Are There Profit (Returns) in Shariah-Compliant Exchange Traded Funds? The Multiscale Propensity

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Abstract

This paper investigates the co-movement of nine Islamic Exchange Traded Fund (ETF) returns using wavelet coherence methods. The results tend to indicate consistent co-movement between most of the ETF returns especially in the long run. The study also uncovers evidence of wide variation of co-movement across the time-scales during the global financial crisis and the Euro debt crisis. Strong co-movement can be observed during the global financial crisis, both for the medium term investors and long term investors. The paper also studies the relationship between different ETF returns using wavelet multi-resolution analysis. The cross-correlation analysis also shows certain significant and positive correlations between the ETF returns, especially during the period of global financial crisis. The findings from these two recent dynamic time-scale decomposition methodologies have important policy implications for risk management and investors' investment policy.

Keywords: Islamic exchange traded fund returns, Wavelet coherence, MODWT

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1.0 Introduction

Exchange Traded Funds (ETF) emanated from the innovation in the capital market. ETFs are tradable securities which derive their value from a pre-defined basket of securities which are constituents of an index. These types of ETFs derive their value (and volatility) from market movements of the underlying stocks, which comprise the portfolio, and these funds are similar to index funds managed by institutional portfolio managers. Index-linked products, such as ETFs, have been increasingly successful because they provide investors with benefits of diversification through one investment product (Gallagher, 2006)[1]. Carty (2001) acknowledged that ETFs have provided investors the advantage of risk diversification, tracking, all-day trading, strategic trading capability, tax efficiency, lowest fees and transparent holdings.

With the Islamic Finance industry showing tremendous growth and innovation during the last decade, demand for Islamic financial instruments is growing at a high pace. Many individual and institutional investors, mainly from Islamic countries, seek to invest only in stocks that are compliant with the Islamic laws (or Shariah). Conventional ETFs have attracted many investors as one of the most innovative products of financial engineering. The structure of Islamic ETF is very much unique as compared to its conventional counterpart, with the extension of Shariah compliant component in the main structure which includes Shariah stock screening methodology. This is due to the fact that Islamic ETF requires strict Shariah compliance from all aspects of the process beginning with the creation and redemption aspect of the Islamic ETF.

ETF performance is a central concern for analyst and investors. Many studies tried to discuss the performance of ETFs, with some studies focusing on the tracking error and ETF volatilities (Abdou Diaw et al (2010), Chu (2011), Lin & Chiang (2005), Chen & Huang (2010) and Curcio et al (2012)). However, research concerning Islamic ETF performance is very limited (Abdow Diaw et al (2010) and Alam (2012)). Studies on conventional ETFs are abundant. Huang & Lin (2011) studied 19 iShares ETFs from June 2003 – March 2009 and shows that ETFs have higher Sharpe measures than target market indices especially in the emerging markets. Although they found no significant performance difference between direct (stock market) and indirect (ETF) methods of investment, it is more effective for investors to use indirect methods to create

[1] Gallagher, David, Reuben Segara (unpublished).

internationally diversified portfolios.

In this study we show evidence of multiscale Islamic ETF returns co-movement and cross-correlation among developed economies, emerging economies and selected country specific ETFs through wavelet analysis. We also show the relative ranking of ETF co-movement and cross-correlation which may differ across the investment horizons because expected returns increase or decrease at different rates in investment horizons. We use daily return of 9 ETF variables from developed market, emerging markets and selected country specific ETFs between May 2008 and March 2014. We use both continuous and discrete wavelet transform techniques to decompose the daily returns into orthogonal components with different timescales. The results show that the ETF return changes with the different time scales used. We also provide evidence that cross-correlation interdependence exists amongst the selected ETF returns variables.

This research, in examining the interaction between Islamic ETF return across different markets is motivated by a number of ways. First, given the limited evidence on the performance of Islamic ETFs, and the absence of empirical research with regards to multiscale performance of ETF, this study contributes to the literature by providing analysis on the multiscale tendency of the Islamic ETF performance across the global markets.

This gap in the literature is surprising given the significant growth and size of assets invested in Islamic ETFs. Secondly, while some research have been conducted to study the performance of Islamic ETFs[2], research which shows relative co-movement and cross-correlation of ETF returns across developed and emerging market still remain unheard of.

There are several advantages of using ETF data in the study. First, these securities are liquid and give investors instant exposure to the underlying index. It is not necessary to buy a “basket” of securities to mimic the index, and ETFs are not subject to the non-synchronous trading problems associated with stock index price data. The ETFs under study here are not vulnerable to potential biases since they are traded securities, not indices that are calculated from underlying individual stock price data (Krause & Tse (2013)).

The rest of the paper is organized as follows: in Section 2, we review the literature

[2] See Abdou Diaw et al (2010), which give a good analysis on the performance of Islamic ETF in Malaysia by looking at the performance of MyETF-DJIM Malaysia Titan 25 (MyETF).

on ETF performance and the wavelet applications. In Section 3, we provide a brief introduction on the ETF considered and their unique aspect. The wavelet technique is explained in Section 4. Empirical results are discussed in Section 5. We conclude in Section 6. Section 7 highlight the limitation of this research and future suggestions.

2.0 Literature Review

There are a few studies conducted on the empirical evidence of the performance of ETF. Rompotis (2008) studied the performance and trading characteristic of German ETFs during the period 2000-2006 and showed they slightly underperform their benchmarks. Rompotis (2011) revealed that majority of selected ETFs (out of a sample of 50 iShares) beat the S&P500 index both at annual and aggregate level while the return superiority of ETFs strongly persists at the short-term level during the six year period 2002-2007. Krause & Tse (2013) studied both US and Canadian ETF in the period of March 2001 – September 2009 and demonstrated via Granger-causality tests which shows U.S. ETF returns lead those of Canada at the broad market level and at four industry level ETF. They also shows that volatility spill overs occur bi-directionally in the market, financials, and technology sectors, but only from the U.S. to Canada for basic materials and energy sectors. Wong and Wai (2011) examines 15 worldwide ETFs across bearish and bullish markets over the period of 1999 to 2007 and shows that ETFs always provide higher returns in a bullish market than in a bearish market by the Sharpe ratio test that shows that ETF returns are not positive, proportional to the market volatility.

Charupat & Miu (2011), in studying Canadian leveraged ETF found that leveraged ETFs[3] are very actively traded and their transactions generally involve much shorter holding periods and much smaller dollar values than transaction in traditional ETFs. Gutierrez et al. (2009) shows that Asian ETF returns are explained by both US returns and local Asian market returns. Intraday returns also shows that US causes returns in all Asian Markets. Volatility spill over are also much stronger from US to Asian ETFs.

