Stock market volatility and exchange rates: MGARCH-DCC and wavelet approaches

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Abstract

This study discusses the relationship between stock price index and exchange rate in Malaysia. Establishing the relationship between stock prices and exchange rate is important for several reasons. Firstly, it may affect the economic decisions in terms of monetary policy and fiscal policy. Secondly, by understanding the relationship of stock prices and exchange rate, it will assist to predict the possibility of financial downturn. This study makes an attempt to examine the positive or negative relationship between stock prices and exchange rate. The causality between stock price and exchange rate is important in order to assist in making economic decision. This study employs MGARCH-DCC and wavelet approach, more specifically the continuous wavelet transform (CWT) and maximum overlap discrete wavelet transform (MODWT). The earlier studies used time-domain framework in their search for a relationship when the true relations might exist at different frequencies. The findings show that there is negative relationship between stock prices index and exchange rate in the case of Malaysia for both Islamic and conventional stock indices. The stock price index leads exchange rate in the long term investment horizon. This empirical research may have several implications for traders, portfolio managers and policymakers. It can be helpful for the traders in explaining the flow of information between stock and foreign exchange markets.

Keywords: Stock volatility, exchange rates, MGARCH-DCC, Wavelets

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I. Introduction

The search for a relationship between stock prices and exchange rates has led to a sizeable literature. The topic is important because these series are considered as leading economic variables. Madura (2008) argued that stock prices are possibly affected by three factors, namely the economic factor (interest rate and foreign exchange rate), market related factor, and firm-specific factor. On the other hand, exchange rates are highly responsive to the stock market changes and global portfolio investments. Therefore, it is suggested that there is a need to evaluate the relationship between stock prices and exchange rates since the results would be able to bring some impact on monetary and fiscal policies.

There are two competing hypotheses on whether or not exchange rates cause stock prices, and conversely. The traditional approach asserts that causal relationship runs from exchange rates to stock prices. The adherents of this approach argue that changes in the exchange rate affect competitiveness of a firm, which in turn influences firm's earnings and net worth and thus the stock prices. However, the proponents of the new portfolio approach posit that stock prices cause exchange rates. They point out that a decrease in stock prices is accompanied by reduction in the wealth of domestic investors, which leads to a lower demand for money, and thus lower interest rates. The lower interest rates trigger capital outflows, and leads to currency depreciation. Therefore, under the portfolio approach, stock price is expected to lead exchange rate. In other words, the correlation would be negative.

The empirical literature provides conflicting findings regarding the dynamic linkage between foreign exchange rate and stock markets. Early studies suggest that foreign exchange rate changes offer little or no predictive power for stock returns volatility, whilst others claim the existence of a strong linkage between foreign exchange rate changes and stock market volatility. Mixed empirical evidence is accompanied by the lack of a theoretical consensus on the relationship between stock and foreign exchange markets. Although sophisticated econometric approaches have been implemented to research this topic, the evidence is

somewhat mixed as to whether foreign exchange market volatility affects (or is affected by) stock market behavior.

The methodological approach has succeeded in capturing the simultaneous influence of two models and help to detect bidirectional causality at different time scales. MGARCH-DCC allows the researcher to see the shifts in conditional correlations and volatilities which is more correct picture to the reality. The wavelet tools aim at studying the chronological specifications for financial and economic variables. Particularly, the decomposition into sub-time series and the localization of the interdependence between time series are the two most widely considered area of the wavelet approach in finance.

The study found that there is negative relationship between stock price index and exchange rate for both Islamic and conventional stock index. In short term holding period, there is low correlation between stock price index and exchange rate while the stock price index leads the exchange rate in long term holding period.

This study is organized as follows. Section II and Section III provides a brief theoretical and empirical overview of the stock indices and exchange rate relationship. Section IV discusses the data and methodology used in the study. Section V presents the empirical results and Section VI contains the conclusions with policy implications.

Theoretical framework

The linkage between foreign exchange and stock markets

Economic theory states that there are various ways in which stock and foreign exchange markets can interact. This makes empirical analysis of the interdependence of these markets so interesting. In particular, theoretical approaches have failed to reach a consensus on the existence of a link between stock prices and exchange rates or on the direction of causality. There are two major forms of relationship between stock and foreign exchange. Dornbush and Fisher (1980) states that it is based on flow- oriented approach. However, Branson (1983) and Frankel (1983) states that it is based on stock-oriented approach.

In the flow-oriented approach, the exchange rate is essentially determined by a country's current account balance or trade balance. These models assume that foreign exchange rate changes affect international competitiveness and trade balance. Consequently, they affect real income and inputs. Flow oriented models claim a positive linkage between the foreign rate and stock prices. A change in exchange rate cannot only directly influence the stock prices of multinational and export oriented firms but it can also affect domestic firms. For a multinational firm, the change of exchange rates immediately influences the value of its foreign operations and continuously affects the profitability of the firm. Domestic firms are also influenced by the change of exchange rates, since they still may import their input and export their output.

