Integration and Comovement of Developed and Emerging Islamic Stock Markets: A Case Study of Malaysia

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Abstract

This paper attempts to analyse the extent of financial integration of two developed (the U.S. and Japan) and two emerging Islamic stock markets (China and India) with the Malaysian Islamic stock market in order for the Malaysian financial traders to make decision about their portfolio diversification, risk management and asset allocation. Despite the growing interest in Islamic finance, there are few empirical studies investigating integration of Islamic stock markets. As a result there is a certain gap in the literature pertaining to this area of research. By applying recent related techniques, this paper examines the correlations among these Islamic stock markets in a time-variant manner to indicate the degree of financial integration among them. It is found that Strong financial integration exists between the Chinese and Malaysian Islamic stock markets. Furthermore, the study suggests that in the long run, investors in Malaysia could gain by diversifying their portfolios in Japan and in the short run the US market is a better option to consider. Overall, the developed Islamic stock markets are better for the Malaysian financial traders rather than the emerging markets.

Key Words: *International Portfolio Diversification, Dynamic Conditional Correlation (DCC), Multivariate GARCH, Islamic Stock Indices, Financial Integration, CWT, MODWT, Wavelet Coherence*

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I. Introduction: The issue motivating this Paper

International stock market linkages are very important for financial decisions of international traders. From the works of Markowitz (1958) and empirical evidence of Grubel (1968), it is recognized that international diversification reduces total risk of a portfolio. Increased comovement between asset returns can diminish the advantage of internationally diversified investment portfolios (Ling and Dhesi, 2010) and changes in comovement patterns call for an adjustment of portfolios.

Growing globalization among economies of the world has increased attention of investors to the comovement among the stock markets around the globe. There are numerous factors integrating financial markets to each other in today's rapid moving finance world. Among those, the existence of robust trading and economic links, the escalation in liberalization activities of governments, the expansion of international finance and trade, swift developments in trading systems and telecommunication, and the establishment of common trading blocs, also positive impact of financial and trade liberalization reforms on the degree of cross country equity market linkages are some factors contributing to financial integration.

The emergence of Islamic financial markets has promoted greater global financial integration. The bringing together of financial institutions and market players across continents to participate in this expansion of inter-regional investment flows has fostered financial linkages among the major regions. This will not only provide great synergies and opportunities but will contribute towards facilitating international financial stability. (Zeti Akhtar Aziz; London summit 2007)

When investors choose their asset allocation for international stocks, they usually tend to divide the world between developed markets and emerging markets, based on the assumption that these two are sufficiently distinct asset classes to justify treating them separately. However, trends in globalization and the increasing size and importance of emerging markets have brought into question the best way to categorize and invest in global stocks.

In existing literature, there are some methods that are usually utilized to measure the level of stock market return (or price) comovement as follows: 1) correlation coefficients (*e.g.*, Koedijk *et al.*, 2002; Longin and Solnik, 1995) to measure comovement; 2) Vector Autoregressive (VAR) models (Malliaris and Urrutia, 1992; Gilmore and McManus, 2002) to estimate spillover effects between stock markets; 3) cointegration analysis (Gerrits and Yuce, 1999; Patev *et al.*, 2006) to find long-term comovements between stock markets; 4) GARCH models (Tse and Tsui, 2002; Bae *et al.*, 2003; Égert and Kocenda, 2010; Mazin *et al.*, 2010) and regime switching models to model spillovers (Garcia and Tsafack, 2009; Schwender, 2010). 5) Wavelet analysis, which can be used to investigate both, stock market comovements and spillovers.

The correlation structure of stock returns is perhaps the most important feature from investors and portfolio managers point of view because hedging and diversification strategies invariably involve some measure of correlation (In and Kim, 2006). In order to diversify risk, portfolio managers in the international market usually split their equity portfolios into a number of regions and select the stocks from each region with a view to outperform the average market rate of return. This cross border diversification strategy has two intertwined features. One is the expected return of the portfolio and the second is the risk of the portfolio. These two issues have been attracted by the researchers and practitioners over the last decade. Usually, risk management of the portfolio becomes intricate when a greater number of stocks are included in the portfolio. Traditional univariate volatility models cannot be applied to measure the volatility of this kind of diversified portfolio because of two reasons. The first is the existence of time dependent cross correlations between the stocks and time dependent variance of the stocks. These two issues are very important to measure the marginal benefits (losses) of adding (deleting) stocks in the portfolio. Multivariate volatility measures, in lieu of univariate volatility measures, resolve the difficulties in measuring dynamic conditional correlations and variances of the portfolio in a multi asset state.

A standard approach for assessing financial market integration is based on the asset-pricing model. De Jong and de Roon (2005) used ordinary least squares estimation to assess the market integration from expected stock returns. Carrieri et al. (2007) and Chambet and Gibson (2008) assessed the degree of integration using the GARCH-in-mean methodology. Bekaert et al. (2011) developed a point-in-time approach to assess the evolution in market integration. They computed the absolute differential between local and global valuation ratios to measure global financial market integration. In this paper, one of the methods employed is the Dynamic Conditional Correlations-Multivariate GARCH which complements the above-mentioned approaches for financial integration. Other than that Continuous Wavelet Transform (CWT) analysis of volatility and correlations, Wavelet Coherence analysis, and the Maximal Overlap Discrete Wavelet Transform (MODWT) analysis have been applied for further robustness and adding more analyses to the research that are the unique contributions of this study.

This paper aims to find out the comovements and integration of international Islamic stock markets by dividing to developed and emerging markets and assess which market is more preferable for Malaysian traders to deal with. The reason for choosing Malaysia as a case study in this research is the aim of this country to become the global hub for Islamic finance and its potential in the global race to build the leading Islamic financial market. The results of the study show that developed markets are better place for portfolio diversification in comparison with emerging markets. Since Malaysia has a high integration with two powers of emerging markets i.e. China and India.

The remainder of the paper is organized as follows: Section II briefly reviews the empirical literature on the integration of stock markets. Section III states the main objective of the study. Theoretical underpinning and methodology used in this paper mentions in sections IV and V. Followed by data, empirical results and discussions in section VI. And finally section VII, concludes and states the policy implications of the study.

II. Literature Review

There are some studies in empirical finance that have attempted to test the integration of stock markets. De Jong and de Roon (2005) used ordinary least squares estimation to assess the market integration from expected stock returns. Carrieri et al. (2007) and Chambet and Gibson (2008) assessed the degree of integration using the GARCH-in-mean methodology. Bekaert et al. (2011) developed a 'point-in-time' approach to assess the evolution in market integration. They computed the absolute differential between local and global valuation ratios to measure global financial market integration.

In a recent study Leen and Teng (2013) examine the financial integration of two world leaders and two emerging powers into the Malaysian stock market by using DCC-MGARCH approach. They found that the financial integration between Malaysia and China started to evolve in April 2004 and strong financial integration between the stock markets in India and Malaysia was observed. In contrast, the volatility spillover effect from the U.S. to Malaysia disappeared, especially in the short term. Nevertheless, the study suggests that in the long run, investors in Malaysia could gain by diversifying their portfolios in China and Japan relative to India and the U.S.

In another recent study, Hussin et al. (2013) investigate co-integration between Islamic stock market in Malaysia, Indonesia and the world by applying the Vector Auto Regression (VAR) method. Their research used monthly data from January 2007 to May 2012. They found that there is no long-run or equilibrium relationship exists between FTSE Bursa Malaysia Emas Shariah (FBMES), Jakarta Islamic Index (JAKISL), and Dow Jones Islamic Market index (DJIM). Based on the result, they concluded that the Islamic stock market of Malaysia does not integrate with Indonesia's, as well as with the world markets in the long run. This will create rooms for investors to diversify their investment portfolios, which puts Malaysia as one of their favoured investment destinations.

Rua and Nunes (2009) in their research claim that the higher strength in the co-movements of stock returns at lower frequencies suggesting higher return from international diversification in the short-term relative to the long-term. However, stock markets are complex systems of interacting investment agents with different term objectives. Hence, time series resulting from this process are formed by a combination of different components operating at different frequencies. Therefore, the standard time series econometric method which considers the frequency and time components separately usually loses one side of information. Specifically, studies based on time series analysis loses frequency aspect and studies based on frequency domain lose the time aspect.

Gazi et. Al (2014) examine the strength of the co-movement between Germany, the center of the euro area, and four major international stock markets (the US, Canada, Japan, Australia) in the time and frequency space by resorting to wavelet analysis using daily data from 01 June 1992 to 26 March 2013. To relate their findings to the standard econometric literature, they connect their approach with the standard econometric approach of (Engle, 2002) dynamic conditional correlations from a multivariate DCC-GARCH model in order to measure the co-movements between Germany and major international stock markets. They found that a clear pattern of comovements at higher frequencies in all markets during the turbulent period of the 2007–2009 financial crises and variation across markets co-movements are found at different frequency levels. The importance of these findings highlights the time and frequency varying features of the co-movements in designing international portfolios.

Pesaran, and Pesaran (2010), estimated conditional volatility and correlation of weekly returns and analyzed the VaR of 2008 stock market crash. They examined the nature of asset return correlations using weekly returns on futures markets and investigate the extent to which multivariate volatility models proposed in the literature can be used to formally characterize and quantify market risk. They applied a multivariate t-version of the Gaussian dynamic conditional correlation (DCC) model proposed by Engle (2002), and showed that the t-DCC model passes the usual diagnostic tests based on probability integral transforms, but fails the value at risk (VaR) based diagnostics when applied to the post 2007 period that includes the recent financial crisis.

Study by Efthymios and Tsionas (2002) investigated the interrelationship between daily returns generated by major stock exchanges. Evidence was found that strong interdependence exists between the daily returns generated by Dow Jones Industrial Index and other selected world indices. Aggarwal et al. (2003) in another paper examined time-varying integration of European equity markets from the period of 1985 to 2002 using daily data for the main EU countries.

Similarly due to the substantial increase of capital flows from developing markets to emerging markets of the Asian countries, considerable attention has also focused on possible linkages and interdependencies in major Asian countries. The general consensus is that correlations between emerging and developed stock markets are generally on the increase (Siklos and Ng; 2001, Tan and Tse; 2002, Click and Plummer; 2005, Lim 2007, Choudhry et al.; 2007, Royfaizal et al.; 2007 and Abbas et al.; 2008).

There are extensive studies on integration and performances among conventional stock markets both in the West and Islamic countries, however studies on stock market integration among Islamic stock markets worldwide are still relatively scarce (Moeljadi, 2012). Empirical efforts to analyse the interdependence and performance of the Islamic stock indices across the globe have been rather a recent phenomenon, mainly due to the increased interest in the area of Islamic banking and finance.

As mentioned some, numerous studies have been done to investigate stock market correlation, linkages, integration or interdependence. Stock markets are said to be integrated when correlation exists between markets. Although the results of these studies are mixed, inconsistent and sometimes contradict each other, the ultimate motivation behind the studies is the benefit of diversification. If evidence of stock market linkage were found, it would imply that there is a common force that brings these markets together. Hence, the benefit of diversification would be limited.

III. The Objectives of the Study

The main objective of this study is to investigate whether there is an integration between FTSE Bursa Malaysia Emas Shariah Index return as a proxy for Malaysian Islamic stock market and some developed and emerging Islamic stock markets such as the U.S., Japan, China, and India to find out if any, how is the nature of this international integration. In addition, we attempt to contribute to the available literature since they are mostly assessing the integration between conventional stock indices and to fill in the gap of the existing studies. The findings of this study will have distinct policy implications for Malaysia which is a potential global hub for Islamic finance and helps to identify unique portfolio diversification opportunities for different set of investors bearing different investment horizons or holding periods of stocks.

IV. Theoretical Underpinnings

Studying international stock market co-movements is an ongoing issue in the finance literature that has important implications for risk management, portfolio diversification, asset allocation and investment decisions. Advantages of portfolio diversification in the domestic market were documented by Markowitz (1952) and motivated by low correlations among domestic assets. International diversification leads to higher return and lower risk compared to domestic diversification [Grubel (1968) and Grauer and Hakansson (1987)]. Therefore, investors should invest not only in the domestic market but also in the international stock market. Moreover, it is now well known that stock market co-movements are not constant but change over time. There has been a large group of researchers who are working on the strength of stock market comovements. Overall, previous works show that international stock market co-movements have increased over time [Hilliard (1979) and Kizys and Pierdzioch (2009)].

Finance theory points out that a low correlation among international equity markets may indicate that investors gain from portfolio diversification. Several studies (e.g. Chelley Steeley, 2000; Wong et al., 2004; Hui, 2005; Berben and Jansen, 2005; Wongswan, 2006) show that the interdependence among the international equity markets has increased substantially since the 1987 U.S. Stock Market Crash. The decreased benefits of international diversification may be due to liberalization of international capital movements, deregulation in financial markets and institutions in various countries, and the improvement in electronic communication systems that make international financial transactions more rapid and less costly. There are two major types of interdependence among international equity markets. A number of studies have previously examined the interdependence of international stock market returns. For example, Hilliard (1979) and Errunza and Losq (1985) focus on the degree of interdependence for returns among international stock markets and find that the first moments of equity returns among the stock markets exhibit a high degree of interaction. Another line of investigation has focused on the interdependence of the second moments, i.e., volatility transmissions, among international markets. In the context of various event issues and different market regimes, recent papers (e.g., Hamao et al., 1990; Theodossion and Lee, 1993; Koutmos and Booth, 1995; Liu and Pan, 1997; In et al., 2001; Jang and Sul, 2002; Leong and Felminglam, 2003; Darrat and Benkato, 2003; Cifarelli and Paladino, 2004; Hoti, 2005) have explored volatility transmissions in addition to mean spillover effects.

