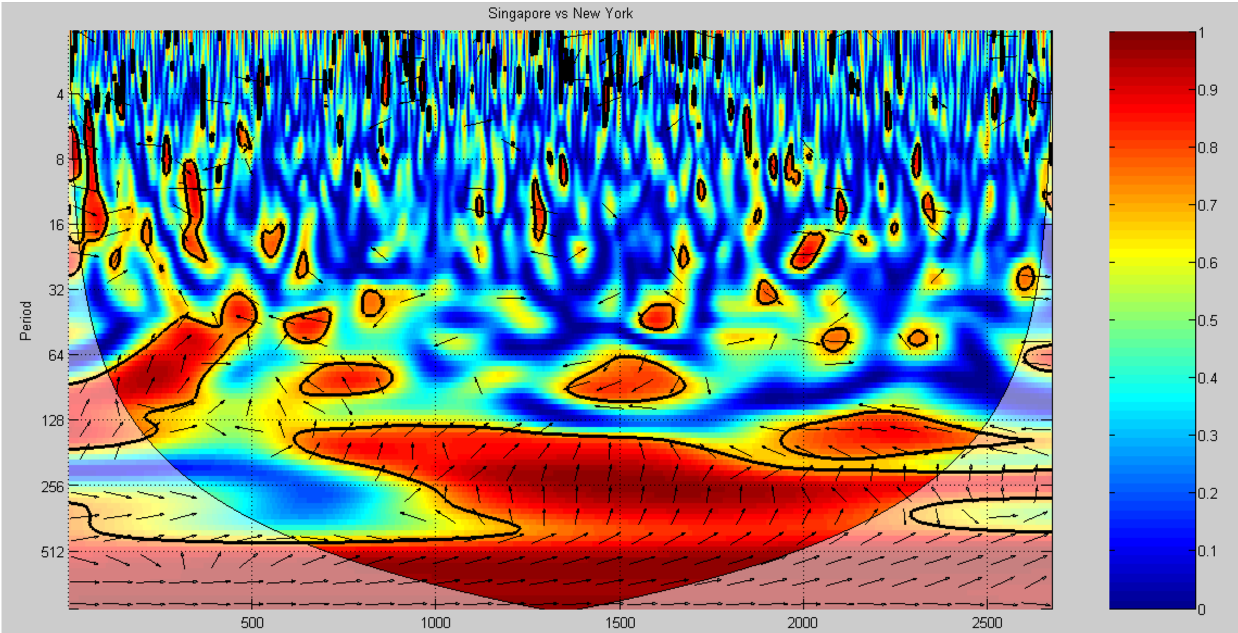


Figure 1.7 Singapore vs New York

The wavelet coherency between Singapore and New York is high at large scales, above the 128 days. It shows several statistically significant islands. On the daily time scales of 4 to 64 days band, the 5 percent significance regions indicate that the stock market indices under analysis do not show high coherency. The high coherency exists among them on the daily time scale of 128 to 512 band.