Local currency depreciation leads to a greater competitiveness of domestic firms given that their exports will be cheaper in international trade. Higher exports will increase the domestic income and hence the firms' stock prices will appreciate since they are evaluated as the present value of the firms' future cash flows. This is support by Joseph (2002) where when exchange rate depreciates, the competitiveness of exports will increase, and the input cost of imports will increase. Thus, generally speaking, depreciation will cause positive (negative) effect for export (import) firms and increase (decrease) their stock prices;

however, appreciation will cause negative (positive) effect for export (import) firms and decrease (increase) their stock prices. Since there are relatively more export-oriented firms in Asian countries (in other words, Asian countries are more export-dominant), currency depreciation usually has a positive effect on the domestic stock market in these countries.

Under the stock-oriented approach, the foreign exchange rate is determined by the demand and supply of financial assets such as equities and bonds. Broadly speaking, there are two types of stock-oriented models which are the portfolio balance and monetary models. The portfolio balance model claims the existence of a negative linkage between stock prices and foreign exchange rates. More precisely, these models consider an internationally diversified portfolio and the function of foreign exchange rate movements in balancing the demand and supply of domestic and foreign financial assets. In this way, an increase in domestic stock price returns will produce an appreciation of the domestic currency.

Two main channels which are direct and indirect are frequently referred in portfolio balance model. The direct channel stipulates that a domestic stock price increase will encourage the international investors to revise their portfolio selection. Specifically, they will jointly buy more domestic assets and sell foreign ones in order to have domestic currency available for buying new domestic assets and, consequently, domestic currency will depreciate. The main idea of the indirect channel is that an increase in domestic stock assets will increase wealth. Demand increases amongst domestic investors leading to higher interest rates. Consequently, higher interest increases foreign demand for domestic currency, in order to buy new domestic assets, which, in turn, leads to domestic currency appreciation.

Under the monetary approach, the foreign exchange rate is assimilated into financial asset prices. Seen as a value of a financial asset which is determined by the present value of anticipated cash-flows, the foreign exchange rate dynamics are determined by all the relevant macroeconomic factors affecting the anticipated value. As a result, if there are common factors affecting the two variables, stock price innovations may have an impact, or be influenced, by the foreign exchange rate's behavior.

Empirical framework

In recent decades, many countries have adopted a floating exchange rate system. According to traditional theory, the change of exchange rate is influenced by international trade. The performance of domestic stock market over the few decades has played important roles in influencing the capital inflow or outflow, indicating the significant impact of changes in stock prices on exchange rate movements. However, in empirical studies, the relationship between stock price index and exchange rate remains unresolved.

Some studies have found evidence supporting the different connections between stock and foreign exchange markets. The studies have been carried out in the context of different countries. In the case of Turkey, Sevuktekin and Nargelecekenler (2007) utilized monthly data from 1986 to 2006 and concluded there was a positive and bidirectional causality between these two financial variables. Sohail and Hussain (2009) examined the long & short run relationship between macroeconomic variables and Lahore stock exchange in Pakistan. The result revealed that real effective exchange rates had a significant positive impact on stock returns in long run.

However, some studies revealed that there is an inverse relation between exchange rate and stock prices. For example, Ibrahim and Aziz (2003) had analyzed dynamic linkages between stock prices and four macroeconomic variables in Malaysia by using Malaysia's monthly data over the period of 1977 to 1998. They found negative relationship between exchange rate and stock prices. In examining dynamic relationship between stocks and exchange rates among six Asian countries (Indonesia, Malaysia, Philippines, South Korea, Thailand, and Taiwan), Doong *et al.* (2005) employed the data between 1989 and 2003 from these countries. The study exhibited that, the stock return is negatively correlated with the contemporaneous change in the exchange rates for all countries except Thailand. Moreover, study on the effect of exchange rate fluctuations and their impact on the Ghana stock

exchange by Adjasi and Harvey (2008) concluded similar result where there is negative relationship between exchange rate volatility and stock market returns.

Besides that, some empirical studies have used different methodology approach in order to measure the connection between stock and foreign exchange market. Phylaktis and Ravazzolo (2005) study the long-run and short-run dynamics between stock prices and exchange rates by using cointegration and multivariate Granger causality tests for some pacific basin countries. Their results indicate that stock prices and foreign exchange markets are positively linked. Yang and Doong (2004) employ a multivariate EGARCH model to capture asymmetries in the volatility transmission mechanism between stock prices and exchange rates for the G7 countries over the period 1979 to1999. Results obtained show that exchange rate changes have a direct impact on future changes of stock prices.