There have also been significant research into the performance of Islamic indices, and conventional indices. Ho, C.S.F. et al (2013) studies the performance of global Islamic

[3] Leveraged ETFs is a publicly traded mutual fund whose goal is to generate daily returns that are in a multiple or a negative multiple of the daily returns on some benchmarks. The first was introduced in US in 2006 and in Canada in 2007.

indices versus conventional indices and provides empirical evidence that Islamic indices outperformed their conventional counterparts during crisis period. However, their results we inconclusive for non-crisis period. Jawadi et al (2013) run similar study but look at financial performance of Islamic and conventional indexes for three major regions; Europe, the USA and the World. Again the study showed that Islamic funds have outperformed conventional funds since the subprime crisis and in turbulent time, with results specific to region under consideration and to the performance criterion.

With regards to wavelet techniques and analysis, Tiwari (2013) use continuous wavelet methodology via cross wavelet analysis such as cross wavelet transform (XWT) and wavelet coherency (WTC) to show time-frequency pattern in the relationship between the oil price returns and inflation and industrial production in Germany from 1958 to 2009. Their results show that there are both phase and anti-phase relationships (multiscale tendency) between oil price returns and inflation and in most of the cases inflation is the leading variable. The dynamics of correlation between energy commodities in the time-frequency space was studied by Vacha & Barunik (2012) using data from November 1993 – July 2010. Using wavelet coherence they found that three commodities of heating oil, gasoline and crude oil show the strongest dependence. Benhmad (2012) uses discrete wavelet transform (DWT) and multiresolution analysis to study the linear and non-linear causal relationship between the real oil price and the real dollar exchange rate from 1970 – 2010 and found there is evidence that they vary over frequency bands as it depends on the time scale (multiscale tendency).

Using discrete wavelet transform (DWT) methodology and the maximal overlap discrete wavelet transformation (MODWT), Reboredo and Castro (2013) study the co-movement between oil prices and US dollar exchange rate for the period January 2000 – October 2011 using multi resolution analysis (MRA). They show that oil price and exchange rate were not dependent in the pre-crisis period, but find evidence of contagion and negative dependence after the onset of crisis. Reboredo and Castro (2014) in studying the relationship between oil and stock market in Europe and USA at the aggregate and sectoral levels using wavelet multi-resolution analysis (MRA), shows empirically that for the period June 2000 to July 2011, oil price changes had no effect on stock market returns in pre-crisis period. However, during the onset of financial crisis, they are evidence of contagion and positive interdependence between the markets under study, which are consistent with the empirical evidence reported in Sadorsky (2001) and El-Sharif et al.

(2005)[4].

Rua & Nunes (2009) studied Germany, Japan, UK and US monthly stock market data from January 1973 – December 2007 via continuous wavelet transform (CWT) and wavelet coherence (WTC) to assess co-movement among these international markets. They found that Germany presents a relatively high degree of co-movement at lower frequencies with US and UK. Similarly, US and UK stock markets have a high degree of co-movement over the last four decades. Japan on the other hand have low co-movement with all other countries considered. Loh (2013), using weekly stock returns data from January 2001 – March 2012, investigated co-movement of 13 Asia pacific stock market returns with that of European and US stock market returns using wavelet coherence method and finds evidence which shows strong co-movement between most Asia-Pacific stock market and that of Europe and US in the long run. There are also evidence which shows time-variation and scale-variation in co-movement between these markets.

3.0 ETF Data

Daily ETF returns data for 9 ETF market in both developed and emerging markets as well as country specific ETF variables (MYETF, DAIWA and EASYETF) are use. The overall sample period of the study is from 28 May 2008 until 31 March 2014 (1524 observations), where there are sourced mainly from DataStream (Thompson Reuters). The list of the variables are tabulated in Table 1[5]. Majority of the data are the iShares MSCI ETF series which were listed in different locations i.e. Frankfurt and London. Both consist ETF basket which tracks three different market which is the US (developed) market, emerging market and world market. Three country specific ETF are also available which are MYETF with market in Malaysia (listed in Malaysia), DAIWA with market in Japan (listed in Singapore) and EASYETF with market in France (listed in Switzerland). The descriptive statistics for all variables are also presented in Table 1.

Table 1: List of ETF in the sample (28 May 2008 – 31 March 2014) and their descriptive statistic

[4] As highlighted in Reboredo & Castro (2014)

[5] Data collected from 28 May 2008 and ended 31 March 2014. This is to allow the study to capture 2 crisis periods, the Global Financial Crisis (GFC) 2008 – 2009, and also to capture the Euro Debt Crisis 2010-2011. One US based Islamic ETF data was not included (JETS DJ Islamic, listed on NYSE) as the data are only available from 1 July 2009 onwards.

Variable	Description	Exchange	Market	Currency
MYETF	MyETF-DJIM Malaysia Titans 25	Kuala Lumpur	Malaysia	MYR
DAIWA	Daiwa FTSE Shariah Japan 100	Singapore	Singapore	USD
IFEMRG	iShares MSCI Emerging Market	Frankfurt	Germany	EURO
IFUS	iShares MSCI US Market	Frankfurt	Germany	EURO
IFWLD	iShares MSCI World Market	Frankfurt	Germany	EURO
ILEMRG	iShares MSCI (London) Emerging	London	Ireland	USD
ILUS	iShares MSCI (London) US	London	Ireland	USD
ILWLD	iShares MSCI (London) World	London	Ireland	USD
EASYETF	EASYETF DJ Islamic (SWX)	Swiss	France	USD

	MYETF	DAIWA	IFEMRG	IFUS	ISWLD	ILEMRG	ILUS	ILWLD	EASYETF
Mean	0.000167	-0.000213	-0.000167	0.000296	0.000162	-0.000256	0.000210	0.000076	0.000072
Std. Dev.	0.010202	0.010060	0.017001	0.012119	0.015748	0.020097	0.013170	0.014240	0.012257
Maximum	0.080043	0.122159	0.118196	0.099224	0.305091	0.132060	0.090099	0.099842	0.123265
Minimum	-0.109199	-0.152269	-0.140826	-0.084432	-0.296913	-0.184571	-0.127201	-0.112689	-0.081325
Skewness	-0.579698	-2.496330	-0.350754	0.137935	0.316458	-0.439936	-0.425719	-0.096715	0.452607
Kurtosis	24.912650	81.845740	14.624630	11.892400	178.126700	15.028040	17.427680	13.623940	23.756130
Jarque-Bera	30575.79	396340.20	8612.13	5026.08	1947531.00	9235.95	13264.07	7169.50	27408.92
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observation	1524	1524	1524	1524	1524	1524	1524	1524	1524

In the table above, we can see that the average returns were similar across markets and the corresponding standard deviations were quite small. Negative value for skewnesss were not common to all ETF returns. All ETF returns also show excessive kurtosis implying fatter tails for return. The Jarque-Bera test strongly rejected the normality of the unconditional distribution for all the series the period under study.