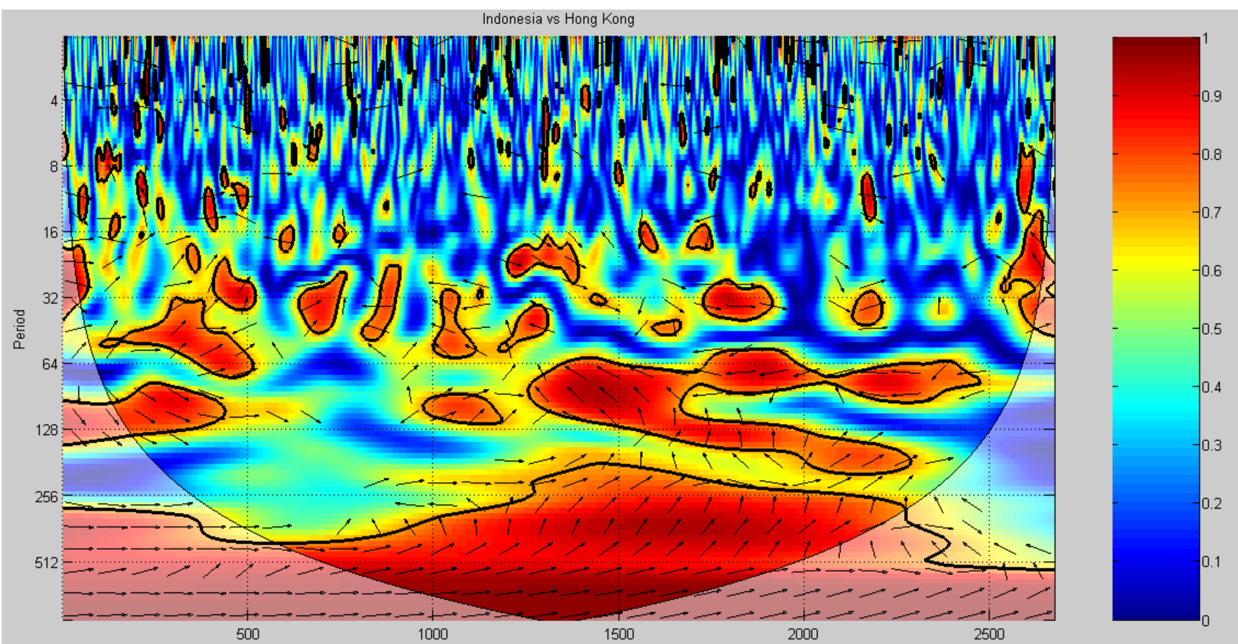


Figure 1.8 Indonesia vs Hong Kong

The wavelet coherency between Indonesia and Hong Kong is high at large scales, above the 128 days. It shows several statistically significant islands. On the daily time scales of 4 to 64 days band, the 5 percent significance regions indicate that the stock market indices under analysis do not show high coherency. The high coherency exists among them on the daily time scale of 256 to 512 band.

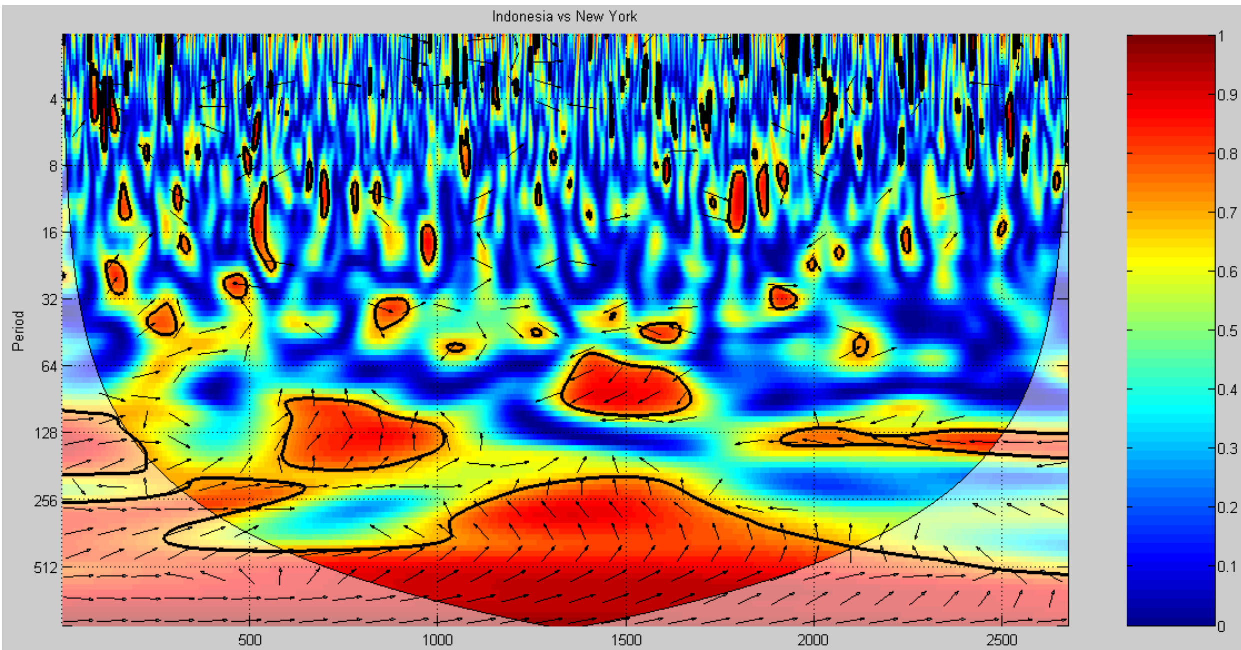


Figure 1.9 Indonesia vs New York

The wavelet coherency between Indonesia and New York is high at large scales, above the 128 days. It shows several statistically significant islands. On the daily time scales of 4 to 64 days band, the 5 percent significance regions indicate that the stock market indices under analysis do not show high coherency. The high coherency exists among them on the daily time scale of 256 to 512 band.