In a more recent paper, Zhao (2010) analyzes the dynamic relationship between the real effective exchange rate and the Chinese stock price, using a VAR with a multivariate GARCH model. The results show that there is no stable long run equilibrium relationship between the two financial markets. Kim (2003) adopted the multivariate cointegration and error correction model in analyzing the relationship between stock and foreign exchange markets in the U.S. from 1974 to 1998. The results showed that stock prices and exchange rates, whether in the long or short run are negatively correlated.

Based on the literature reviews, it is generally concluded that there are no uniformity of the relationship between stock price and exchange rate. Although previous studies have properly documented the relationship between stock prices and exchange rates, the empirical results show conflicting evidence. The findings from the previous studies vary depending on the country's economic status and methodology used in the analysis.

Data and methodology

Data

The study uses the daily data of the exchange rate, Islamic equity indices and conventional equity indices in Malaysia in order to measure the relationship between exchange rate and stock indices. The exchange rate is measured in Malaysian Ringgits to 1 US $. The Islamic equity indices use in this study is FTSE Bursa Malaysia Hijrah Shariah Index (FBMHS) which is denote as HJS while the conventional equity indices use in this study is FTSE Bursa Malaysia KLCI (FBMKLCI) denote as KLCI. The length of observation is daily from 28 February 2007 to 28 February 2015. It is worthily noting that the sample period includes some major events such as spectacular increase in oil prices, throughout the 2007 and 2008, the subsequent global financial and economic collapse in late 2008 and early 2009 and the gradual recovery of global markets in 2010. All data are sourced from Datastream.

As to the methodology, the daily returns of individual indices for both Islamic and conventional indices are calculated from the stock price (P) while the changes in exchange rate is calculated from the exchange rate (XR) values. The variables are transformed to log difference to work with return series not for the reason of stationarity.

$$r_t = log\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

$$r_t = log\left(\frac{XR_t}{XR_{t-1}}\right) \tag{2}$$

The study employs daily returns instead of levels for at least two main reasons. Firstly, the study concerned only with daily price dynamics over time. Secondly, non-stationary which is one of the major stylized facts in stock market behavior cannot pose problem when using wavelets and therefore filtering data is not necessary. This study sample

the daily return series at different scale crystals as follows: d1 (2-4 days), d2 (4-8 days), d3 (8-16 days), d4 (16-32 days), d5 (32-64 days), d6 (64-128 days), d7 (128-256 days) and d8 (256-512 days).

Methodology

The study implements the multivariate GARCH DCC (MGARCH-DCC) and wavelet tools namely wavelet coherency to capture the correlation between two time series (CWT and MODWT).

Multivariate GARCH – Dynamic Conditional Correlation (MGARCH-DCC)

MGARCH-DCC approach allows the researcher to observe and analyze the precise timings of shift in conditional correlations and volatilities. The main merit of DCC in relation to other time varying methods such as Kalman filters and Flexible Least Squares is that it accounts for changes in both the mean and variances of the time series. In other words, DCC allows for changes both in the first moment (mean) and the second moment (variance). Estimation of MGARCH-DCC involves two step processes to simplify the estimation of time varying correlations. In first stage, univariate volatility paremeters are estimated by using GARCH model. In stage two, the standardized residuals from first stage are used as inputs for estimating a time varying correlation matrix.

$$H_t = D_t R_t D_t \tag{3}$$

$H_t : Conditional\ covariance\ matrix$

$D_t : Diagonal\ matrix\ of\ conditional\ time\ varying\ standardized\ residuals$

$R_t : Time\ varying\ correlation\ matrix$

Wavelet

The wavelet approach allows us to detect stock market interactions which are hard to test out using any other modern econometric time-series models. As we know, markets consist of traders operating in different time horizons and therefore these traders can behave differently depending on dissimilar time resolutions (daily, monthly, and weekly). There are many advantages of using wavelet approach. Firstly, wavelets can be used to overcome the problems due to non-stationarity of the series signals. Second, wavelet can be a very useful technique for analyzing financial relations especially when there is a distinction between short and long run relations. Wavelets are localized in both time and scale (frequency band) and can be used to decompose any observed variable on scale by scale (different frequency bands) basis in order to analyze the dynamics of co-movement across different time horizons without losing any information. The main advantage of the cross-wavelet coherency-phase analysis is its ability to analyze transient dynamics for the association between two time series.

Continuous Wavelet Transform (CWT)

For the wavelet decomposition, this study follow the studies of Grinsted et al. (2004) and Aguiar-Conraria and Soares (2011) which apply wavelet coherency in the form of continuous wavelet transform (CWT) on the return series in order to capture co-movement in time-frequency space. The continuous wavelet transform of a time series x_t with respect to ψ is a function of two variables given by the following convolution:

$$W_x(\tau, s) = \int_{-\infty}^{+\infty} x(t)\bar{\psi}_{\tau,s}(t)dt = \frac{1}{\sqrt{s}}\int_{-\infty}^{+\infty} x(t)\bar{\psi}\left(\frac{t-\tau}{s}\right)dt, \quad (4)$$

where the bar denotes the complex conjugate, τ is the time position or translation parameter controlling its location, s is the scale or dilation parameter that controls the width of the

wavelet, and $1/\sqrt{s}$ is a normalization factor to make sure that the wavelet transforms are comparable across scales and time series.