4.0 Methodology

The present work represents an important contribution to the literature because the relationship between ETF returns may exist at different moments in time and different frequencies. Therefore, the use of the wavelet analysis enables a reconciliation of the results of time series analysis and frequency domain analysis. The wavelets also allow for observing structural breaks and nonlinearities in data series.

For each ETF series, we use daily return series (1524 observations) in the sample. Daily returns are calculated from ETF price (P) as follows:

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

After calculating the return series or every stock and for the market, wavelet analysis is used to be able to separate out each return series into its constituent multiresolution (multihorizon) components. The appealing feature of the Wavelet transform in analysing the ETF data is a three dimensional diagram that demonstrates time series information at different frequencies (low and high), time (short term or long term scale) horizons and strength of association is measured by colour coding.

The wavelet can be classified in two groups, such as; discrete and continuous. In this present study, the methodological discussion is based on the continuous wavelet transform in examining the ETF series which is suitable or preferable for orthogonal wavelet bases. The framework of continuous wavelet transform (CWT), cross wavelet transform (XWT) and wavelet coherency (WTC) is being borrowed from Tiwari (2013).

Discrete wavelet transform (DWT), in particular the maximal overlap discrete wavelet transform (MODWT) in a Multi Resolution Analysis (MRA) framework is also adopted in this study and the methodological discussion is being borrowed from Durai and Bhaduri (2009)

4.1 Continuous Wavelet Transform (CWT)[6]

A wavelet is a function of zero mean and is localize in both frequency and time. Wavelet can be characterized by how localized it is in time (Δt) and frequency (Δ❻). Heisenberg uncertainty principle tells us that there is always a trade-off between localization in time and frequency. Without properly defining Δt and Δ❻, we will note that there is a limit to how small the uncertainty product Δt ∃ Δ❻ can be. A Morlet wavelet can be defined as:

[6] The description of CWT, XWT and WTC is heavily drawn from Grinsted et al. (2004) as described in Tiwari (2013)

$❺_0(η) = π^{-1/4}e^{iω_0η}e^{-1/2η^2}$ (2)

where $❻_0$ is dimensionless frequency and η is dimensionless time. When using wavelet for feature extraction purpose, the Morlet wavelet (with $❻_0$ = 6) is a good choice. This is because it provides a good balance between time and frequency localization. The idea behind CWT is to apply wavelet as a band pass filter to the time series. The wavelet is stretched in time by varying it scale (s), so that η = s ∃ t and normalizing it to have unit energy[7]. For the Morlet wavelet (with $❻_0$ = 6) the Fourier period ($②_{wt}$) is almost equal to the scale ($②_{wt}$ = 1.03 s). The CWT of time series ($❹_n$, n = 1,…,N) with uniform step δt, is defined as the convolution of $❹_n$ with the scaled and normalized wavelet. We can write:

$$W_n^x(\text{s}) = \sqrt{\frac{δt}{s}} \sum_{n'=1}^{N} x_n \, , ❺_0 \left[(n' - n)\frac{δt}{s} \right] \quad (3)$$

Wavelet power can be defined as $|W_n^x(\text{s})|^2$. The complex argument of $W_n^x(\text{s})$ can be interpret in the local phase. The CWT also has an edge artifacts because the wavelet is not completely localized in time. It is therefore useful to introduce a cone of influence (COI) in which edge effects cannot be ignored. Here we take the COI as the area in which the wavelet power caused by a discontinuity at the edge has dropped to e^{-2} of the value at the edge.

4.2 Cross wavelet transform

The cross wavelet transform (XWT) of two time series x_n and y_n is defined as $W^{XY} = W^X W^{Y*}$, where W^X and W^Y are the wavelet transform of x and y respectively, * denotes complex conjugation. The complex argument $\arg(W^{xy})$ can be interpreted as the local relative phase between x_n and y_n in time frequency space. The theoretical distribution of the crosswavelet power of two time series with background power spectra P_k^X and P_k^Y is

[7] Wavelet filter has unit energy. This property ensures that the coefficients from the wavelet transform will have the same energy as the data. Therefore, no information are excluded thorough the wavelet transform and also no extra information re added in the process. See also M. Masih et al (2009).

given in Torrence and Compo (1998)[8] as:

$$D\left(\frac{|W_n^X(s)W_n^{Y*}(s)|}{\sigma_X\sigma_Y} < p\right) = \frac{Z_v(p)}{v}\sqrt{P_k^X P_k^Y} \tag{4}$$

where $Z_v(p)$ is the confidence level associated with the probability p for a pdf defined by square root of the product of two ❹^2 distributions.

4.3 Wavelet Coherency (WTC)

Wavelet Coherency (WTC) can be defined as the ratio of the cross-spectrum to the product of the spectrum of each series, and can be thought of as the local correlation, both in time and frequency, between two time series. We can use the Wavelet coherence (WTC) as a tool for analysing to represent the relationships between two processes by searching frequency bands and time intervals. Specifically this procedure associated with linear correlation analysis that helps revealing intermittent correlations between two phenomena (Gurley and Kareem, 1999; Gurley et al., 2003)[9], and their significant linear cohesion relationship.

Thus, WTC near one shows a high similarity between the time series, while coherency near zero shows no relationship. While the wavelet power spectrum depicts the variance of a time-series, with times of large variance showing large power, the cross wavelet power of two time-series depicts the covariance between these time-series at each scale or frequency. Aguiar-Conraria et al. (2008, p. 2872)[10] defines WTC as "the ratio of the cross-spectrum to the product of the spectrum of each series, and can be thought of as the local (both in time and frequency) correlation between two time-series".