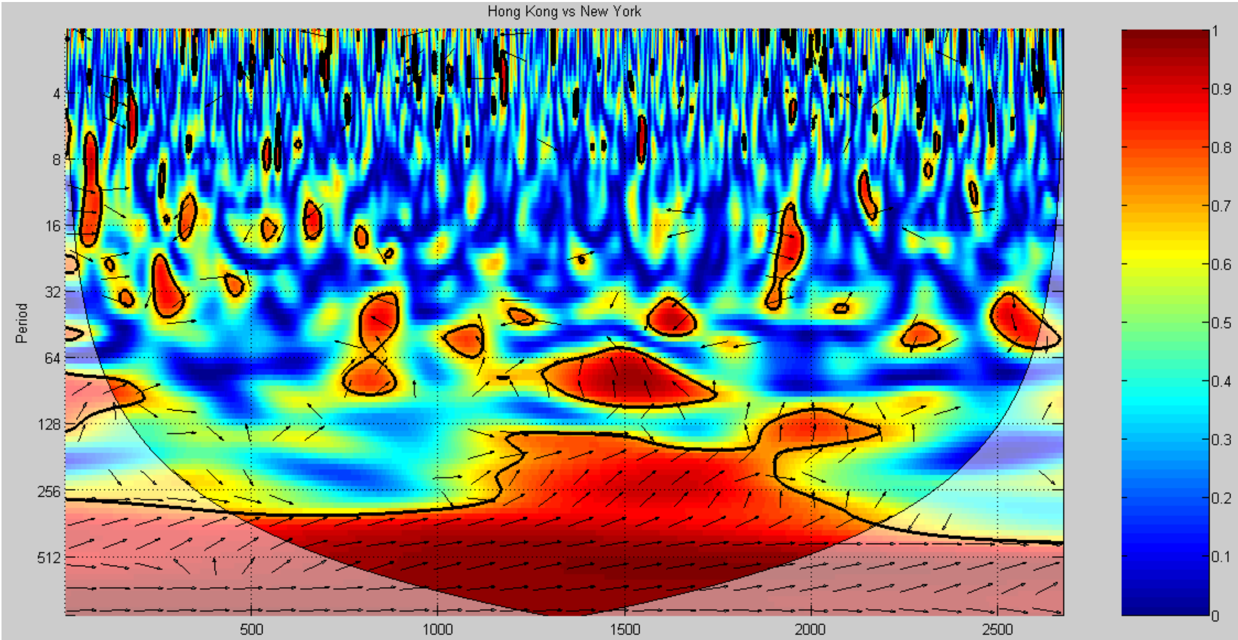


Figure 1.10 Hong Kong vs New York

The wavelet coherency between Hong Kong and New York is high at large scales, above the 128 days. It shows several statistically significant islands. On the daily time scales of 4 to 64 days band, the 5 percent significance regions indicate that the stock market indices under analysis do not show high coherency. The high coherency exists among them on the daily time scale of 256 to 512 band.

In the following, the analysis of the association between the two series using wavelet co-variance and correlation will be discussed. As can be seen from Figure down there, the variance for indexes investigated tends to be lower when the scale reaches higher. This is shown that the risk is moving downward as when the scale become bigger. It also show that, starting at D6, it starts to be flat. This suggesting that the investor better to hold their investment after quarterly of the year.

The MODWT base wavelet covariance of the two indexes analysis is based on the effects across time scales and frequency bands. It shows how the two series are associated with one and another.

From the results, it can be concluded that wavelet covariance slowly fluctuated in the analysis period within a flattening tendency for a long run interval; such as between Indonesia and New York (Figure A) and Malaysia vs Indonesia (Figure B). It is also evident that the covariance is negative for all decomposition.