The study of asset return volatility has been one of the major topics of vast empirical research in the financial time series over the past decade. A well-known stylized fact of financial data is the phenomenon of volatility clustering, which exhibits phases of relative tranquility followed by periods of high volatility. The multivariate GARCH models have been proven to be very successful at capturing volatility clustering and the dynamic relationships among volatility processes of multiple-asset returns.

Islamic equity investment based on Islamic Jurisprudence or Shariah principles has gained considerable attention during the recent global financial crisis. It is noted that speculative trading and unsafe lending practices adopted by major international banks were among the major causes for the global financial crisis (Cyree et al., 2011; Caprio, 2009; Ashraf and Goddard, 2012). Shari'ah principles specifically forbid investment in any company engaged in transactions based on usury (reba), excessive risk taking such as trading in derivatives and insurance (gherar), gambling activities (meiser), trading in alcohol (khumar), and/or pork products. Shariah principles allow investments in lower leveraged companies and financial instruments linked with real assets (sukuk). The restriction on leverage and trading in financial assets including derivatives may result in a very different risk adjusted performance of Islamic equity investments from that of similar conventional investments during the downturn of capital markets.

V. Data and Methodology Used

The data employed for this research is daily times series closing stock price for five indices starting from 29th October 2007 to 15th April 2014, a total of 1687 days. An earlier start date was not possible since we wanted to have the same starting date of observations for all the selected indices. The explanatory variables selected for this study as are depicted in Table 1 are: FTSE Bursa Malaysia Emas Shariah Price Index (FTMY) as a proxy for Malaysian Islamic stock market, FTSE Shariah China Price Index (FSCN) as a proxy for Chinese Islamic stock market and FTSE Shariah India Price Index (FSIN) as a proxy for Indian Islamic stock market (FSIN). FSCN and FSIN are representatives of emerging stock markets. Also FTSE Shariah Japan 100 Price Index (FSJP) and Dow Jones Islamic US Price Index (DJUS) as proxies for Japan and US stock markets and representatives of developed markets. All the data were taken from Thomson-Reuters DataStream database. By applying Log Difference functions (1) on all the Index prices we could get the Indices returns to continue the study.

$$R_{it} = \ln\left(\frac{P_{it}}{P_{it-1}}\right) \text{ for stock } i \text{ at day } t \qquad (1)$$

Table 1: *Selected indices for the study*

Index	Definition
FSMY	FTSE BURSA MALAYSIA EMAS SHARIAH

FSCN	FTSE SHARIAH CHINA
FSIN	FTSE SHARIAH INDIA
FSJP	FTSE SHARIAH JAPAN 100
DJUS	DOW JONES ISLAMIC US

V.I. Multivariate GARCH – Dynamic Conditional Correlation

DCC model is based within the family of GARCH models. With the DCC model one can "pinpoint precisely the timing and nature of plausible changes in the time series co-movement". That is in addition to measuring and accounting for the volatility of the series, the correlations can be measured and predicted. For each time point, the DCC method gives a value that serves as the forecasted correlation between series for the next period. The estimation of DCC is broken into two stages, which simplifies the estimation of a time varying correlation matrix. *In the first stage*, univariate volatility parameters are estimated using GARCH models for each of the variables. *In the second stage*, the standardized residuals from the first stage are used as inputs to estimate a time varying correlation matrix.

Following Engle (2001), H_t is a conditional covariance matrix and is: $H_t = D_t R_t D_t$

Where, R_t = k × k time varying correlation matrix (R_t varies over time) and

D_t = k × k diagonal matrix of conditional, i.e. time varying, standardized residuals ε_t, that are obtained from the univariate GARCH models.

The log-likelihood of the above estimator can be written as:

$$
\begin{aligned}
L &= -\frac{1}{2}\sum_{t=1}^{T}\left(k\log(2\pi)+2\log|H_t|+r_t' H_t^{-1} r_t\right) \\
&= -\frac{1}{2}\sum_{t=1}^{T}\left(k\log(2\pi)+2\log|D_t R_t D_t|+r_t' D_t^{-1} R_t^{-1} D_t^{-1} r_t\right) \\
&= -\frac{1}{2}\sum_{t=1}^{T}\left(k\log(2\pi)+2\log|D_t|+\log(|R_t|+\varepsilon_t' R_t^{-1}\varepsilon_t\right)
\end{aligned}
$$

Where, $\varepsilon_t \sim N(0, R_t)$ are the residuals standardized on the basis of their conditional standard deviations. First, the conditional variances for any individual asset can be obtained from the univariate GARCH model as follows:

$$h_{it} = \omega_i + \sum_{p=1}^{P_i}\alpha_{ip} r_{it-p}^2 + \sum_{q=1}^{Q_i}\beta_{iq} h_{it-p} \quad for\ i = 1,2,3\ldots,k$$

Then proposed dynamic correlation structure is:

$$Q_t = (1-\sum_{m=1}^{M}\alpha_m - \sum_{n=1}^{N}\beta_n)\bar{Q} + \sum_{m-1}^{M}\alpha_m(\varepsilon_{t-m}\varepsilon_{t-m}^{'}) + \sum_{n=1}^{N}\beta_n Q_{t-n}$$

$$\mathrm{R}_t = Q_t^{*-1} Q_t Q_t^{*-1}$$

Where, $\bar{Q}$ is the unconditional covariance of the standardized residuals resulting from the univariate GARCH equation and Q* is a diagonal matrix composed of the square root of the diagonal elements of Q_t, which is as follows:

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11}} & 0 & \cdots & 0 \\ 0 & \sqrt{q_{22}} & \cdots & 0 \\ \vdots & \vdots & \vdots & 0 \\ 0 & 0 & \cdots & \sqrt{q_{kk}} \end{bmatrix}$$

The typical element of R_t will be $\rho_{ijt} = \frac{q_{ijt}}{\sqrt{q_{ii}q_{jj}}}$ and the matrix R_t will be positive definite/constant. The K assts covariance H_t is thus a positive definite/constant and can be written as $H_t = D_t R_t D_t$.

The decomposition of H_t allows separate specification of the conditional volatilities and conditional cross asset returns correlations. For example, one can utilize the GARCH (1,1) model for the variance $\sigma_{i,t-1}^2$, namely

$$V(r_{it}|\Omega_{t-1}) = \sigma_{i,t-1}^2 = \bar{\sigma}_i^2(1-\lambda_{1i}-\lambda_{2i}) + \lambda_{1i}\sigma_{i,t-2}^2 + \lambda_{2i}r_{i,t-1}^2$$

Where, $\bar{\sigma}_i^2$ is the unconditional variance of the ith asset return.

λ_1 *and* λ_2 are asset specific volatility parameters (individual asset return volatilities). Under the restriction$\lambda_{1i} + \lambda_{2i} = 1$, *the unconditional variance disappears in the above equation and we have the Integrated GARCH (IGARCH) model, which tells us that conditional variance is non-stationary, and then the shock to variance is permanent.*

A more general mean reverting specification is given by

$$q_{ij,t-1} = \bar{\rho}_{ij}(1-\phi_1-\phi_2) + \phi_1 q_{ij,t-2} + \phi_2\tilde{r}_{i,t-1}\tilde{r}_{j,t-1}$$

where, $\bar{\rho}_{ij}$ is the unconditional correlation between r_{it} *and* r_{jt} *and* $\phi_1 + \phi_2 < 1$.

One would expect $\phi_1 + \phi_2$ to be close to 1 in order to non-mean reverting (does not come back to mean or equilibrium). The non-mean reverting case can be obtained when $\phi_1 + \phi_2 = 1$. Therefore, in order to test the existence of non-mean reversion, we need to put restriction of $\phi_1 + \phi_2 = 1$.

Dynamic conditional correlation (DCC) is useful in a number of ways. DCC allows for the analysis of time variation in both mean and variance equation. Whereas, Constant conditional correlation (CCC) is intended to examine time varying relationships entered only in the mean equation. DCC allows looking at how correlations change over time. DCC approach follows

ARCH model solution to modeling the evolving nature of volatility. Specifically, ARCH models estimate a weighted average of a variable's entire history of volatility with more weight given to the recent past and less weight given to the long past observations. Similarly, the DCC model estimates a weighted average of correlations that incorporates the entire history of a relationship between variables. The DCC approach allows series to have periods of positive, negative, or no correlation. Thus both direction and strength of the correlation can be considered. When two series move in the same direction, the correlation increases and is positive. When they move in the opposite directions, the correlation is decreased and may become negative. The DCC approach allows asymmetries, meaning that the weights are different for positive and negative changes to a series, which is an insightful advantage of this model.

Pukthuanthong and Roll (2009) and Carrieri et al. (2007) highlighted that cross-country correlation of stock returns might not be an appropriate measurement of financial integration because low correlations could be observed even if the two countries were perfectly segmented (Pukthuanthong and Roll, 2009). This study analyses the time-varying volatility correlation, instead of correlation in return series, for several reasons. First, Pukthuanthong and Roll (2009) recommended the use of variance from stock market index returns as a measurement of integration. Second, it is not sensible to model the return series as independent and identically distributed over time because the return series are actually interdependent with the increase in data frequencies (Teräsvirta, 2006). Hence, Jones et al. (2004) suggested that volatility is a better measurement of stock market risk compared to stock returns. Furthermore, volatility provides constructive information for diversifying portfolios that minimises the total risk of a portfolio in the long run.

The DCC-MGARCH model is applied to analyse economic time series with time-varying volatility. The time-varying correlation estimated from this model indicates market integration. Markets become more integrated when the conditional correlation increases over time (Yu et al., 2010). This model is able to capture the volatility correlation between two markets, either directly through its conditional variance or indirectly through its conditional covariances. The model is also able to examine the volatility spillover from one market to another market. The MGARCH model can simultaneously consider n stocks' return volatility and correlation on time-dependence. The DCC-MGARCH model is a dynamic model with time-varying means, variances and covariances of return series.

V.II. Continuous Wavelet Transformation

Wavelets are mathematical tools that are widely applied for analysing time series. The starting point in such an analysis is based on decomposing a time series on scale by scale basis in order to control the series structure at different time horizons. Percival, D., & Walden, A. (2000). Wavelets basis are obtained from some source functions (φ, Ψ) called (father,mother) wavelet by dilations and translations (Gencay *et al*. (2002). Usually the wavelet basis elements are defined by;

$$\varphi_{j,k}(t) = 2^{-j/2}\varphi\left(\frac{t-2^j k}{2^j}\right) \text{ and } \psi_{j,k}(t) = 2^{-j/2}\psi\left(\frac{t-2^j k}{2^j}\right) \quad (1)$$

One usually associates some coefficients

$$S_{J,k} \approx \int \varphi_{J,k}(t) f(t) dt \text{ and } d_{j,k} \approx \int \psi_{j,k}(t) f(t) dt \quad (2)$$

The $S_{j,k}$ are known as the smoothness coefficients or approximation coefficients and the $d_{j,k}$ the detail coefficients or wavelet ones.Ramsey J.B.,(2002).The wavelet series of f at the level J is:

$$f_J(t) = \sum_k S_{J,k}\varphi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + ... + \sum_k d_{1,k}\psi_{1,k}(t) \quad (3)$$

This series represents the decomposition of the signal into orthogonal signal components at different scales. More specifically, the detail coefficients $d_{j,k}$,…, $d_{1,k}$ capture the higher frequency oscillations and so they represent fine scale deviations of the trend. The $S_{j,k}$'s represent the smooth coefficients that capture the trend. So that, the wavelets series approximation of the original signal f is composed of a superposition of smooth part signal and detail signal parts as follows:

$$f(t) = S_J + D_J + D_{J-1} + ...+ D_1 \quad (4)$$

Where:

$$S_J(t) = \sum_k s_J \varphi_j(t)$$
$$D_j(t) = \sum_k d_{jk}\psi_{jk}(t)$$

will be much intersted to see the effects of the mother wavelet and this would give us the required multi-time scale information.

An additional appealing feature of wavelet modelling is that the multi-resolution decomposition of the wavelet transform can be used to identify contagion and interdependence between markets. Shock transmission due to contagion is rapid and quickly fades; hence, in a matter of days, changes in wavelet correlations between time series at higher frequencies are associated with contagion, whereas changes at lower frequencies are associated with interdependence or comovement (Gallegati, 2012).

The wavelet method results are relatively easy to interpret and offer considerable amount of information on co-movements and led-lag relationships among the stock markets encompassing time as well as frequency domain aspects within. Moreover, this approach permits to evaluate co-movements across different investment horizons and to distinguish between short term and long term investors.