Maximum Overlap Discrete Wavelet Transform (MODWT)

Maximum Overlap Discrete Wavelet Transform (MODWT) is used with its advantage on the flexibility of the length of data which means not requiring the integral power of 2, as well as the time invariant property. The wavelet family symmlet 8 is chosen in order to get the least asymmetry property, which is more appropriate for financial series. The transformed return series *r(t)* is represented as a linear combination of wavelet functions as follows:

$$r(t) = \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \ldots + \sum_k d_{1,k}\psi_{1,k}(t), \tag{5}$$

where:

j is the number of scale crystals (intervals or frequencies);

k is the number of coefficients in the specified component;

$\phi_{j,k(t)}$ and $\psi_{j,k(t)}$ are the father and mother orthogonal wavelet pair that are given respectively by:

$$\phi_{J,k}(t) = 2^{-J/2}\phi\left(t - \frac{2^J k}{2^J}\right) \tag{6}$$

$$\psi_{J,k}(t) = 2^{-j/2}\psi\left(t - \frac{2^j k}{2^j}\right) \tag{7}$$

Father wavelets represent the low-frequency (smooth) parts of the series, whereas mother wavelets represent the high-frequency (detailed) parts of the series. $s_{j,k}$ and $d_{j,k}$ are wavelet coefficients that are approximated by the following integrals:

$$\int \phi_{J,k}(t)f(t)dt \approx s_{J,k} \tag{8}$$

$$\int \psi_{J,k}(t)f(t)dt \approx d_{J,k} \tag{9}$$

$s_{J,k}$ are called the 'smooth' coefficients that represent the underlying smooth behavior of the series, while $d_{j,k}$ are called the 'detail' coefficients that represent the scale deviations from the smooth process. These coefficients are the measures of the contribution of the corresponding wavelet function to the total series. After decompose the return series into j crystals, the crystals d_j are recomposed into a time domain. The entire excess return series is replicated in multi-resolution decomposition as follows:

$$\hat{r}^J = D_1 + \cdots + D_J + S_J \tag{10}$$

Dj is the recomposed series in the time domain from the crystal d_j and S_J is the recomposition of the residue. The reconstituted return series $\hat{r}^J$ contain the separate components of the original series at each frequency j. Dj represent the contribution of frequency j to the original series. After obtaining the recomposed series for each frequency, the study follows Ramsey and Lampart (1998) in estimating beta in different time scales. The coefficient β^j_i the key variable the study are trying to examine, which change depending on the timescale j. The study can estimate wavelet covariance $\tilde{\gamma}_{XY}(\lambda_j)$ and wavelet variance, $\tilde{\sigma}_X(\lambda_j)$ and $\tilde{\sigma}_Y(\lambda j)$. For correlation, the wavelet correlation coefficient, $\rho_{XY}(\lambda j)$, provides a standardized measure of the relationship between the two time series subjected to multiple timescales. The unbiased estimator of the wavelet correlation for timescale j is defined by

$$\tilde{\rho}_{XY}(\lambda_j) = \frac{\tilde{\gamma}_{XY}(\lambda_j)}{\tilde{\sigma}_X(\lambda_j)\tilde{\sigma}_Y(\lambda_j)} \tag{11}$$

where, $\tilde{\sigma}_X(\lambda_j)$ and $\tilde{\sigma}_Y(\lambda j)$ are the unbiased estimators of the wavelet variances while $\tilde{\gamma}_{XY}(\lambda_j)$ is the unbiased estimators of the wavelet covariance. The study follow Genc¸ ay et al. (2002) for a simple wavelet-based approach to testing for significant difference. In particular, the study will test whether wavelet correlation coefficients on a scale-by-scale basis between Islamic and conventional pairs are significantly different. The significant change is identified by observing approximate confidence intervals between Islamic and conventional pairs. The null hypothesis of no statistically significant difference can be rejected when 95% approximate confidence intervals are non-overlapping.

Empirical results

Table 1 shows the list of variables used in identifying the relationship between exchange rate and stock indices for both Islamic and conventional in Malaysia. The variables consist of exchange rate, Islamic stock indices and conventional stock indices. The variables are transformed to log difference to work with return series not for the reason of stationarity.