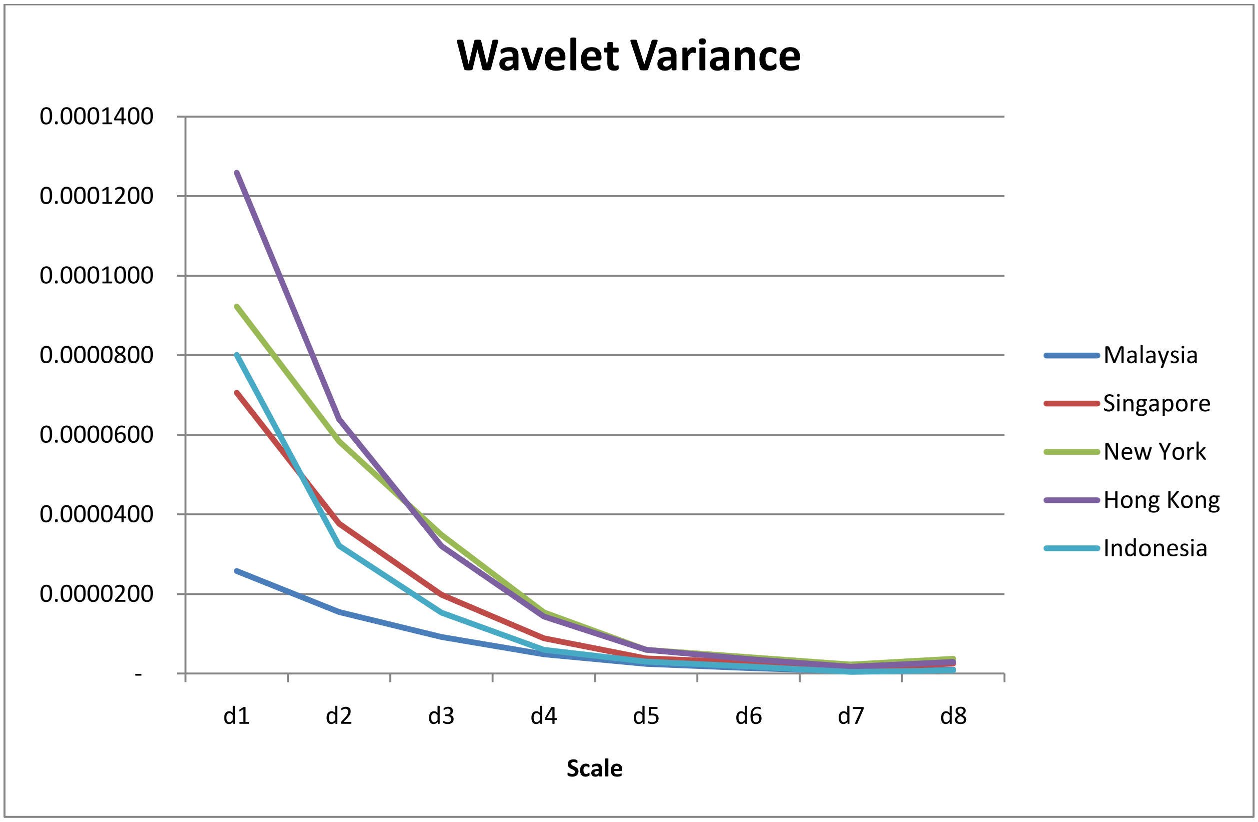
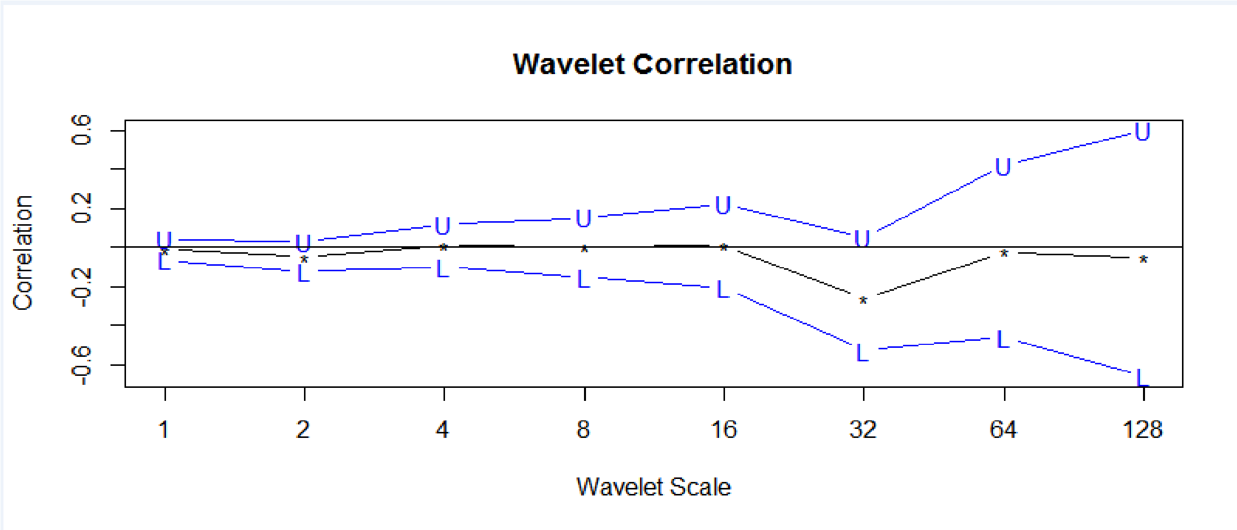