V.III Maximum Overlap Discrete Wavelet Transform (MODWT)

Furthermore, we utilize Maximum Overlap Discrete Wavelet Transform (MODWT) with as a wavelet function to obtain a multiscale decomposition of the return series. The Maximum Overlap Discrete Wavelet Transform (MODWT) will be used with the advantage on the flexibility of the length of data (not requiring the integral power of two) as well as time invariant property. Co-movements between stock market returns may not only be time varying, but also scale dependent (Gencay et al., 2001), and can be analysed with wavelet tools. A MODWT-based estimator has been shown to be superior to the earlier DWT-based estimators (Percival, 1995). The MODWT is a variant of the discrete wavelet transform (DWT) that, unlike the classical DWT, can handle any sample size and not just those that are multiples of 2^x. The MODWT is highly redundant, non-orthogonal transform – this enables alignment of the decomposed wavelet and scaling coefficients at each level with the original time series, thus allowing a ready comparison between the series and its decompositions. This feature is not in DWT. The MODWT variance estimator is also asymptotically more efficient than the same estimator based on the DWT. MODWT is generally known as stationary wavelet transform, shift or translation invariant DWT, time invariant DWT, and non-decimated DWT. Hence, this research makes use of the MODWT method which can be described as follows.

Let $\boldsymbol{X}$ be an N-dimensional vector whose elements represent the real-valued time series $\{X_t: t = 0, \ldots, N-1\}$. For any positive integer, J_0, the level J_0 MODWT of $\boldsymbol{X}$ is a transform consisting of the $J_0 + 1$ vectors $\widetilde{\boldsymbol{W}}_1, \ldots, \widetilde{\boldsymbol{W}}_{J_0}$ and $\widetilde{V}_{J_0}$, all of which have dimension $\boldsymbol{N}$. The vector $\widetilde{\boldsymbol{W}}_J$ contains the MODWT wavelet coefficients associated with changes on scale $\tau_j = 2^{j-1}$ (for $j = 1, \ldots J_0$) while $\widetilde{\boldsymbol{V}}_{J_0}$ contains MODWT scaling coefficients association with averages on scale $\lambda_{J_0} = 2^{J_0}$. Based on the definition of MODWT coefficients we can write (Percival and Walden, 2000, p. 200):

$$\widetilde{\boldsymbol{W}}_J = \widetilde{W}_J \boldsymbol{X} \text{ and } \widetilde{\boldsymbol{V}}_J^0 = \widetilde{V}_J^0 \boldsymbol{X}$$

Where $\widetilde{W}_J$ and $\widetilde{V}_{J_0}$ are N x N matrices. Vectors are denoted by bold italics. By definition, elements of $\widetilde{W}_J$ and $\widetilde{V}_{J_0}$ are outputs obtained by filtering $\boldsymbol{X}$, namely:

$$\widetilde{W}_{j,t} = \sum_{l=0}^{L_j-1} \widetilde{h}_{j,l}\ X_{t-l\ modN}$$

and

$$\widetilde{V}_{j,t} = \sum_{l=0}^{L_j=1} \widetilde{g}_{j,l}\ X_{t-l\ modN}$$

For $t = 0, \ldots\ldots, N-1$, where $\widetilde{h}_{j,l}$ and $\widetilde{g}_{j,l}$ are jth MODWT wavelet and scaling filters. The MODWT treats the series as if it were periodic, whereby the unobserved samples of the real-valued time series $X_{-1}, X_{-2}, \ldots, X_{-N}$ are assigned the observed values at $X_{N-1}, X_{N-2}, \ldots, X_0$. The MODWT coefficients are thus given by:

$$\widetilde{W}_{j,t} = \sum_{l=0}^{N-1} \widetilde{h}^{\circ}_{j,l}\ X_{t-l\ modN}$$

and

$$\widetilde{V}_{j,t} = \sum_{l=0}^{N-1} \widetilde{g}^{\circ}_{j,l} X_{t-l\,modN} (\text{for } t = 0, \ldots, N-1;$$

$\widetilde{h}^{\circ}_{j,l}$ and $\widetilde{g}^{\circ}_{j,l}$ are periodization of $\widetilde{h}^{\circ}_{j,l}$ and $\widetilde{g}^{\circ}_{j,l}$ to circular filters of length N)

Wavelet variance is defined for stationary and non-stationary processes with stationary backward differences. Considering only the non-boundary wavelet coefficient, obtained by filtering stationary series with MODWT, the wavelet variance $\nu_X^2(\tau_j)$ is defined as the expected value of $\widetilde{W}^2_{j,t}$. In this case $\nu_X^2(\tau_j)$ represents the contribution to the (possibly infinite) variance of $\{X_t\}$ at the scale $\tau_j = 2^{j-1}$ and can be estimated by the unbiased estimator (Percival and Walden, 2000, p. 306):

$$\hat{\nu}_X^2(\tau_j) = \frac{1}{M_j} \sum_{t=L_j-1}^{N-1} \widetilde{W}^2_{j,t}$$

where $M_j \equiv N - L_j + 1 > 0$ is the number of non-boundary coefficients at the jth level.

The MODWT correlation estimator for scale τ_j is obtained by making use of the wavelet cross-covariance and the square root of wavelet variances:

$$\hat{\rho}_{X,Y}(\tau_j) = \frac{\hat{\nu}_{X,Y}(\tau_j)}{\hat{\nu}_X(\tau_j)\hat{\nu}_Y(\tau_j)}$$

Where $|\hat{\rho}_{X,Y}(\tau_j)| \leq 1$. The wavelet correlation is analogous to its Fourier equivalent, the complex coherency (Gencay et al., 2002, p. 258).

VI. Empirical Results and Discussion

The descriptive statistics of the Shariah indices are reported in Table 2 below. Descriptive statics show that standard deviation is largest for FTSE Shariah China index return and lowest for FTSE Bursa Malaysia EMAS Shariah index return, which indicates that FSCN is the most volatile variable. These standard deviations show absolute time independent volatility of the returns. In line with theory, higher the risk, higher the return, FTSE Shariah China index offers the highest return over the observation period.

Table 2: *Descriptive Statistics of indices returns*

	FSMY	FSCN	FSIN	FSJP	DJUS
Mean	0.000185	-0.000414	-0.000268	-0.000248	0.000237
Median	0.000264	0.000000	0.000000	0.000000	0.000629
Maximum	0.004232	0.049550	0.025923	0.019430	0.015963
Minimum	-0.012373	-0.048131	-0.021877	-0.015422	-0.013013
Std. Dev.	0.000901	0.003401	0.002498	0.002372	0.001859
Skewness	-1.72902	0.026534	-0.009298	-0.275063	-0.073011
Kurtosis	27.27395	57.84404	15.59868	10.52918	13.38779
Observations	1687	1687	1687	1687	1687

Graphs of the Islamic stocks returns in figure 1 depicts that FTSE Shariah China Stock return is more volatile than any other Islamic stock return and after that FTSE Shariah India index return is more volatile. The least volatility is observed from FTSE Bursa Malaysia Emas Shariah Index return. The gray areas in the graphs show the recession period during years 2008 – 2009 and we can see sharp volatilities of stock returns that are clearly the consequence of global financial crisis of 2008.

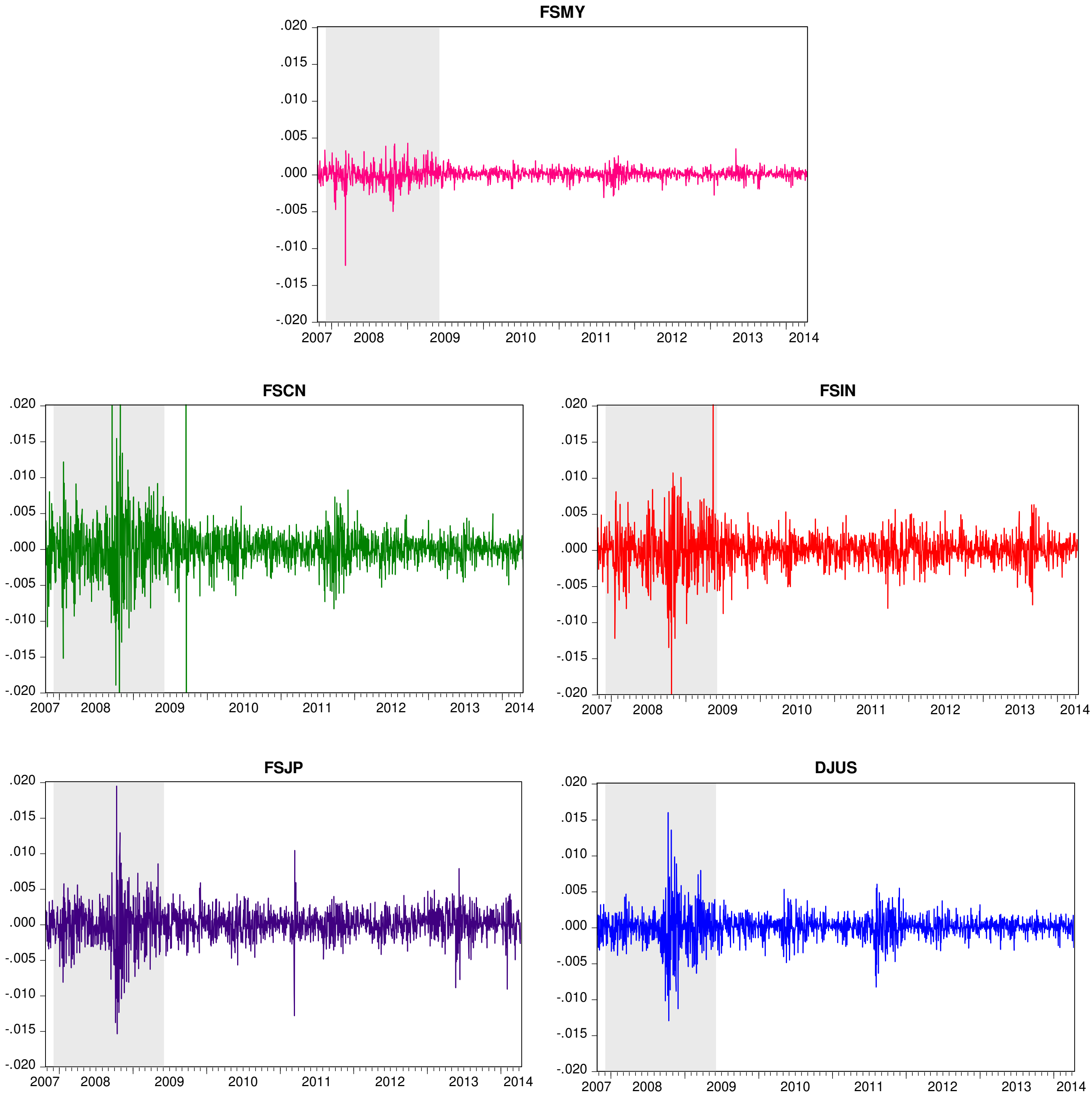


Figure 1: *Graphs of FSMY, FSCN, FSIN, FSJP and DJUS*

DCC estimation results under normal distribution are presented in table 3 and 4. Volatility parameters are presented in table 3 and unconditional volatilities and unconditional correlations are presented in table 4.

Table 3: *DCC Estimation results using Normal Distribution*

Parameter	Estimate	T-Ratio	Probability
λ1_FSMY	0.90044	55.88	0.000

	(0.0161)		
λ2_FSMY	0.09756	8.32	0.000
	(0.0117)		
λ1_FSCN	0.88121	58.67	0.000
	(0.0150)		
λ2_FSCN	0.09153	6.22	0.000
	(0.0147)		
λ1_FSIN	0.89597	59.43	0.000
	(0.0150)		
λ2_FSIN	0.09845	8.12	0.000
	(0.0121)		
λ1_FSJP	0.87007	45.46	0.000
	(0.0191)		
λ2_FSJP	0.09053	6.18	0.000
	(0.0146)		
λ1_DJUS	0.86534	49.25	0.000
	(0.0175)		
λ2_DJUS	0.11367	7.10	0.000
	(0.0159)		
δ1	0.97135	148.85	0.000
	(0.0065)		
δ2	0.01297	5.85	0.000
	(0.0022)		
Max. Log-likelihood		24356.2	

Note: Standard Errors in parentheses.

Table 4: *Unconditional Volatilities and Unconditional Correlations (Normal Distribution)*

	FSMY	FSCN	FSIN	FSJP	DJUS
FSMY	**0.00815**	0.44518	0.36915	0.43218	0.13119
FSCN	0.44518	**0.02595**	0.44669	0.50218	0.20424
FSIN	0.36915	0.44669	**0.01935**	0.3153	0.29545
FSJP	0.43218	0.50218	0.31530	**0.01633**	0.12629
DJUS	0.13119	0.20424	0.29545	0.12629	**0.01404**

DCC estimation results under T - distribution are presented in table 5 and 6. Volatility parameters are presented in table 5 and unconditional volatilities and unconditional correlations are presented in table 6.

Table 5: *DCC Estimation results using T - Distribution*

Parameter	Estimate	T-Ratio	Probability
λ1_FSMY	0.90442	50.24	0.000
	(0.0180)		
λ2_FSMY	0.08546	5.61	0.000

	(0.0152)		
λ1_FSCN	0.89533	58.88	0.000
	(0.0152)		
λ2_FSCN	0.09723	7.14	0.000
	(0.0136)		
λ1_FSIN	0.90673	59.96	0.000
	(0.0151)		
λ2_FSIN	0.08155	6.54	0.000
	(0.0124)		
λ1_FSJP	0.89618	48.79	0.000
	(0.0183)		
λ2_FSJP	0.08450	6.11	0.000
	(0.0138)		
λ1_DJUS	0.88161	52.41	0.000
	(0.0168)		
λ2_DJUS	0.10606	7.28	0.000
	(0.0145)		
δ1	0.97468	127.49	0.000
	(0.0076)		
δ2	0.01256	4.83	0.000
	(0.0025)		
df	6.8605	14.82	0.000
	(0.4626)		
Max. Log-likelihood		25724.0	

Note: Standard Errors in parentheses.