Table 1. *List of variables under study*

Code	Description	Log 1st difference form
Exchange rate (XR)	Exchange rate :Malaysian Ringgits to 1 US $	DXR
Islamic stock indices (HJS)	FTSE Bursa Malaysia Hijrah Shariah Index (FBMHS)	DHJS
Conventional stock indices (KLCI)	FTSE Bursa Malaysia KLCI (FBMKLCI)	DKLCI

Table 2 reports the descriptive statistics for the stock indices return and exchange rate changes time series. From these summary statistics, several traits can be identified. Firstly, Hijrah Shariah Index (HJS) has the highest mean return as compared to Kuala Lumpur Composite Index (KLCI) and exchange rate (XR). It shows that Islamic stock market gives high return compared to conventional stock market. Additionally, it can be seen that the selected stock index and exchange rate are characterized by higher levels of volatility given that the standard deviations are significantly higher than the mean. HJS is more volatile compared with KLCI as HJS gives more return than KLCI. Skewness normality tests indicate that return distributions are negatively and significantly skewed for all time series. In addition, high excess kurtosis values suggest that all the stock return and exchange rate changes distributions are highly leptokurtic relative to normal distribution. This result is confirmed by the Jarque-Bera test statistics which reject the hypothesis of normality of stock index returns and exchange rate changes at the 1% significance level.

Table 2. *Descriptive statistics*

	DHJS	DKLCI	DXR
Mean	0.000317	0.000202	1.42E-05
Std. Dev.	0.008497	0.007820	0.004210
Skewness	-1.25529	-1.26084	-0.19042
Kurtosis	21.07861	19.45616	5.906457
Jarque-Bera	28969.23	24101.71	747.1914
	[0.0000]	[0.0000]	[0.000]
Observations	2087	2087	2087

Unconditional Volatility and Unconditional Correlation

In order to estimate the dynamic correlations, this study looks at the summarized results of maximum likelihood estimates of lambda 1 (λ_1) and lambda 2 (λ_2) as shown in Table 3. The table also summarized the delta 1 (δ_1) and delta 2 (δ_2) estimates while comparing between multivariate normal distribution and multivariate t-distribution. From table 3, it is observed that the maximized log-likelihood value for t-distribution is larger than normal distribution. This suggests that the t-distribution is more appropriate representation of the fat tailed nature of indices. This is support by the value of degree of freedom in t-distribution which is 5.4297, well below the critical level of 30. Henceforth, the analysis of this study under MGARCH-DCC will works with the t-distribution estimates.

Table 3. *Estimates of λ_1, λ_2, δ_1 and δ_2 for the HJS, KLCI and XR*

		Normal Distribution		T- Distribution	
	Parameter	**Estimate**	**T-Ratio**	**Estimate**	**T-Ratio**
Lambda 1 (λ_1)	DHJS	0.8806	71.2311	0.9099	78.1078
	DKLCI	0.8408	51.2634	0.8809	50.0431
	DXR	0.8652	34.1018	0.8673	36.6848
Lambda 2 (λ_2)	DHJS	0.1033	10.0215	0.0802	8.0715

	DKLCI	0.1325	10.2430	0.1020	7.1673
	DXR	0.0927	6.1870	0.0915	6.3754
Delta 1 (δ_1)		0.7582	8.5176	0.8332	14.5312
Delta 2 (δ_2)		0.0294	5.0413	0.0262	4.3649
Max. Log Likelihood		23086.3		23320.3	
Degrees of Freedom				5.4297	16.7312

Table 4 shows the unconditional volatility and correlation matrix for the three variables. The on-diagonal elements represent the volatilities while the off-diagonal elements represent the correlation between the variables. The table shows that Hijrah Shariah (HJS) return has highest volatility as compared with Kuala Lumpur Composite Index (KLCI) and exchange rate (XR). Besides that, there is high positive correlation between the HJS and KLCI which represent by 93.16%. However, there is negative correlation between XR and both stock indices. When there is appreciation in Malaysian Ringgit, the customers have to spend more to buy Malaysian goods. This can drive down sales which in turn reduce the value of stock prices.

Table 4. *Estimated Unconditional Volatility and Correlation Matrix*

	DHJS	DKLCI	DXR
DHJS	0.0081	0.9316	-0.3366
DKLCI	0.9316	0.0075	-0.3614
DXR	-0.3366	-0.3614	0.0043

Dynamic Conditional Correlation

Till this point, the analysis and interpretations have focused on unconditional volatilities and unconditional correlations. In other words, the analysis has been made on the underlying assumption that volatilities and correlations stay constant over the period of study which known as Constant Conditional Correlation (CCC). Intuitively, this assumption seems flawed as changing dynamics of capital markets, economic setup, political and natural events may affect all of the economic variables. It is closer to the reality and logical to comprehend that the volatility and correlation are dynamic in nature and changing according to time period which is known as Dynamic Conditional Correlation (DCC).