Following Tiwari (2013) as well as Torrence and Webster (1999) the WTC of two time series can be defined as follows:

$$R_n^2(s) = \frac{|S\,(s^{-1}W_n^{XY}(s))|^2}{S(S^{-1}|W_n^X(s)|^2)\exists S(S^{-1}|W_n^X(s)|^2)} \tag{5}$$

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[8] As highlighted in Tiwari (2013)
[9] As highlighted in Uddin et al (2013)
[10] As highlighted in Tiwari (2013)

where S is a smoothing operator. This definition closely resembles that of a traditional correlation coefficient. It is also useful to think of the wavelet coherence as a localized correlation coefficient in time frequency space. Without smoothing coherency is identically 1 at all scales and times. The smoothing operator S can be further scribe as a convolution in time and scale:

$$S(W) = S_{scale}\left(S_{time}\left(W_n(s)\right)\right) \tag{6}$$

where S_{scale} denotes smoothing along the wavelet scale axis and S_{time} denotes smoothing in time. For the Morlet wavelet a suitable smoothing operator is given by:

$$S_{time}(W)|_s = \left(W_n(s) * C_1^{-t^2/2s^2}\right)|_s \tag{7}$$

$$S_{scale}(W)|_n = \left(W_n(s) * C_2 \checkmark(0,6s)\right)|_n \tag{8}$$

where c_1 and c_2 are normalization constants and $\checkmark$ is the rectangle function. The factor of 0.6 is the empirically determined scale de-correlation length for the Morlet wavelet (Torrence and Compo, 1998)[11]. The normalization coefficients are determined numerically since in practice both convolutions are done discretely. Since theoretical distributions for wavelet coherency have not been derived yet, to assess the statistical significance of the estimated wavelet coherency, one has to rely on Monte Carlo simulation methods.

Following Tiwari (2013) and Aguiar-Conraria and Soares (2011) the focus of this study will be on the WTC, instead of the wavelet cross spectrum. Aguiar-Conraria and Soares (2011, p. 649) gives two arguments for this: "(1) the wavelet coherency has the advantage of being normalized by the power spectrum of the two time-series, and (2) that the wavelets cross spectrum can show strong peaks even for the realization of independent processes suggesting the possibility of spurious significance tests".

4.4 Cross wavelet phase angle

The phase for wavelets shows any lag or lead relationship between components,

[11] As highlighted in Tiwari (2013)

and as per Tiwari (2013), it is defined as:

$$\varphi_{x,y} = tan^{-1}\frac{I\{W_n^{xy}\}}{R\{W_n^{xy}\}}, \varphi_{x,y} \in [-\pi, \pi] \qquad (9)$$

where I and R are the imaginary and real parts, respectively, of the smooth power spectrum.

The phase difference are useful to characterize phase relationship between two time series. A phase difference zero indicates that the time series move together (analogous to positive covariance) at the specific frequency. If $\varphi_{x,y} \in [0, \pi/2]$, then the series move in-phase, with time series y leading x. On the other hand, if $\varphi_{x,y} \in [-\pi/2, 0]$, then x is leading. An anti-phase relation (analogous to negative covariance) occurs if we have a phase difference of ⑥ (or - ⑥) meaning $\varphi_{x,y} \in [-\pi/2, \pi] \cup [-\pi, \pi/2]$. If $\varphi_{x,y} \in [\pi/2, \pi]$ then x is leading, and the time series y is leading if $\varphi_{x,y} \in [-\pi, -\pi/2]$.

4.5 Discrete Wavelet Transform (DWT)[12]

This paper also uses discrete wavelet transform (DWT) particularly maximal overlap discrete wavelet transform (MODWT) in a Multi Resolution Analysis (MRA)[13] framework. MRA is a linear reconstruction property of the individual wavelet decompositions.

For a time series X with arbitrary sample size ***N***, the ***j***th level MODWT wavelet $(\widetilde{W_j})$ and scaling $(\widetilde{V_j})$coefficients are defined as:

$$\widetilde{W_{j,t}} = \sum_{l=0}^{L_1 - l} \widetilde{h_{j,l}} \quad X_{t-l \bmod N} \qquad \widetilde{V_{j,t}} = \sum_{l=0}^{L_1 - l} \widetilde{g_{j,l}} \quad X_{t-l \bmod N} \qquad (10)$$

where $\widetilde{h_{j,l}} = \widetilde{h_{j,l}} \ / \ 2^{j/2}$ are the MODWT wavelet filters, and $\widetilde{g_{j,l}} = \widetilde{g_{j,l}} \ / \ 2^{j/2}$ are the

[12] The description of DWT and MODWT is heavily drawn from Durai & Bhaduri (2009) and Kim & In (2005)

[13] As highlighted by Durai and Bhaduri (2009), for more details on MRA, readers are encouraged to see Mallat (1989) and Percival and Walden (2000).

MODWT scaling filters. For a time series X with N samples, the MRA yields an additive decomposition through MODWT given by:

$$X = \sum_{j=1}^{j_0} \widetilde{D}_j + \tilde{S}_{j_0} \qquad (11)$$

Where

$$\widetilde{D_{j,t}} = \sum_{l=0}^{N-l} \widetilde{h_{j,l}}\ \widetilde{W}_{j,t+l \bmod N} \qquad \widetilde{S_{j,t}} = \sum_{l=0}^{N-l} \widetilde{g_{j,l}}\ \widetilde{V}_{j,t+l \bmod N} \qquad (12)$$

Based on equation (11), at scale j, a set of coefficients $\{\boldsymbol{D_j}\}$ each is obtained with the same number of samples (***N***) as in the original signal (*X*). These are called wavelet "details" and they capture local fluctuations over the whole period of a time series at each scale. The set of values S_{j0} provide a "smooth" or overall "trend" of the original signal. Adding $\boldsymbol{D}_j$ to $\boldsymbol{S}_{j0}$, for j=1,2,…, j_0, gives an increasingly more accurate approximation of the original signal. This additive form of reconstruction allows us to validate each wavelet sub-series ($\boldsymbol{D}_{j,}\ \boldsymbol{S}_{j0}$) separately and add the individual validation to generate an aggregate inference. Also, at each scale *j*, wavelet correlation between two time series *X* and *Y* for the decomposed "details" and "scaling" coefficients can be obtained using simple correlation method[14].

The basic idea of the wavelet variance is to substitute the notion of variability over certain scales for the global measure of variability estimated by the sample variance (Percival and Walden, 2000). If we assume that the dependence structure of ETF returns is independent of time, then we may define the wavelet variance of an asset. The wavelet variance is estimated using the MODWT coefficients for scale $\lambda_j = 2^{j-1}$ through:

$$\tilde{\sigma}_l^2(\lambda_j) = \frac{1}{\widetilde{N}_j} \sum_{t=L_j-1}^{N-1} \left[\tilde{d}_{j,t}^l\right]^2, \quad l = X, Y \qquad (13)$$

[14] Durai and Bhaduri (2009)

where $\tilde{d}_{j,t}^{l}$ is the MODWT wavelet coefficient of variables l at scales $②_j$. $\tilde{N}_j = N - L_j + 1$ is the number of coefficients unaffected by the boundary, and $L_j = (2^j - 1)(L - 1) + 1$ is the length of the scale $②_j$ wavelet filter.