Table 6: *Unconditional Volatilities and Unconditional Correlations (T - Distribution)*

	FSMY	FSCN	FSIN	FSJP	DJUS
FSMY	**0.00815**	0.44518	0.36915	0.43218	0.13119
FSCN	0.44518	**0.02595**	0.44669	0.50218	0.20424
FSIN	0.36915	0.44669	**0.01935**	0.3153	0.29545
FSJP	0.43218	**0.50218**	0.31530	**0.01633**	0.12629
DJUS	0.13119	0.20424	0.29545	**0.12629**	**0.01404**

Table 5 presents the maximum likelihood estimates of λ_{i1} and λ_{i2} (Volatility Parameters) for the five Islamic stock index returns, and δ_1 *and* δ_2 (Mean reverting parameters, ϕ_1 *and* ϕ_2). It is observed that all volatility parameters are highly significant, which implies gradual volatility decay i.e. high riskiness of the stocks return gradually decays (dies out) following a shock in the market, which makes the return highly volatile. Even if we add λ1_FSMY and λ2_FSMY (0.90442 + 0.08546 = 0.98988 < 1), which is less than unity, implies that the volatility of FTSE Bursa Malaysia Emas Shariah index return is not following IGARCH, i.e. the shock to volatility is not permanent. Similarly, for the remaining Shariah stock returns $\lambda 1i + \lambda 2i < 1$, which implies that their volatilities are not following IGARCH.

Table 6 reports the estimated unconditional volatilities and unconditional correlation cross correlations between returns of Islamic indices. The off diagonal elements represent unconditional correlation and diagonal elements (bold red) represent unconditional volatilities of the Islamic stock returns.

We can observe that unconditional volatility of return for FTSE Shariah China (0.02595) is the highest and lowest is for FTSE Bursa Malaysia Emas Shariah index (0.00815), which implies that FTSE Bursa Malaysia Emas Shariah stock returns are more stable than any other Islamic stock returns. This result is similar to the return graphs in figure 1. Investors should be aware of these volatilities before investing in the Islamic stock portfolio.

With regard to the cross return correlation, we observe that correlation between returns from Japanese and Chinese Shariah stocks (0.50218) is the highest and positive. This high positive correlation shows the possible direction of movement and the degree of association (+50%) between these Shariah indices returns. It is also a concern for the investors as any movement in the return of either of the two causes another to move in the same direction. In fact, Japanese stock market is the most structured and developed market in Asia, which leads other markets in Asia. Interestingly, correlation between Japan and the US Islamic stock returns (0.12629) is the lowest. This result shows that volatility of the US Islamic stock return has least impact on the volatility of Japan Islamic stock returns.

With comparing the maximum likelihood estimates of the t-DCC model on Islamic indices daily returns, we observe that all return volatility estimates are statistically significant and near to unity, which implies gradual decay in volatility under both T-DCC model and the DCC model with normality assumption. The maximized log likelihood value under t-DCC model (25724.0) is significantly larger than (24356.2) under the DCC model with normality assumption. The estimated degree of freedom is 6.86, well below the values of 30. These conclusions are robust to the way returns are standardized for computation of cross asset return correlations.

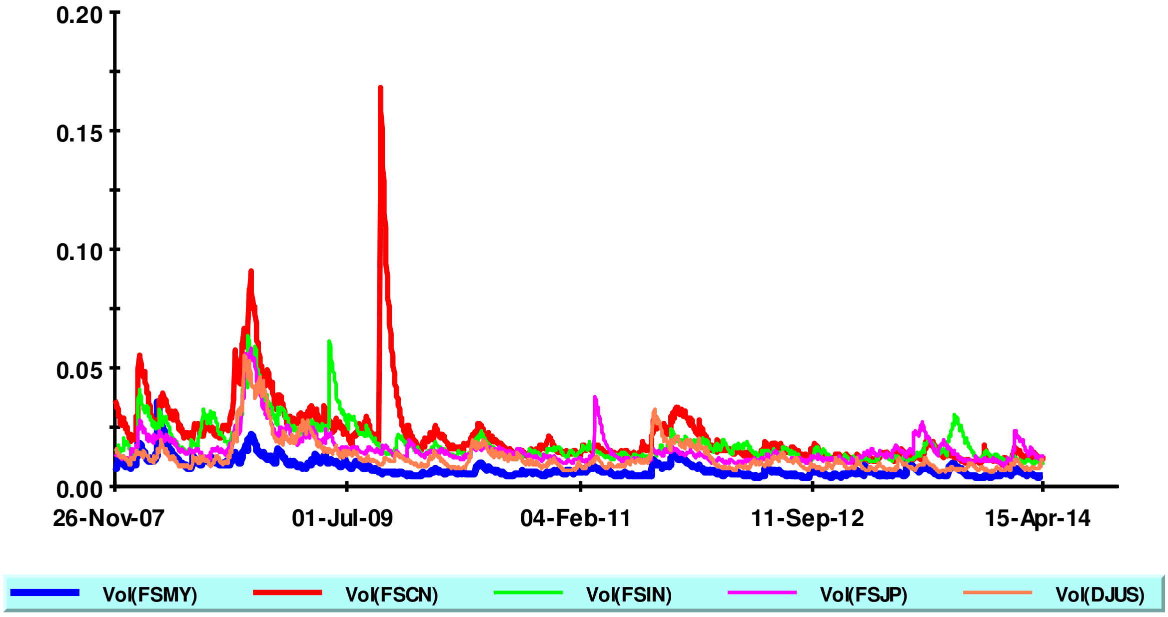


Figure 2: *Plot of the Conditional Volatilities*

From the above graph (figure 2), we can observe that the conditional volatilities of all Islamic stock returns move more closely together except during the financial crisis, when China Shariah stocks returns are highly volatile as compared to other Islamic stock returns. The convergence of volatilities could reflect a closer financial integration between the markets.

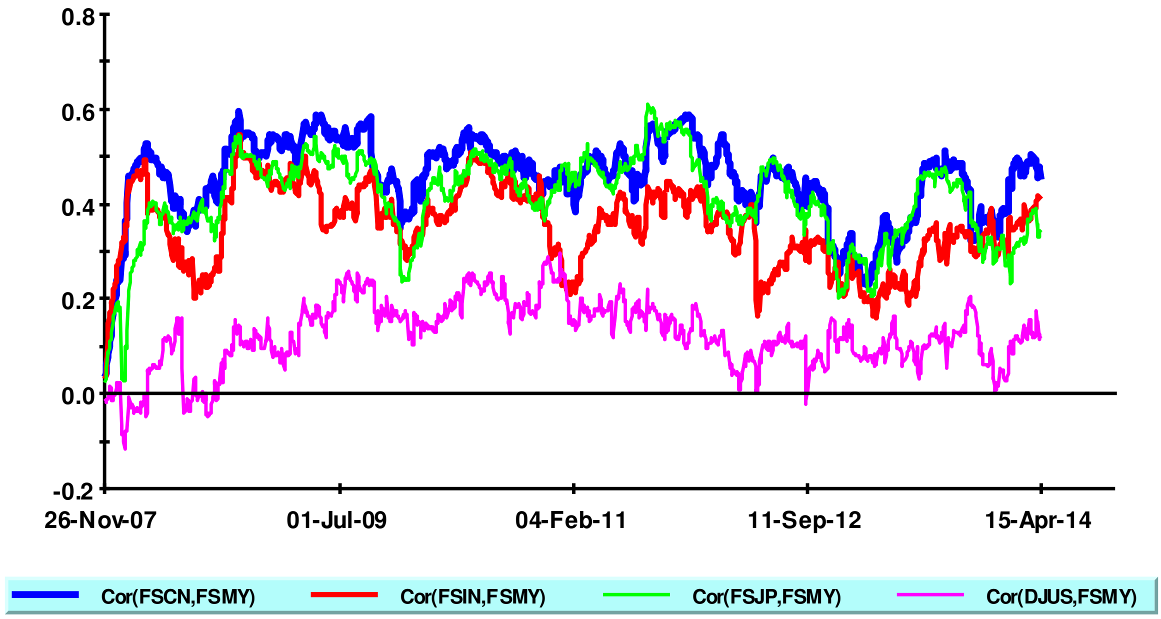


Figure 3: *Plot of the Conditional Correlations (FSMY with others)*

From figure 3, we observe that conditional correlations of returns on Islamic stocks have been fluctuating over time. Conditional correlations of Malaysia Islamic stock return with other Islamic stocks are highly fluctuating over the periods. Conditional correlation of Malaysia

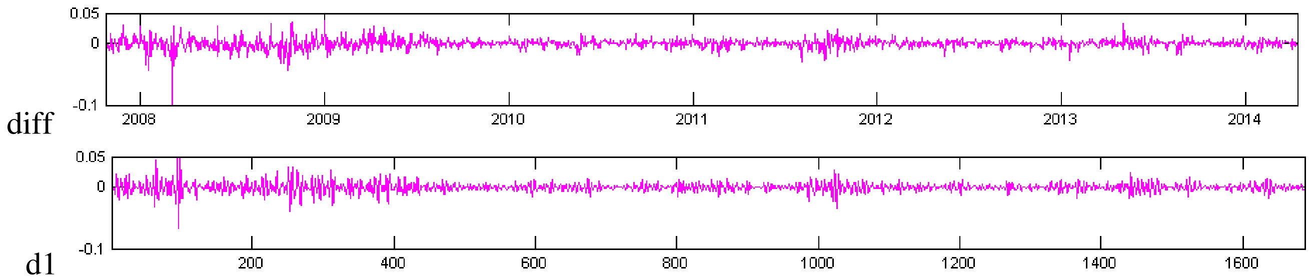
Islamic stock return with China is more volatile over the period and with the US is less volatile and almost stable over time in comparison with other markets.

To investigate the multiscale relationships, we use wavelet analysis to decompose a time series into various time scales. The main advantage of wavelet analysis is its ability to decompose the data into several time scales and to handle non-stationary data, localization in time, and the resolution of the signal in terms of the time scale of analysis. Since it is likely that there are different decision making time scales among traders, the true dynamic structure of the relationship between stock returns will vary over different time scales associated with those different horizons. Since we use daily data, the wavelet scales would be as follows in table 8:

Table 8: *Interpretation of time scales*

Scale	Component	Frequency resolution
Scale 1	d1	2-4 days
Scale 2	d2	4-8 days: approximately one week
Scale 3	d3	8-16 days: approximately 2 weeks
Scale 4	d4	16-32 days: approximately one month
Scale 5	d5	32-64 days: approximately 2 months
Scale 6	d6	64-128 days: approximately 4 months
Scale 7	d7	128-256 days: approximately one year
Scale 8	d8	256-512 days: approximately 2 years

Figures 7a-10e show the LA(8) MODWT MRA for the five Shariah stocks returns using various time scales (d1 to d7). In each plot, the topmost panel shows the original time series. Below it, from top to bottom are the wavelet details d1, d2, …, d7. By looking at the below figures, we can observe that as the time scale increases from d1 to d7, the wavelet coefficients show a progressively smoother movements which implies that the short term noise in the stock market is eliminated.