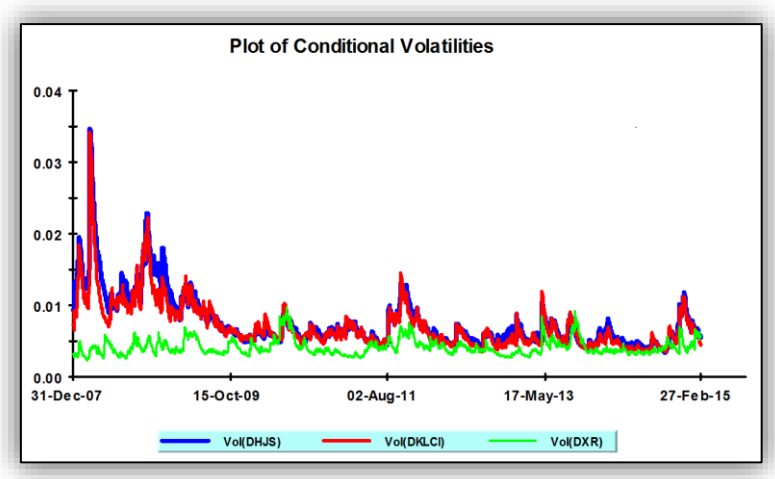


Figure 1. *Conditional Volatilities*

Figure 1 shows the conditional volatilities of stock indices return and exchange rate changes. Form the figure, it shows that the volatilities of Hijrah Shariah (HJS) and Kuala Lumpur Composite Index (KLCI) are moving together and the highest volatilities occur in year 2008 due to the Global Financial Crisis. However, the volatilities of exchange rate changes are less volatile as compared to stock indices return volatilities.

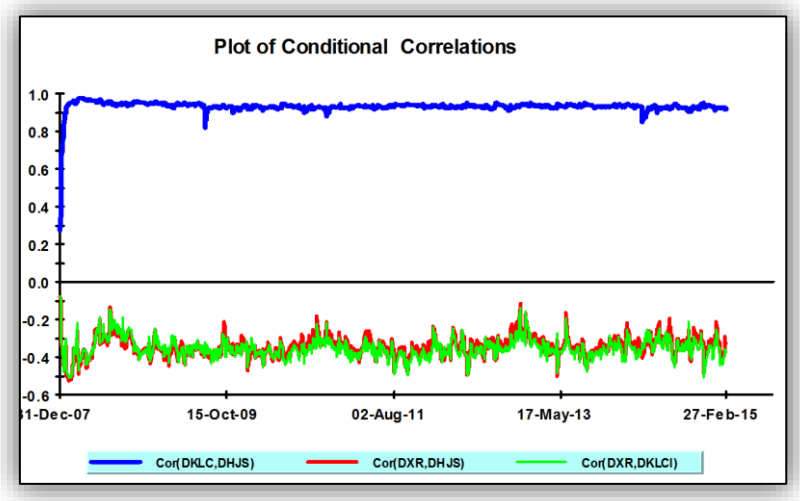
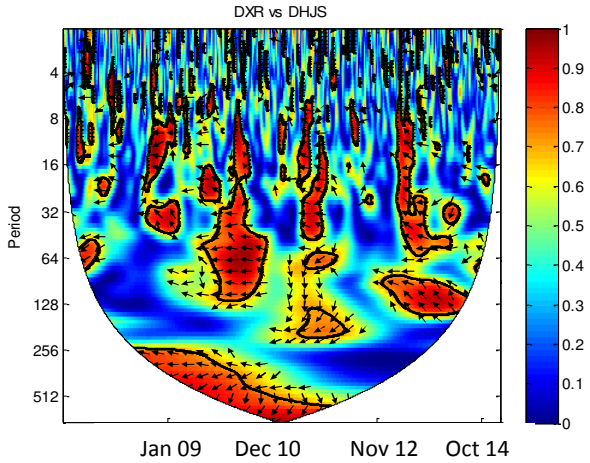


Figure 2. *Conditional Correlations*

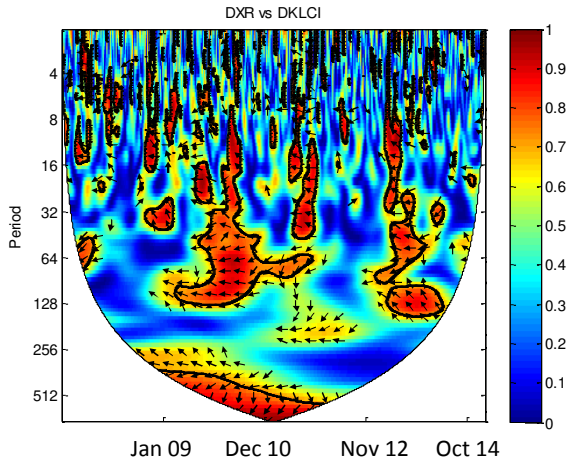
Figure 2 shows the conditional correlations between KLCI and HJS, XR and HJS and XR and KLCI. It shows that there is high correlation between KLCI and HJS which means that both will have same impacts if something happen to the market while there is negative correlation between XR and stock indices return. As the exchange rates appreciate, the stock indices return will depreciate.