The wavelet covariance can also decompose the sample covariance into different time scales. The wavelet covariance at scale $②_j$ can be expressed as follows:

$$Cov_{XY}\left(②_j\right) = \frac{1}{\tilde{N}_j} \sum_{t=L_j-1}^{N-1} \tilde{d}_{j,t}^{X}\, \tilde{d}_{j,t}^{Y} \tag{14}$$

Notice that the estimator does not include any coefficients that make explicit use of the periodic boundary conditions. A biased estimator of the wavelet covariance can be constructed by simply including the MODWT wavelet coefficients effected by the boundary and normalizing. Given that covariance does not take into account the variation of the univariate time series, it is natural also to introduce the concept of wavelet correlation (Kim & In (2005)):

$$\tilde{\rho}_{XY}\left(②_j\right) = \frac{Cov_{XY}\left(②_j\right)}{\tilde{\boldsymbol{v}}_X\left(②_j\right)\tilde{\boldsymbol{v}}_Y\left(②_j\right)} \tag{15}$$

As with the usual correlation and coefficient between two random variables, $|\,\tilde{\rho}_{XY}\left(②_j\right)| < 1$. The wavelet correlation is analogous to its Fourier equivalent, the complex coherency (Gencay et al., 2002, p. 258).

5.0 Empirical Results and Discussions

5.1 Wavelet Coherence (WTC)

The focus of this paper was an attempt to investigate cross-market co-movement between ETF returns (between emerging market such as Malaysia and other developed market such as Japan, Europe, US and rest of the world as a robustness test. The wavelet squared coherency (wavelet coherence plot) is presented through a contour plot as we have three dimensions involved. The horizontal axis refers to time while the vertical axis refers to frequency. For ease of interpretation, the frequency is converted to time units in days, e.g. 2-8 days, 8-32 days, 32-128 days and 128-256 days. The coloured scale (the 3rd scale) is for the wavelet squared coherency where increasing red colour corresponds to an increasing value and mimics the height in a surface plot. The warmer the colour of the region with the thick black line, the longer the degree of dependence between the pair of ETF returns. Through inspection of the graph one can identify both the frequency bands (in the vertical axis) and time intervals (in the horizontal axis) where the series move together[15].

In fact, the wavelet coherency which was calculated based on continuous wavelet transform's (CWT) methodology allows a better interpretation of the results for the evolution of the variables' variances at different time scale[16]. In the case of CWT, the level of decomposition and the type of wavelet transform do not represent a challenge, thus simplifying the identification of common features in the variable characteristics.

Back to the contour plot, as explained above the co-movement is presented in a contour plot with three dimensions: time, frequency and colour code. In order to access whether the series move together and is the strength of the co-movement changes across frequencies and over time, we look at the contour plot. The colour code for coherency ranges from blue (low coherency – close to zero) to red (high coherency – close to one). The tick black contour (cone shaped) represents the 5% significance level against the red noise. What it means is that the wavelet squared coherency is statistically significant within such delimited time-frequency area. In particular, the 5% significance level was determined from a Monte Carlo simulation of 10,000 sets of two white noise time series with the same length as the series under analysis (Rua & Nunes (2009)). The phase difference between the two ETF returns is indicated by the arrows on the contour plot.

[15] As the continuous wavelet transform at a given point in time uses information of neighboring data points, results should be read carefully close to the beginning or the end of the time series (Rua & Nunes (2009)).

[16] We define the short scale as up to 32 days, the medium scale as 32-128 days and the long-run scale as 128-256 days (1 year). The daily data have been transformed in daily of scales to facilitate the result interpretation.

Arrows pointing to the right mean that the variables are in the phase; to the right and up,

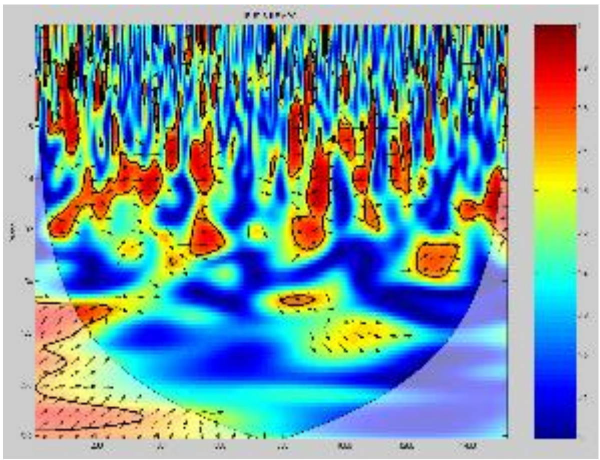


Figure 1a: co-movement between IFUS & ILEMRG

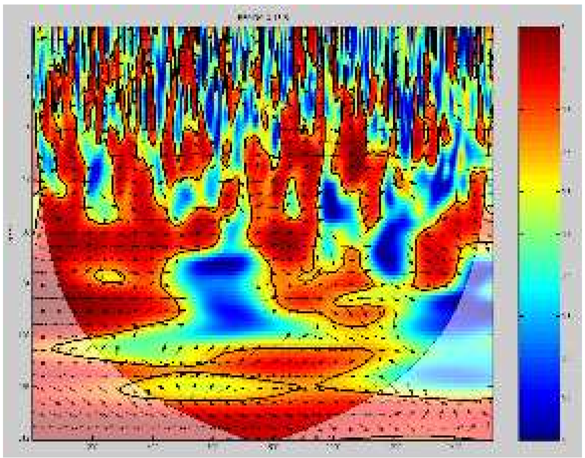


Figure 1b: co-movement between ILUS & IFEMRG

with the first variable is lagging and to the right and down, with first variable is leading. Arrows pointing to the left mean that the variables are out of the phase; to the left and up, with first variable is leading and to the left and down, with first variable is lagging. "In the phase" indicates that variables will be having cyclical effect on each other and "out of the phase" or "anti-phase" shows that variable will be having anti-cyclical effect on each other (Uddin G.S. et al (2013)).

Again, for ease of interpretation, the horizontal axis which represent the time is segregated into different time scale as shown in Table 2 below. The corresponding Years are also shown for ease of reference in interpreting the data. All computations have been done using MATLAB.