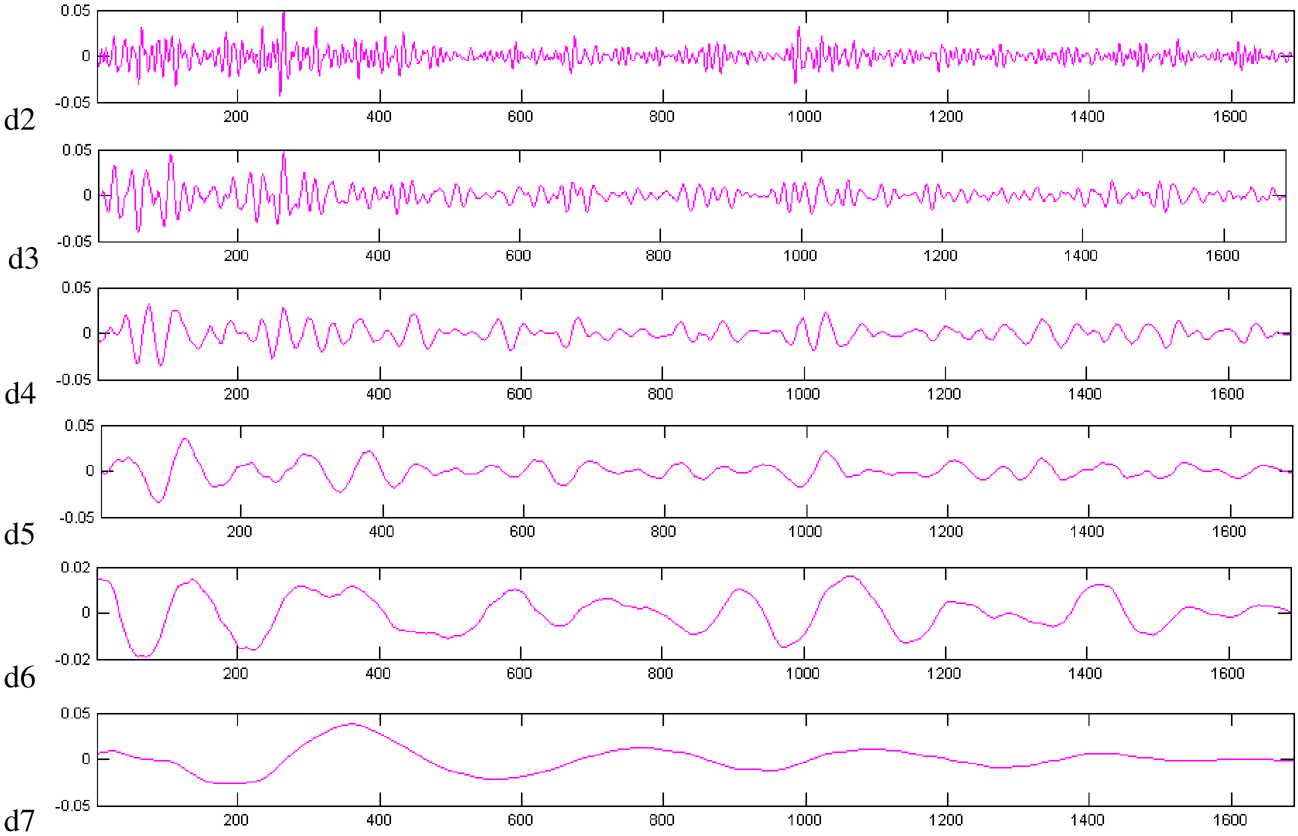
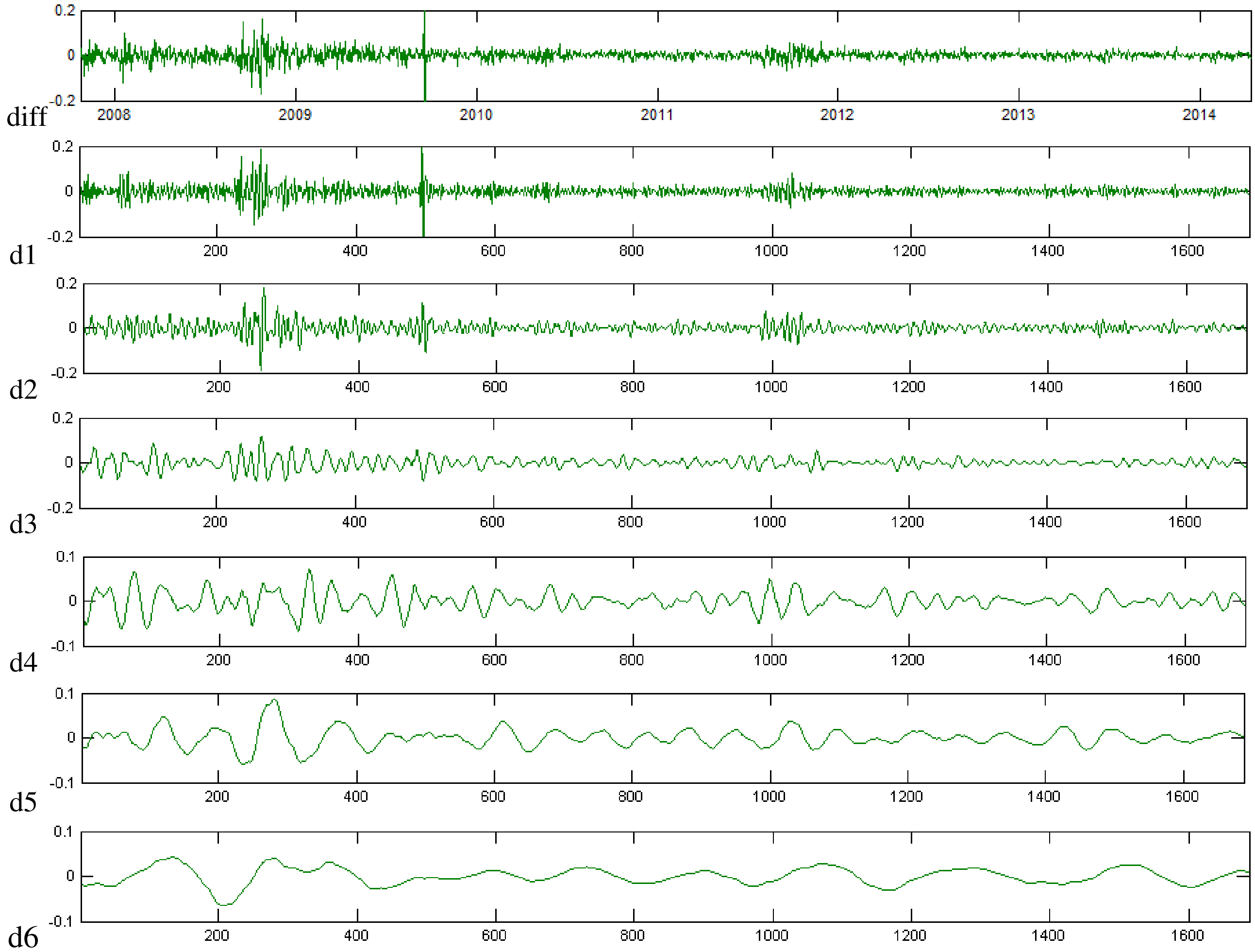


Figure 7a: *Multiresolution analysis for FSMY, MRA analysis of the MODWT*



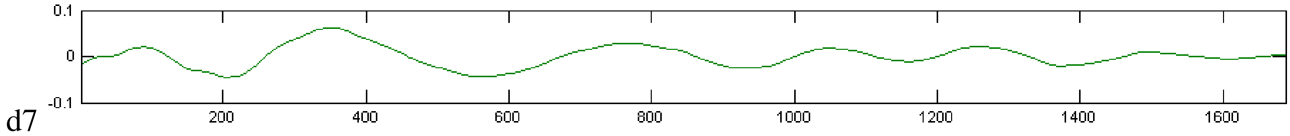


Figure 7b: *Multiresolution analysis for FSCN, MRA analysis of the MODWT*

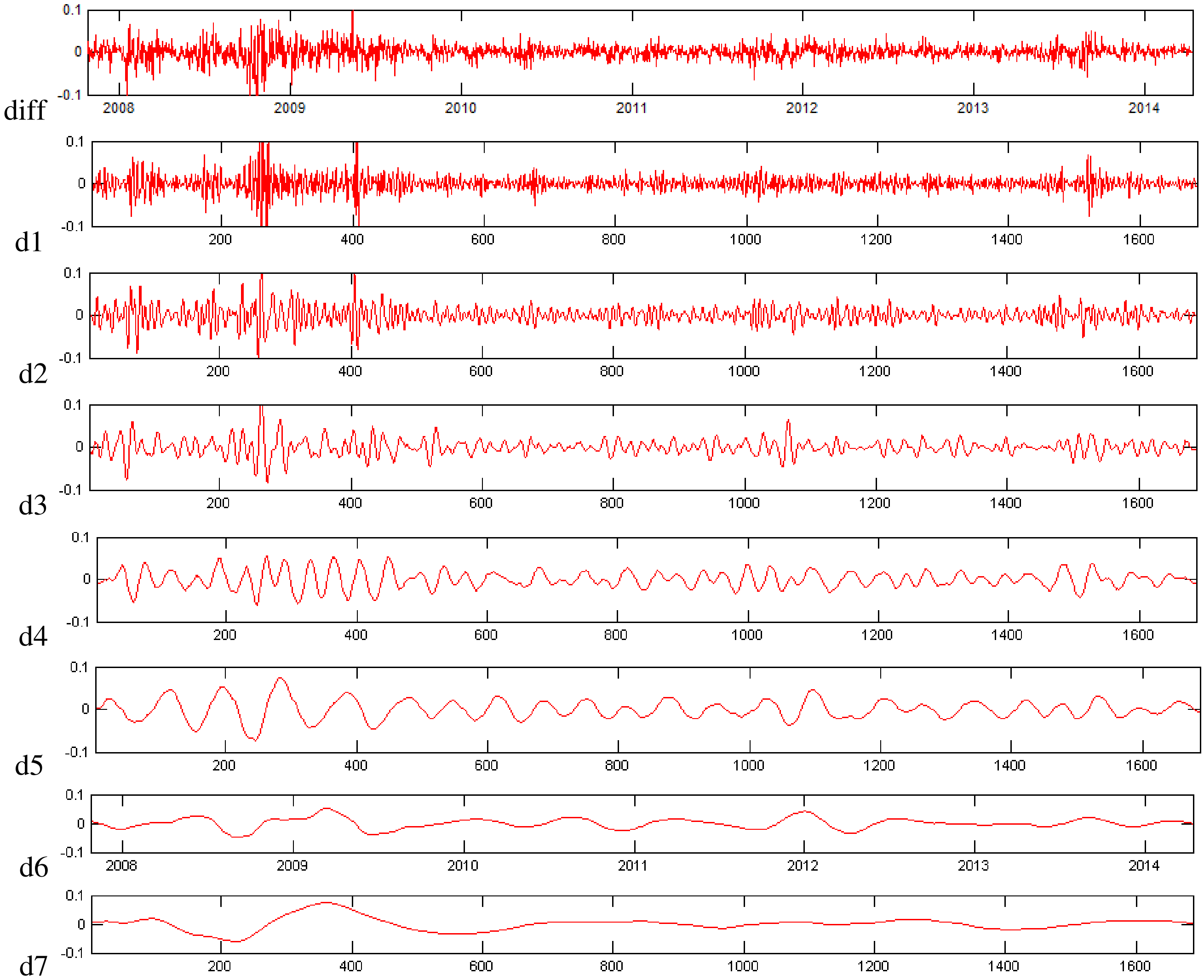
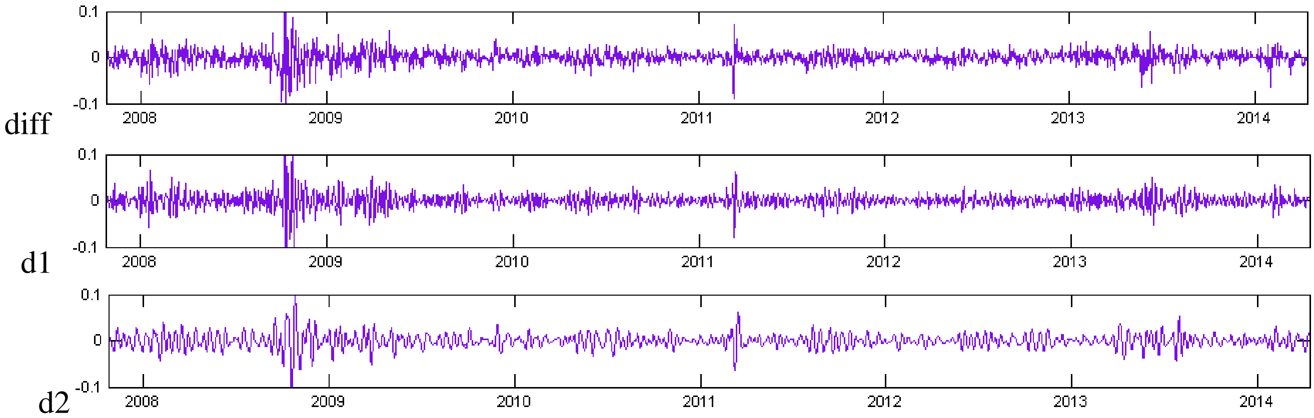