Continuous Wavelet Transform (CWT)

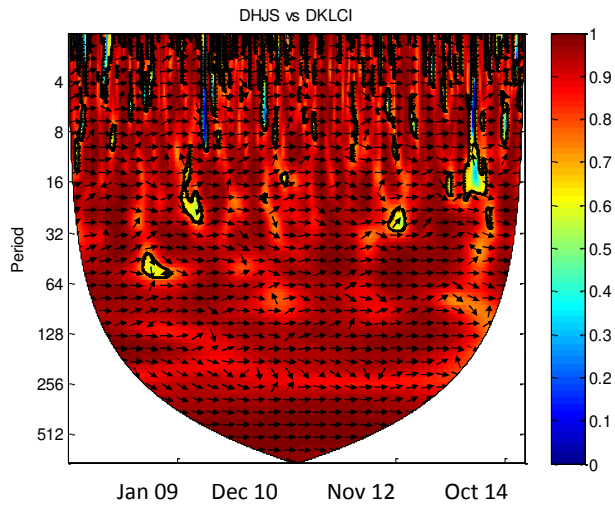
The wavelet approach are mostly applied to the analysis of stock market indices include the use of the discrete wavelet transform. In wavelet approach, the decomposition of time series consists on the decomposition of signal into set of coefficients. However, the same type of analysis can be done more easily and in a straightforward manner using the continuous wavelet transform (CWT).

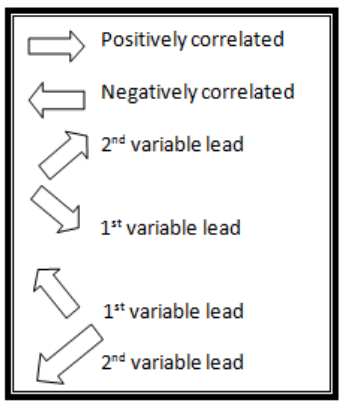


(3-a) DXR versus DHJS



(3-b) DXR versus DKLCI





(3-c) DHJS versus DKLCI

Figure 3. *Cross wavelet coherence*

Figure 3 shows the estimated cross wavelet coherence between the three variables which are Hijrah Shariah (HJS), Kuala Lumpur Composite Index (KLCI) and exchange rate (XR). The cross wavelet coherence has the power to investigate the varying characteristics of the relationship between the two variables in the time frequency domain. In these plots, the horizontal axis refers to time intervals whereas the vertical axis represents the frequency component, which is converted to time units (daily). In the cross wavelet coherence pictures, color code for power ranges from blue (low coherency) to red (high coherency). Besides that, the pointing arrows represent wavelet phase-difference which reveals the information of the lead-lag relationship (market dynamic) in time-frequency space. The values for the 5% significance level represented by the curved line are obtained from the Monte Carlo simulations.. All pictures show the cross-coherency between two variables. The name of the variable presented first is the first series while the other one being the second.

Figure (3-a) shows the wavelet coherence between exchange rate (XR) changes and Hijrah Shariah (HJS) return at different time scales. It is interesting to see that the direction of arrows at different frequency bands over the study period is not the same. The study found that for a very short holding periods consisting of 2-4 days and 4-8days, there is low correlation between XR and HJS along the observation period. For the short investment horizon consisting of 8-16, 16-32 and 32-64 days holding periods, there is high correlation between XR and HJS in year 2009, 2011 and 2013 and the arrow shows that XR changes leads the HJS return. However, moving towards medium investment horizons consisting of 64-128 and 128-256 days, the HJS return leads the XR changes in year 2011 but the XR changes start to lead back in year 2013. For long-term investors consisting of 256-512 days holding periods, there are strong correlations between XR changes and HJS return from 2008 to 2011 due to financial crisis of 2007 and the HJS return leads the XR changes at this time period. This finding posits that stock prices Granger-cause exchange rates. A decrease in stock prices is accompanied by reduction in the wealth of domestic investors which leads to a lower demand for money, thus lower interest rates. The lower interest rates trigger capital outflows and leads to currency depreciation.

Figure (3-b) shows the wavelet coherence between exchange rate (XR) changes and Kuala Lumpur Composite Index (KLCI) return at different time scales. The study found that at very short investment horizon of 2-4 days and 4-8days, there is low correlation between XR changes and KLCI return along the observation period. There is no clear lead-lag relationship between these two variables at this time horizon. However, at the short investment horizon consist of 8-16, 16-32 and 32-64 days holding periods, the correlation between XR changes and KLCI return start to have high correlation at certain time period. The high correlation between these variables is clearer in year 2009 until 2011 and 2012 to 2013 in medium investment horizons consisting of 64-128 and 128-256 days. For long-term investors consisting of 256-512 days holding periods, there are strong correlations between XR changes and KLCI return from 2008 to 2011 and the lead variable is changing from XR changes to KLCI as the holding period becomes longer.