Table 2: Mapping between time scale in the wavelet coherence plot and the corresponding Years

Time scale	**0-200**	**200-400**	**400-600**	**600-800**	**800-1000**	**1000-1200**	**1200-1400**	**>1400**
Year range	June'08-Mar'09	Mar'09-Dec'09	Dec'09-Sep'10	Sep'10-Jun'11	Jun'11-Apr'12	Apr'12-Jan'13	Jan'13-Oct'14	>Oct'14
Remarks	Global Financial Crisis		Eurozone Debt Crisis					

The results show that the co-movement between ETF returns which tracked developed market (IFUS / ILUS) and ETF returns which track emerging market (ILEMRG, IFEMRG) is unstable and the pattern of relationships is not consistent across

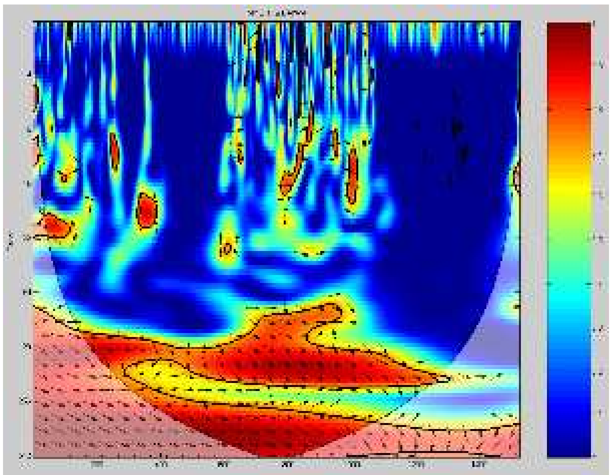


Figure 2a: co-movement between MYETF & DAIWA

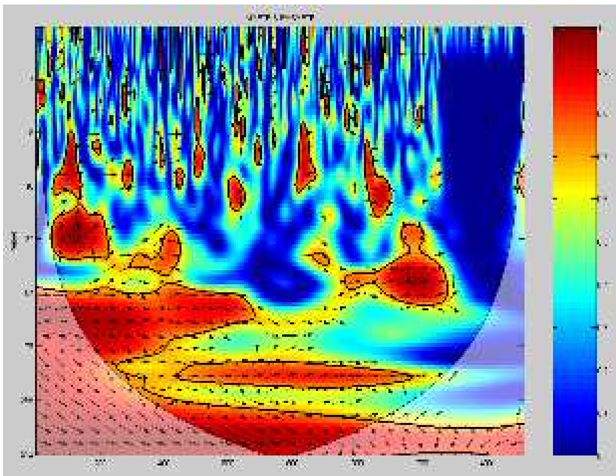


Figure 2b: co-movement between MYETF & EASYETF

time scales. From Figure 1a, we can see that weak co-movement during the frequency 64 days and above for all time scale. This shows opportunity for portfolio diversification for ETF investors between IFUS and ILEMRG. There is also evidence of contagion effect between developed market (US) and the emerging market based on the strong intermittent co-movement at frequency scale 8-32 days. However, less portfolio diversification opportunity arise between investors in ILUS and IFEMRG as there is a strong co-movement between the ETF returns, except for a brief period between May 2010 and June 2011 where there was weak co-movement suggesting diversification opportunities for medium term investors (32-128 days) during the onset of Eurozone financial crisis.

Country specific ETF returns also shows interesting multiscale propensity. As can be seen in Figure 2a, MYETF returns (market: Malaysia) has very strong co-movement with DAIWA returns (market: Japan) for frequency scale 128 days and above. What this means is that investors with a medium term to long term holding period may not be able to enjoy diversification opportunity between these two ETF returns. There is an in-phase relationship between both ETF returns, in which MYETF is the leading variable for most of the time. The strong co-movement between both Malaysia and Japan market may indicates stronger economics correlation between the both countries in the long term. However, diversification opportunity do exist for investor with shorter term horizon (i.e. shorter holding periods) as there are weak co-movement between MYETF and DAIWA for frequency range 4-128 days. The co-movement between MYETF returns (market: Malaysia) and EASYETF returns (market: France) also has strong co-movement especially for medium to long term investors (i.e. frequency of 64 days and above). As with previous case, there is in-phase relationship during these time scale and MYETF is the leading variable for most of the time. This fact shows the effect of Euro debt crisis which does not provide the appetite for investors to divest in both developing market (MYETF) and Euro market (EASYETF) as the co-movement are strong. For short terms investor, there is opportunity for diversification as the co-movement of both ETF returns are weaker, except for certain intermittent time scale for investor with frequency scale of 8-16 days.