Figure 7c: *Multiresolution analysis for FSIN, MRA analysis of the MODWT*



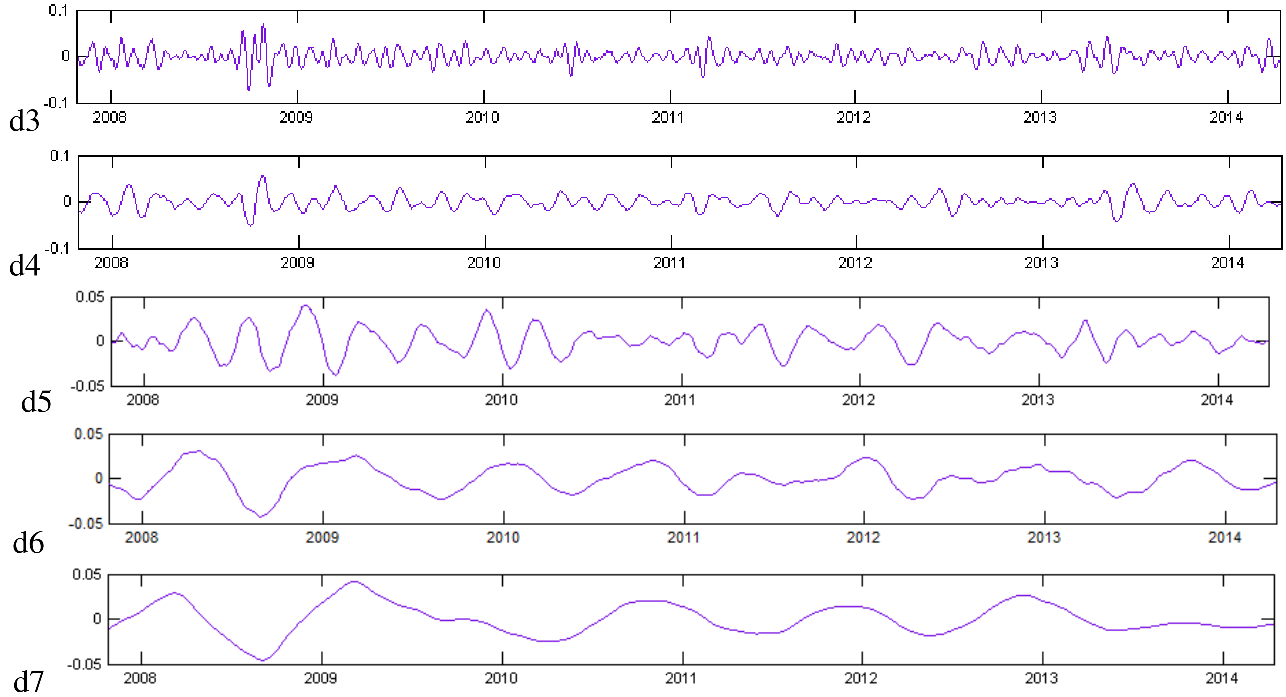
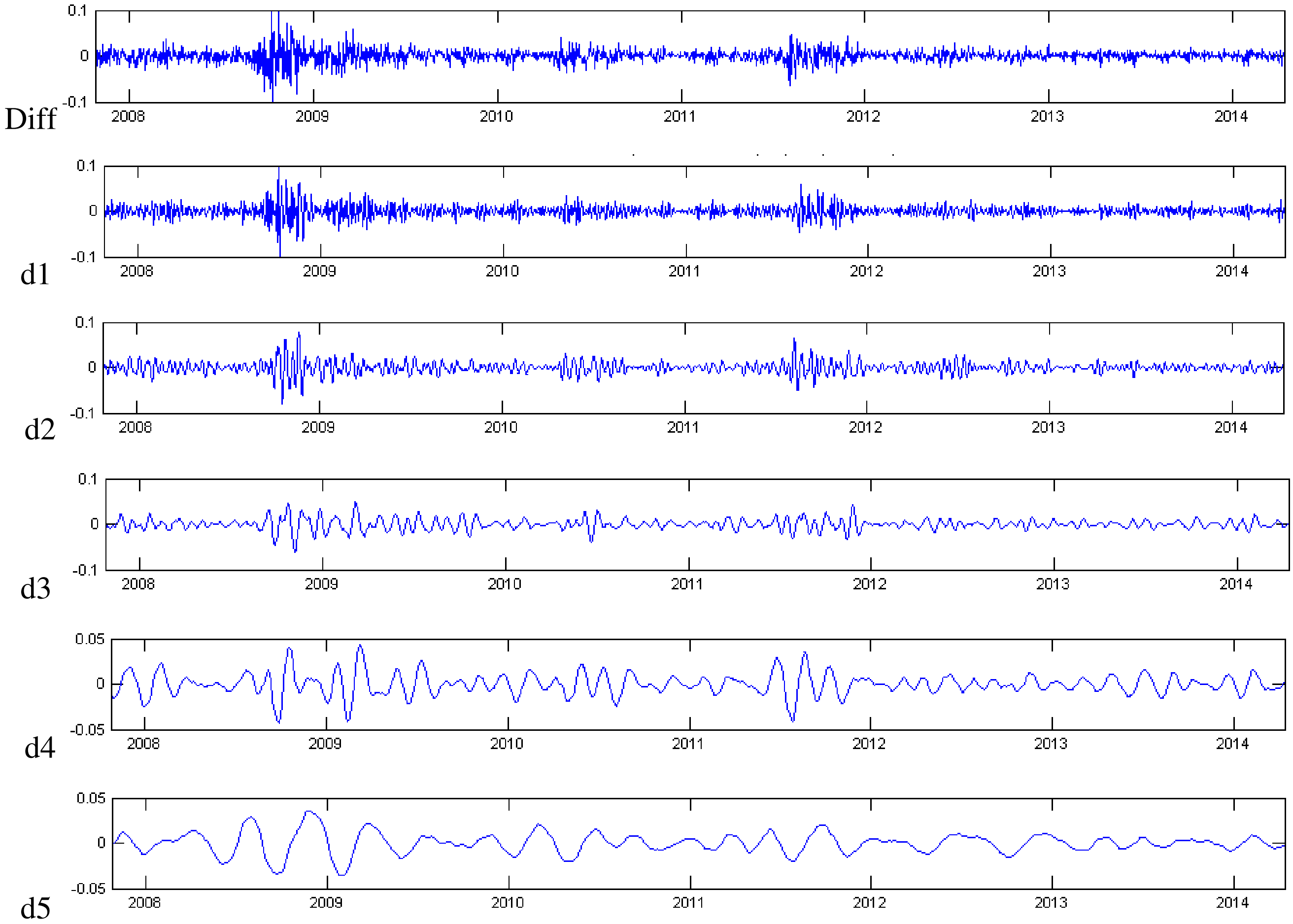


Figure 7d: *Multiresolution analysis for FSJP, MRA analysis of the MODWT*



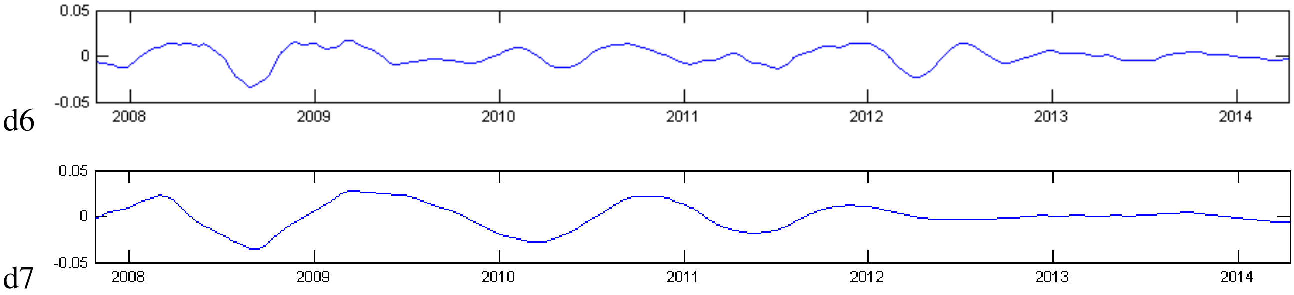


Figure 7e: *Multiresolution analysis for DJUS, MRA analysis of the MODWT*

From the wavelet variances for the five Shariah stock returns in figure 8, it is found that the wavelet variance decreases as the wavelet scale increases, implying that an investor with a short investment horizon has to respond to every fluctuation in the realized returns, while for an investor with a longer horizon, the long run risk is significantly less.

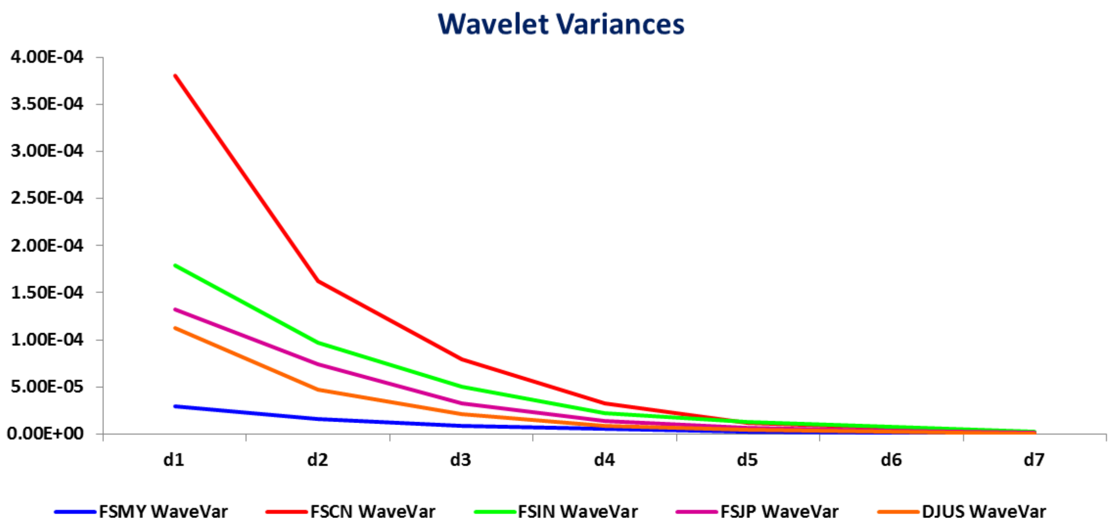


Figure 8: *Estimated wavelet variances of five selected Islamic stock returns, The MODWT-based wavelet variance using wavelet filter LA (8)*

In addition to examining the variances, it is also important to know how Shariah stock returns are associated with together. We want to examine whether the correlations between stock returns change as time horizon increases. Figure 9 shows the estimated wavelet correlations of FTSE Bursa Malaysia Emas Shariah index return with other four developed and emerging stock market powers. As can be seen in below figure for China, the correlation with Malaysia Stock returns is positive and growing during whole the scales. India shows a positive correlation with Malaysia Shariah stock returns, also for Japan, correlation with Malaysia stock returns is positive. However in case of the US in scale 1 the correlation between Malaysia and the US is negative but in the higher scales it changes to positive correlation. These results imply that the correlation between Malaysia and four selected Shariah stock returns depends on the time scales and on the country.

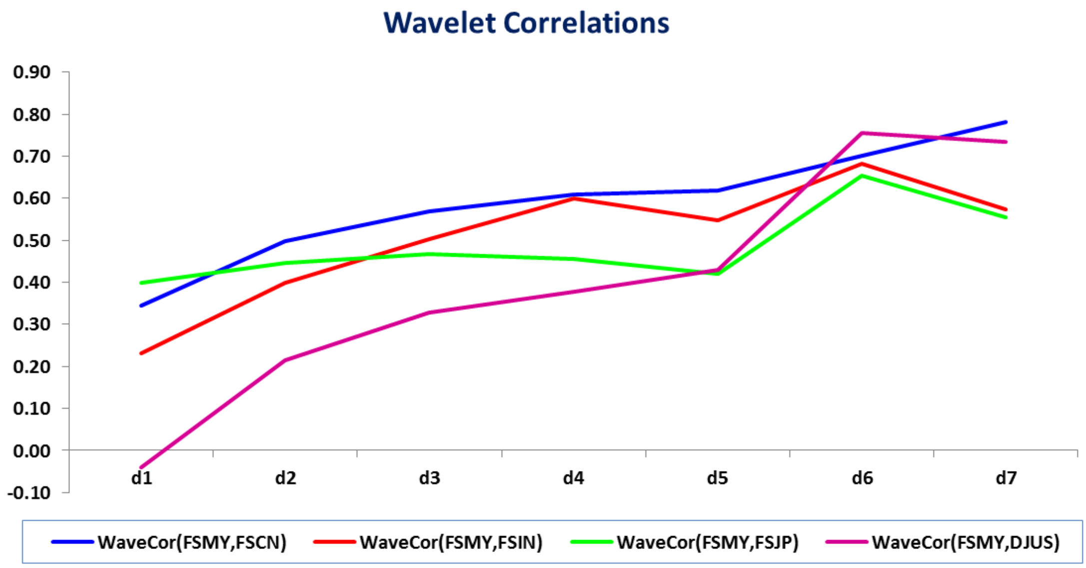


Figure 9: *Estimated wavelet correlations of FSMY with other Islamic stock returns. The MODWT-based wavelet correlation using wavelet filter LA (8)*

Table 9: *MODWT Correlations of FSMY with other four Islamic stock returns*

Scale	WaveCor (FSMY,FSCN)	WaveCor (FSMY,FSIN)	WaveCor (FSMY,FSJP)	WaveCor (FSMY,DJUS)
S1	**0.35**	**0.23**	**0.40**	**-0.04**
S2	**0.50**	**0.40**	**0.45**	**0.22**
S3	0.57	**0.50**	**0.47**	**0.33**
S4	0.61	0.60	**0.46**	**0.38**
S5	0.62	0.55	**0.42**	**0.43**
S6	0.70	0.68	0.65	0.75
S7	0.78	0.57	0.55	0.73

Further Table 9 depicts the MODWT correlations of FTSE Bursa Malaysia Emas Shariah index return with the reaming four selected Islamic stock returns. As it is shown by red color, those stock returns correlations that are lower than 0.5 are considered to be in the portfolio basket. And those returns with higher than 0.5 correlations are highly cointegrated and hence not effective for portfolio diversification. In a very short period of time like less than 2 weeks, the US market is the better place to invest and after that India can be considered. But for a medium period of time India and China are not effective for diversification and better option is Japan and the US. For a longer period of time only Japan can be considered in the portfolio.

Since wavelet correlation does not provide information on lead and lag relationships among the stock returns, we used wavelet cross-correlation which can capture transit relationships between two time series at different frequencies. Figures 10a – 10d report the wavelet cross-correlations for the seven levels of resolution between FTSE Bursa Malaysia Emas Shariah index return and other four stock returns. We know that if the curve is significant on the right side of the graph, it means that the FSMY is leading other Islamic stock indices. On the other hand, if the curve is significant on the left side of the graph, 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. As in is observed from the below graphs almost in all the 4 cross-correlations, Malaysia is leading the other Islamic markets that can be as a result of high motivation of Malaysia to become a global hub for Islamic finance and have the highly performed market with the intensive plans that facilitate this objective.