Figure (3-c) shows the wavelet coherence between the stock indices used which are Hijrah Shariah (HJS) and Kuala Lumpur Composite Index (KLCI). The coherency plots between Islamic equity markets, as compared to conventional equity markets clearly shows that they mostly have demonstrated the same patterns along the observation period. This tends to indicate that the impacts of crises as well as the degree of integration for Islamic equity markets are more or less similar as those of their conventional counterparts. This is understandable since Sharia screening has adopted the principle of tolerance so that Islamic investors would not be at a disadvantage when they want to comply with Islamic rules in their investment. As a result, the movements of Islamic and conventional equity indices more or less tend to be similar.

Robustness and Validation of Results – MODWT

Maximum Overlap Discrete Wavelet Transform (MODWT) approach is used for the robustness and validation of the results in Multivariate Generalized Autoregressive Conditional Heteroskedasticity-Dynamic Conditional Correlation (MGARCH-DCC) and Continuous Wavelet Transform (CWT). In MODWT, the researcher is required to specify the time scales for the returns whereby this study had eight scales (2-4 days, 4-8 days, 8-16 days, 16-32 days,32-64 days, 64-128 days, 128-256 days and 256-512 days). The study used MODWT to examine the variance and correlations of Hijrah Shariah (HJS) return, Kuala Lumpur Composite Index (KLCI) return and exchange rate (XR) changes at different time scales.

Table 5. *Wavelet Variance*

MODWT SCALLING	DXR	DHJS	DKLCI
2-4 days	0.00000887	0.00003143	0.0000264
4-8 days	0.00000457	0.00001839	0.0000152
8-16 days	0.00000211	0.00001014	0.0000084
16-32 days	0.00000099	0.00000529	0.0000047
32-64 days	0.00000056	0.00000243	0.0000022
64-128 days	0.00000033	0.00000130	0.0000012
128-256 days	0.00000014	0.00000031	0.0000003
256-512 days	0.00000003	0.00000025	0.0000002

Table 5 shows the wavelet variance of XR changes, HJS and KLCI return at different time scales. From the table, it shows that the volatilities of all variables are decreasing as the time horizon increases. It gives the idea that short time holding period is more risky as compared to long term holding period.

Table 6. *Wavelet Correlation*

MODWT SCALLING	DXR VS DKLCI	DXR VS DHJS	DHJS VS DKLCI
2-4 days	-0.32274	-0.29343	0.91848
4-8 days	-0.39067	-0.36057	0.93063
8-16 days	-0.43768	-0.42064	0.93466
16-32 days	-0.39532	-0.41207	0.94509
32-64 days	-0.42126	-0.45245	0.94514
64-128 days	-0.39985	-0.38358	0.95427
128-256 days	-0.52680	-0.48490	0.95016
256-512 days	-0.53882	-0.55098	0.98759

Table 6 shows the wavelet correlations between all three variables. There are negative correlations between XR and both stock indices return which are HJS and KLCI. These results are consistent with the one obtained in MGARCH-DCC analysis. It shows that as the exchange rate appreciate, the stock return either Islamic or conventional will decrease according to time scales. However, the correlations between XR and KLCI are a little bit higher than correlations between XR and HJS.

Besides that, there are high correlations between HJS and KLCI return where the findings are in line with the one obtained in CWT analysis. The correlations are increasing according to time horizon.

Conclusions and policy implications

The study examines empirically the causal links between stock market volatility and exchange rate by using daily data from 2007 to 2015 in Malaysia. The knowledge on the relationship between the two markets would be helpful in preventing the spread of an economic crisis. On the whole, the related literature discussing the theoretical foundation of the relationship between stock and foreign exchange markets can be divided in two directions which are the international trading effect and the portfolio balance effect. This study is concluded to three key findings on the basis of empirical evidence. Firstly, there is negative correlation between stock market and exchange rate. This finding is equal to the empirical findings of Doong *et al.* (2005) in case of six Asian countries. Secondly, there is low correlation between stock market and exchange rate in short term investment horizon. However, in long term holding period, the stock market leads the exchange rate. This finding consistent with portfolio balance approach which claims the negative linkage between stock prices and foreign exchange rate. Moreover, under portfolio balance approach, stock prices lead the exchange rates.

Such empirical research may have several practical implications for traders, portfolio managers and policymakers. It can be helpful for traders in explaining the flow of information between stock and foreign exchange markets. Results may also be useful for assessing the informational efficiency of emerging stock markets. Portfolio managers and hedgers may be better able to understand the dynamic linkage between foreign exchange markets and equity markets. Specifically, they may be better able to adopt appropriate hedging strategies to better guard against currency risk during future crises that may occur in emerging countries. From a financial stability perspective, the volatility transmission across the two markets is also an important consideration for policymakers.

Finally, it is recommended for the future empirical research focusing on other stock market indices and exchange rate. The further study is encouraged to analyze other factors including macroeconomic variables and fundamental factors. It may be useful to extend the analytical framework used in this study to other developing countries by using different types of analysis approach.

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