Figure 1.11 Wavelet variance



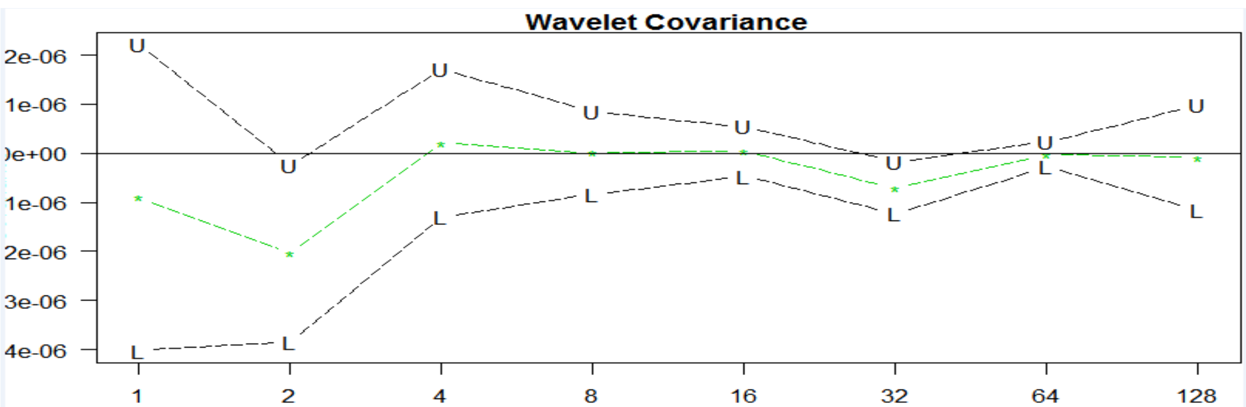


Figure : Wavelet covariance and wavelet correlation between Indonesia and New York.

The wavelet correlation also being used to examine the magnitude of the association of each series. However, the figures show no differences between the short run and the long run. More graphs for the other indexes investigated were provided in the Appendixes section.

For all the indexes that being investigated, there are negative correlation between them. It is also observed that there is a general tendency in the correlation coefficients to move downwards with the scale, except for the very long-run.