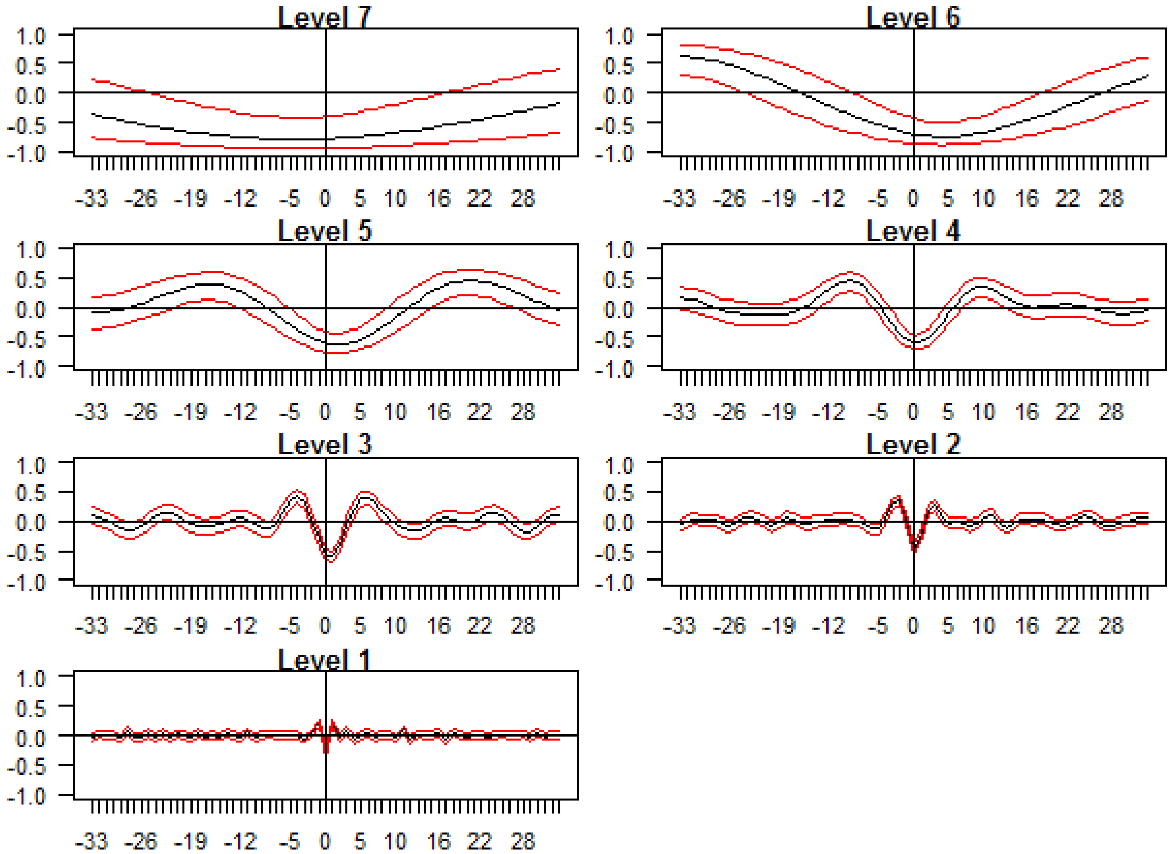


Figure 10a: *Cross Correlation between FSMY and FSCN*

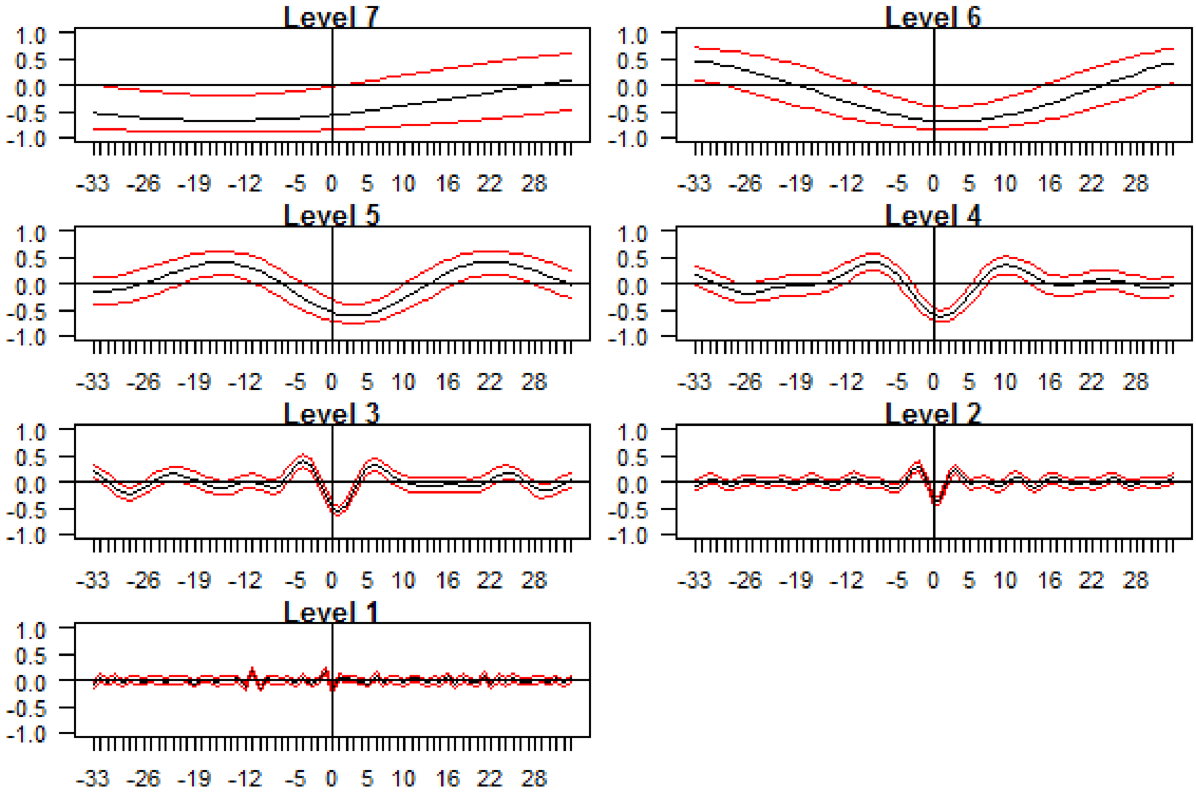


Figure 10b: *Cross Correlation between FSMY and FSIN*

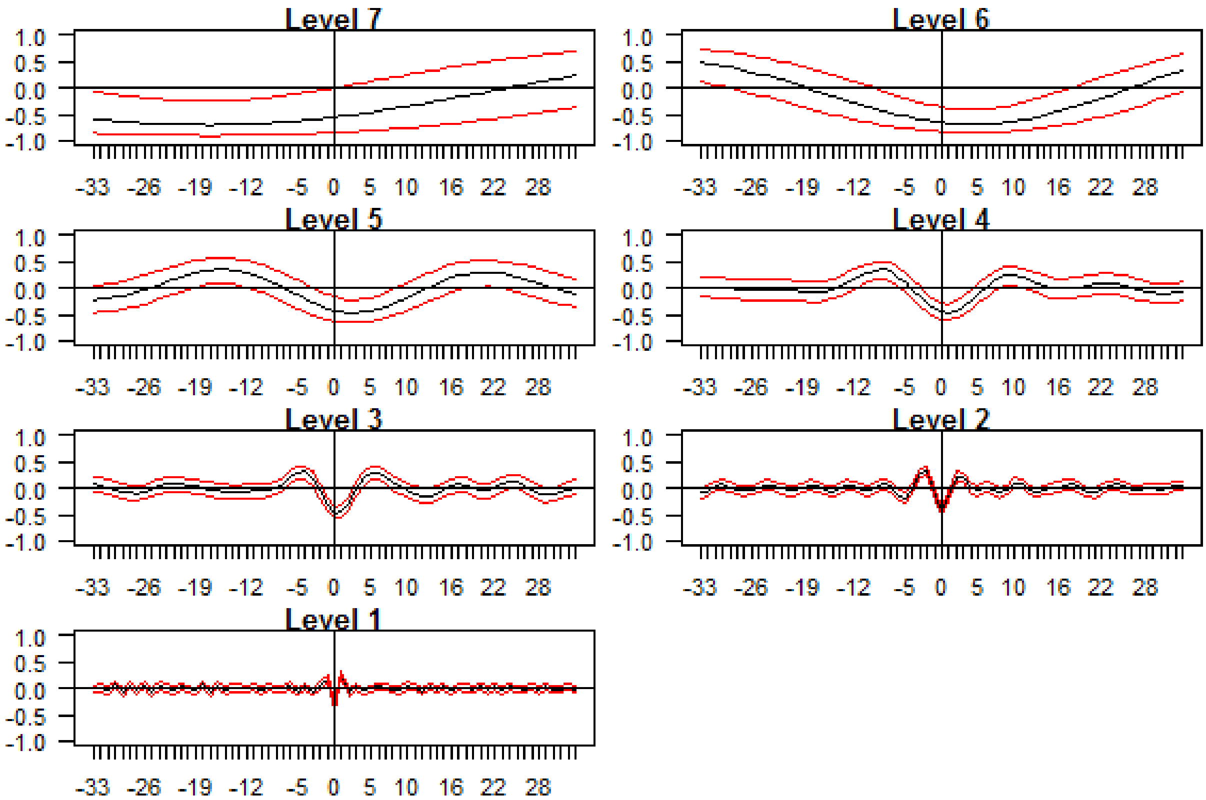


Figure 10c: *Cross Correlation between FSMY and FSJP*

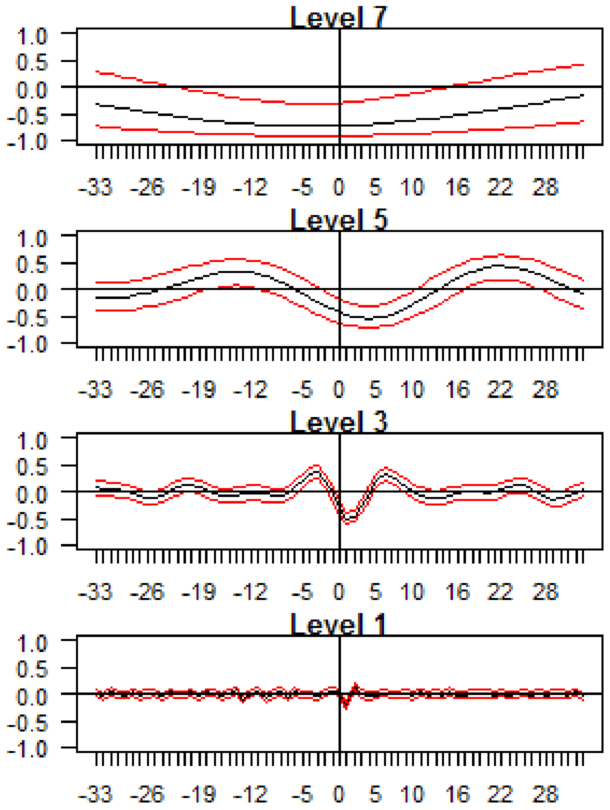


Figure 10d: *Cross Correlation between FSMY and DJUS*

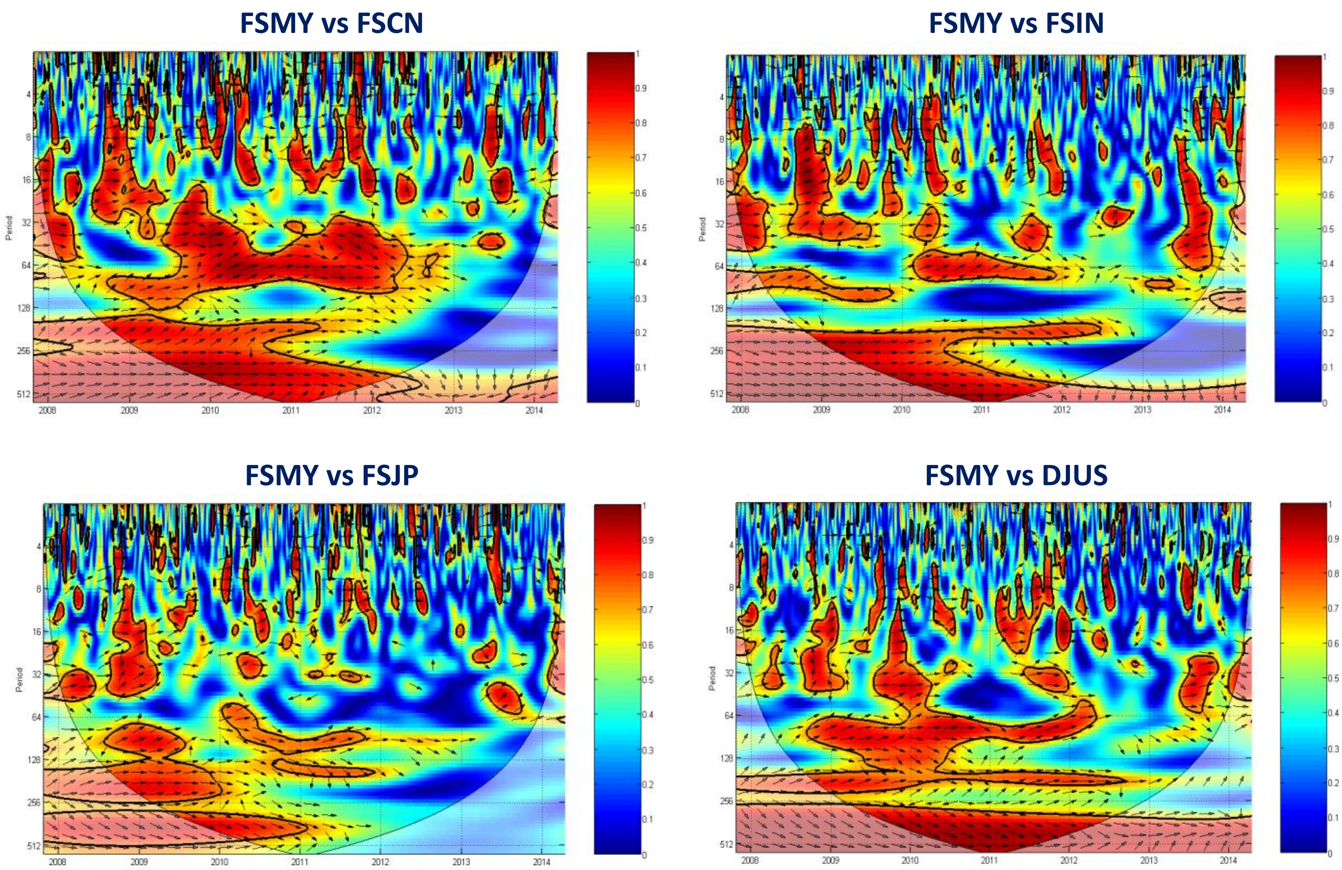


Figure 4: *Plot of the Conditional Correlations (FSMY with others)*

For further analysis and by applying Wavelet coherence, Figures 4 presents the estimated continuous wavelet transform and phase difference of Malaysian Islamic stock returns with other stock market returns from scale 1 up to scale 8 (see Table 8) . Time is shown on the horizontal axis in terms of number of trading days, while the vertical axis refers to the investment horizon. At a glance we can observe that the correlations between Malaysia and China stock returns are higher due to the greater number of red spots on the coherence diagram.

Now by splitting the investment horizons to the periods that satisfy the financial players in the market based on their areas of interest like speculation, hedge, short term investment and long term investment we can observe the following results:

For very short holding periods consisting of 2-4 days and 4-8 days, we can find that China markets returns are consistently strongly correlated to Malaysian returns over the past 6 years thus offering not a good portfolio diversification opportunity. Particularly during financial crisis 2008-2009 and Euro Sovereign Debt 2011-2012 crisis, this correlation is higher. On the other hand, as depicted in the graph FSMY vs DJUS, the correlation between Malaysia and the US Islamic market is lower that suggests an effective portfolio diversification opportunities especially for speculators.

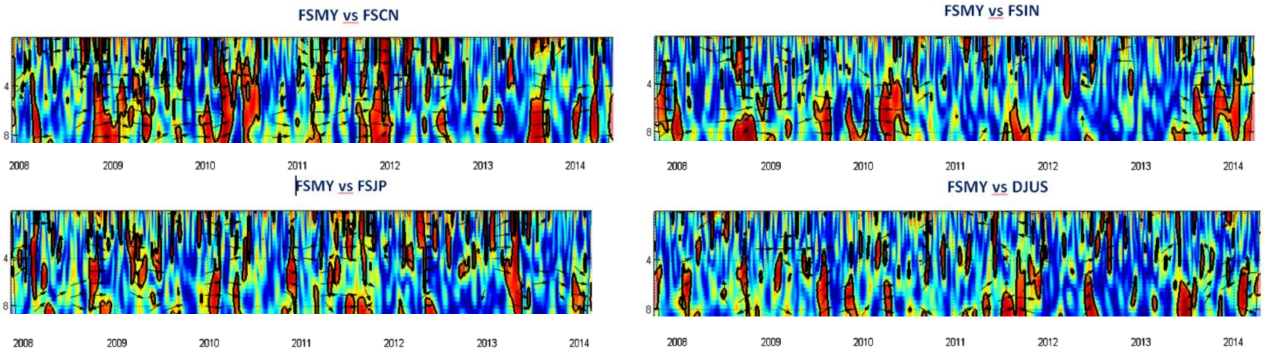
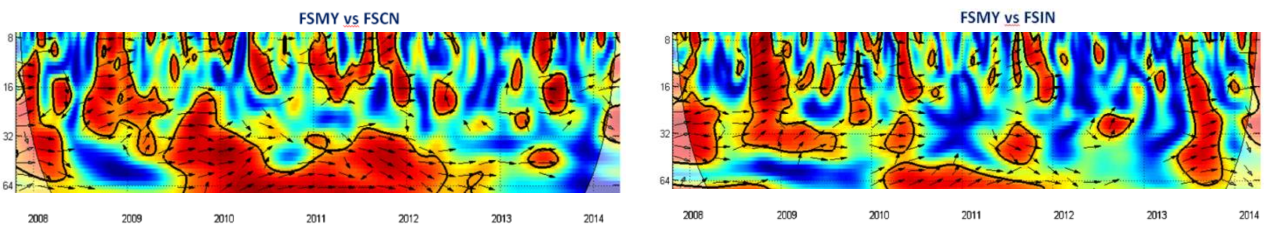


Figure 5a: *Plot of the Conditional Correlations (FSMY with others) for a very short period of less than one week*

For the short investment horizon consisting of 8-16, 16-32 and 32-64 days holding periods which are less than 2 month period, once again we find that China market returns are consistently strongly and positively correlated with Malaysia stock returns then eliminating the portfolio diversification opportunity in this market. For this period of time Japan Islamic market return shows lower level of interdependence with Malaysia as a result good opportunity for those investors looking for short term investments.



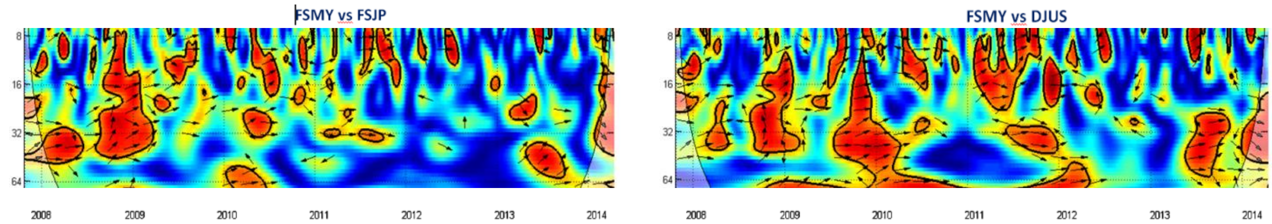


Figure 5b: *Plot of the Conditional Correlations (FSMY with others) for a period of less than 2 months*

Moving towards medium investment horizons consisting of 64-128 and 128-256 days, interestingly we observe that with or without considering the crisis periods Japan has lower integration with Malaysia and still in this period China and Malaysia have high integration. As a result investing in Japan Islamic market is a better portfolio decision.

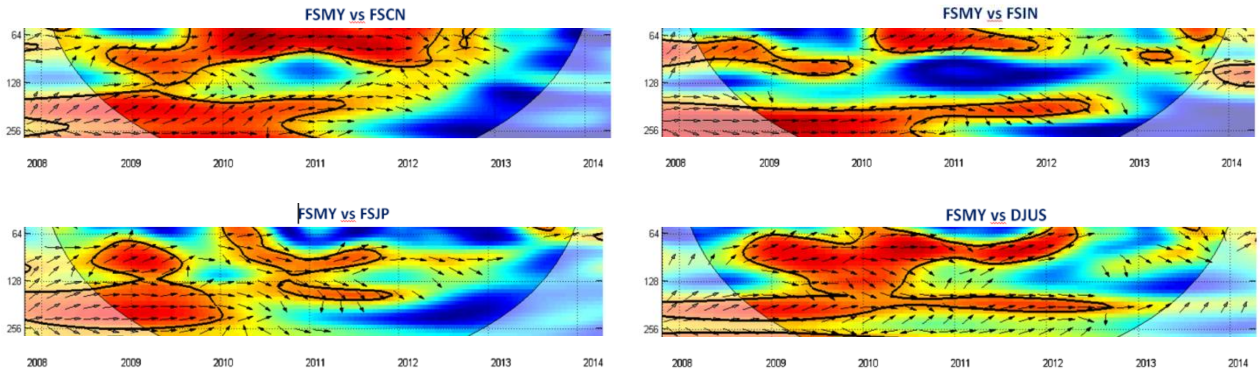


Figure 5c: *Plot of the Conditional Correlations (FSMY with others) for a period of more than 2 months to one year*

Last but not least, for long-term investors by considering 256-512 days holding periods, there are very strong correlations in returns for the US and Malaysia that eliminate potential international portfolio diversification opportunities. However Japan Islamic stock market is a very good opportunity for these investors to invest in.