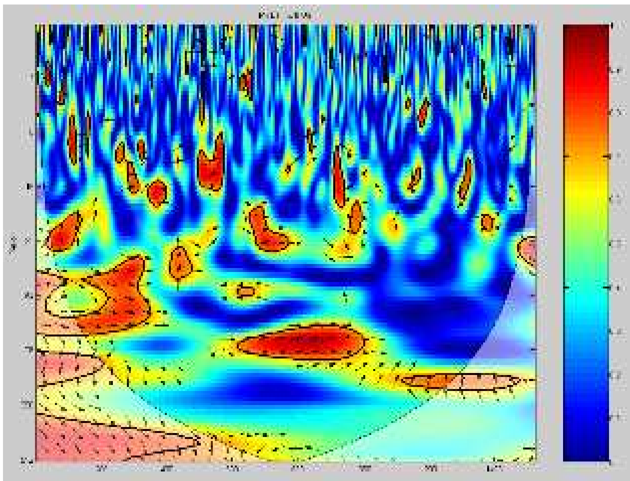


Figure 3a: co-movement between MYETF & IFUS

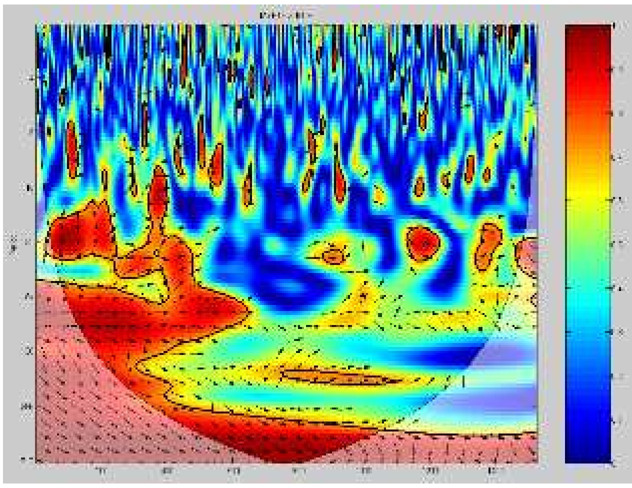


Figure 3b: co-movement between MYETF & ILUS

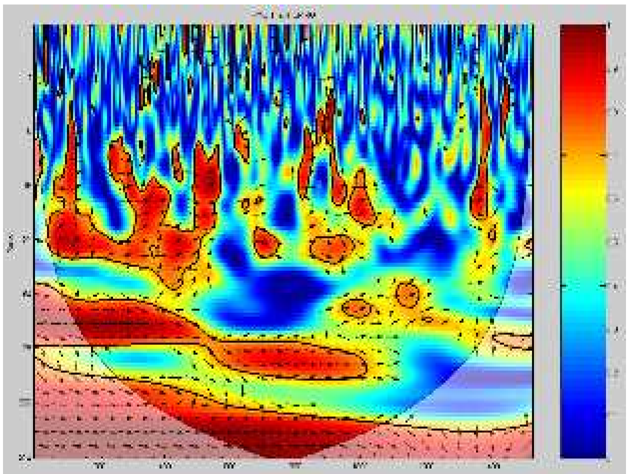


Figure 3c: co-movement between MYETF & IFEMRG

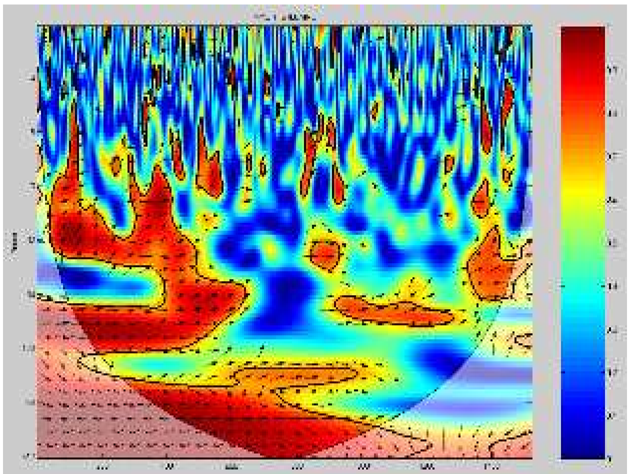


Figure 3d: co-movement between MYETF & ILEMRG

There is also multiscale propensity between ETF returns of a country specific and ETF returns of developed market (US) and emerging market. Figure 3 shows the co-movement between MYETF returns (market: Malaysia) and IFUS & ILUS returns (market: US) and between MYETF and IFEMRG & ILEMRG ETF returns (market: Emerging). In general, there is weak co-movement between MYETF and ILUS for most frequency scale and time scale suggesting excellent diversification opportunity between both ETF markets. However, based on Figure 3b, except for short term investor (investor with short holding period), there is strong co-movement between MYETF and ILUS for short to medium term investor (16-32 days holding period and 64-128 days holding period), especially during and aftermath of the financial crisis. Figure 3b illustrate the fact of spill-over effect of global financial crisis which started in US to the developing market. Strong co-movement also appears for long term investor (>256 days) for the whole of time scale. Nevertheless, there are still diversification opportunity for medium term investors

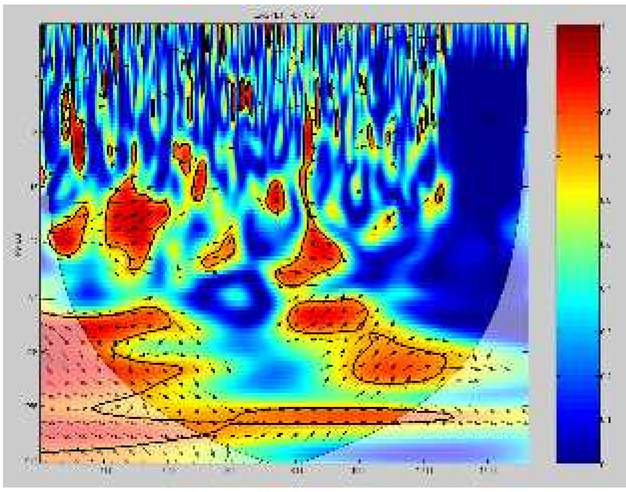


Figure 4a: co-movement between EASYETF & IFUS

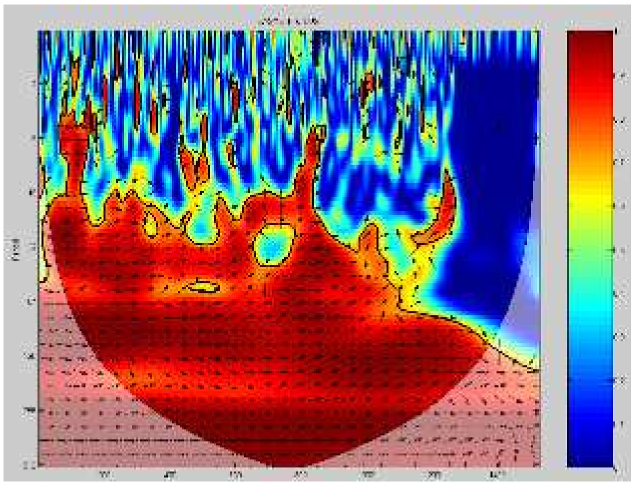


Figure 4b: co-movement between EASYETF & ILUS

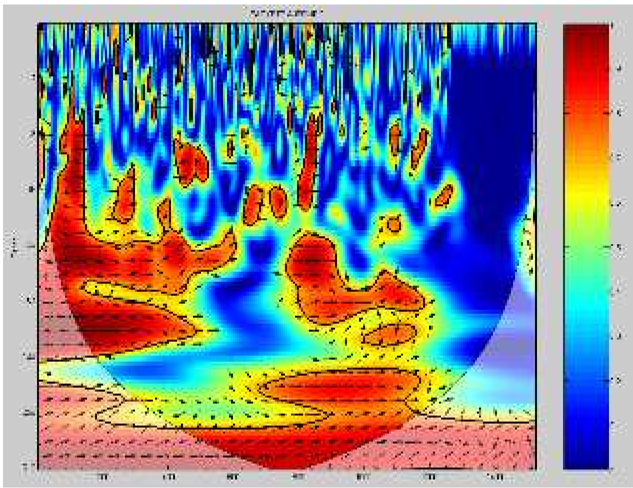


Figure 4c: co-movement between EASYETF & IFEMRG

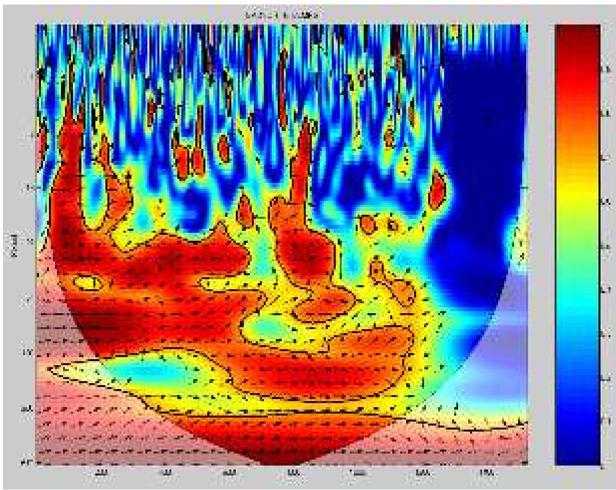


Figure 4d: co-movement between EASYETF & ILEMRG

post global financial crisis period.