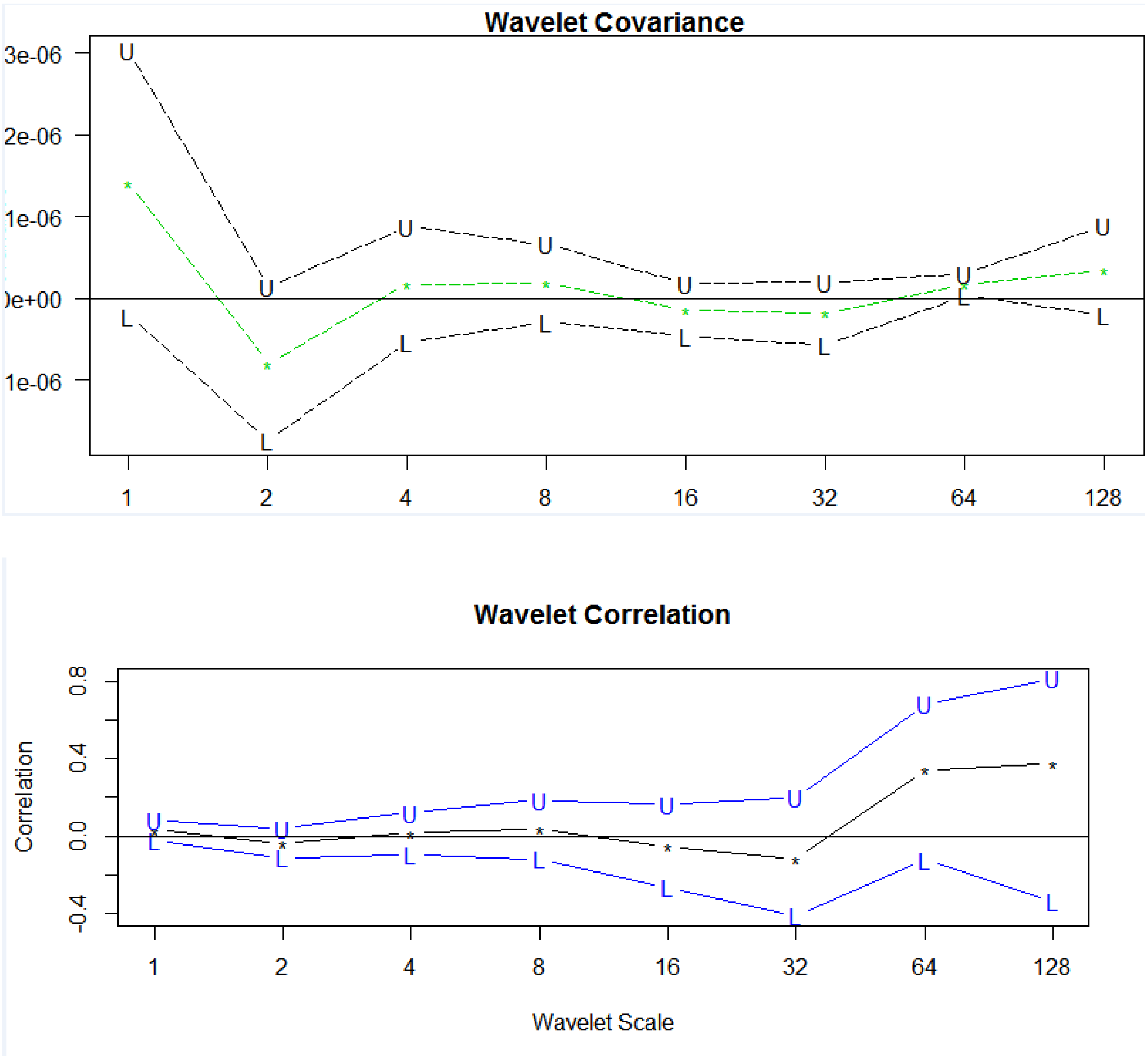


Figure : Wavelet covariance and wavelet correlation between Malaysia and Indonesia.

In addition, it is also observed an existence of linear relationship between the wavelet variance and wavelet scale. The variance for most of the indexes decreases as the wavelet scale increases. A wavelet variance in a particular time scale indicates the contribution to the sample variance, and this contribution decreases in the long-run for all the indexes investigated.

The cross correlation also being provided in this writing. It used to test the causal relationship between the indexes investigated, Appendix C. It shows that the short and medium term fluctuations for the indexes are more closely related than those over the long term.

CONCLUSION

As an investor it is important to understand the relationship among various markets to diversify risk and to derive high return. In this paper, Wavelets were applied to assess the co-movement and interactions of East and West stock index, namely; FBKLCI (Malaysia), FSSTI (Singapore), INDU (Indonesia), HIS (Hong Kong) and JCI (New York). Wavelet becomes an important addition to time-series methods which allows researcher to decompose relationship in the time-frequency scale. Therefore, in this writing, the continuous Wavelet Transform analysis and MODWT analysis had been applied to show the relationship among indexes investigated. Most likely, the wavelet coherency between indexes exists above the 32 days band. On the daily time scales of 4 to 16 days band, the 5 percent significance regions indicate that the stock market indices under analysis do not show high coherency. The high coherency exists among them on the daily time scale of 32 to 512 days band. The figures for correlation show no differences between the short run and the long run. For all the indexes that were investigated, there are negative correlation between them which shows a tendency in the correlation coefficients to move downwards with the scale, except for the very long-run. In addition, it is also observed that there exists a linear relationship between the wavelet variance and wavelet scale. The variance for most of the indexes decreases as the wavelet scale increases. The cross correlation showed that the short and medium term fluctuations for the indexes are more closely related compared to those over the longer term. The present study can be extended for further analysis.

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