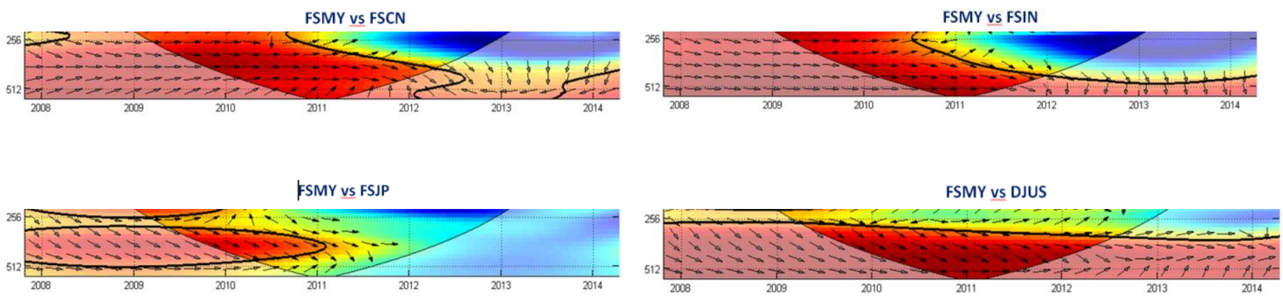


Figure 5d: *Plot of the Conditional Correlations (FSMY with others) for a long period of more than one year*

We can consider figure 9 in mind at the time of observing figures 4-8 to understand when there is a correlation between markets which market is leading and which one is lagging. It is interesting that up to almost half of the year 2010, in the long term the US is leading Malaysia but after that Malaysia is becoming the leader.

The result from both the CWT and MODWT are consistent.

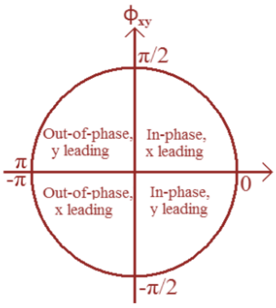


Figure 6: *Phase difference circle*

VII. Conclusion and Policy Implications

This study applied dynamic conditional correlation (DCC) model under multivariate GARCH (MGARCH), Wavelet coherence, Continuous Wavelet transformation and MODWT analysis on five Shariah stock returns in line with the objective of this study, which is to find conditional correlation, integration and variance of the Islamic stock returns. Apart From the analysis, this study has the following concluding remarks:

- This study finds one significant feature of Islamic stock returns. Interestingly, volatility of Islamic stock returns is influenced by the regional market conditions such as emerging Islamic stock market as Malaysia is highly correlated with Chinese Islamic stock return. Least correlation found with the US Islamic stock return.
- With respect to return volatility, Chinese Islamic stock return is at the top and Malaysian Islamic stock return is at the bottom followed by the US, Japanese, and Indian Islamic stock returns.
- Islamic stock return is also affected by financial crisis, which is evident by the downturn in 2008-2009 for all concerned Islamic stocks. Especially, Chinese and Indian stock returns were severely volatile during this period of time.
- Our findings indicate that Malaysian Islamic stock market traders who have allocated their investment across the developed stock markets like the US and Japan have greater portfolio benefits according to their holding period stocks. However investing in Emerging markets such as China and India are not considered as opportunities for investments especially at medium and long period of time. In the long-run, where investor stock holding periods exceed one year, almost all the markets under the research are highly correlated yielding minimal portfolio diversification benefits.

The findings of this study have several implications for the policy makers of Islamic stock markets and market players. Policy makers should take into account the effect of global financial turmoil in order to claim the superiority of the Islamic stock market. May be the effect of financial turmoil is relatively lower in Islamic stock market as compared to the conventional stock market mainly because of strict stock screening process according to Shariah principles, avoiding any toxic investment, and following prohibitions in Shariah. Market players including investors, following the findings of the study, may be able to set more effective and smart portfolio strategies with Islamic stocks in order to maximize their returns.

VIII. Limitations of the Study

Like any other researches, this study has limitations as well. By including more indices not only Islamic but also conventional, we could have more comprehensive results that can help the financial players and policy makers.

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