With regards to emerging market, the co-movement between MYETF and IEMRG / ILEMRG are quite similar with short term investor (short holding period) have opportunity for diversification as there is weak co-movement between the ETFs returns. Strong co-movement exist for long term investor (>256 days) for the whole time period.

The same result can be observed if we plot the wavelet coherence plot for EASYETF returns (market: France) against IFUS (market: US) and IFEMRG (market: Emerging). However the co-movement between EASYETF returns and ILUS returns shows a very strong co-movement between the two indicating no diversification opportunity exist. As compared between MYETF and ILEMRG, EASYETF has stronger co-movement with ILEMRG for medium term investor (holding period of 32-128 days) especially during the onset of global financial crisis and also for long term investors (holding period >128 days) which is during the onset of Euro debt crisis. This indicates a

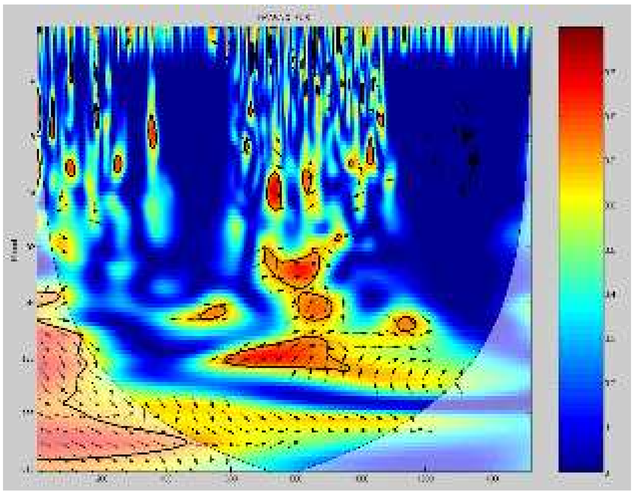


Figure 5a: co-movement between DAIWA & IFUS

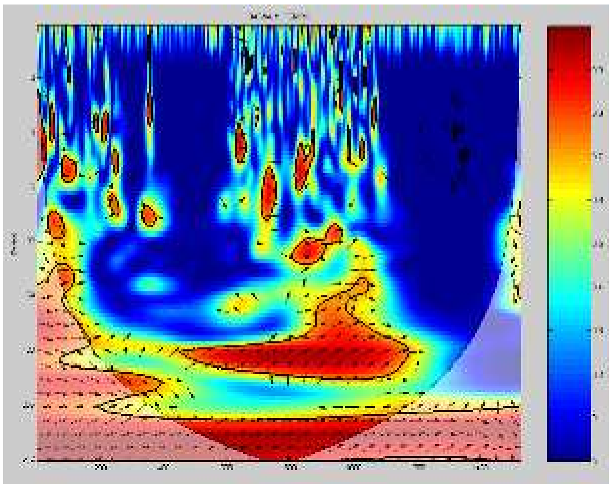


Figure 5b: co-movement between DAIWA & IFEMRG

strong correlation between EASYETF which has a market in Euro (i.e. France) and ILUS (market: US).

Finally, the co-movement between DAIWA (market: Japan) against IFUS and IFEMRG also shows potential of diversification for investors especially for short and medium term investors. There is strong co-movement between DAIWA and IFEMRG for investors with holding period of approximately 128 days where there exist and in-phase relationship between both ETF returns with DAIWA returns is lagging against IFEMRG returns.

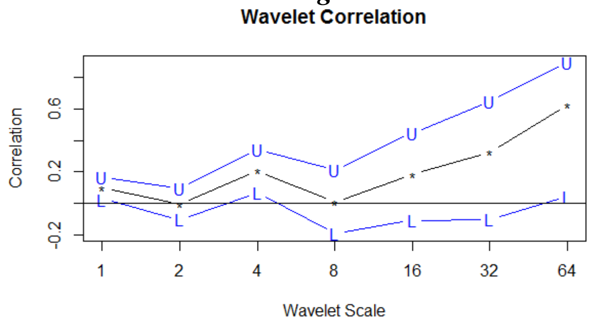
Based on above results, we can conclude that co-movement between the markets (developed, emerging, country specific) concentrate at longer time scale. There was also an increase in co-movement between markets during global financial crisis and the Euro debt crisis. For the country specific ETF returns, the co-movement of MYETF against the Developed (US) and Emerging market concentrated at the 32-128 days frequency scale during global financial crisis, the co-movement of EASYETF against the Developed (US) and Emerging market concentrated heavily from the 32-256 days frequency scale during both global financial crisis and Euro debt crisis, and the co-movement of DAIWA concentrated at the 64-128 days frequency scale only during the Euro debt crisis.

5.2 Maximal overlap discrete wavelet transform (MODWT)

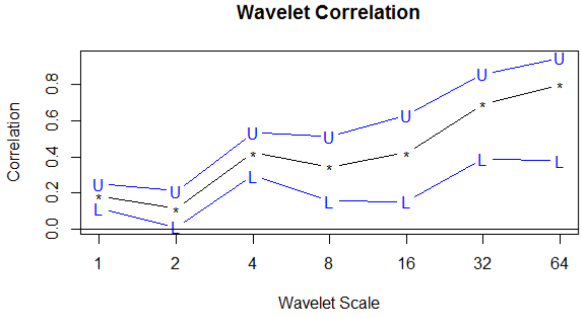
Using wavelet coefficients for level 1 to 7, in this section we estimated the wavelet correlation for each pair of selected ETF returns. The correlation results for different level of resolutions are displayed in Figure 6. The solid and dashed lines correspond to the wavelet correlation coefficient for the whole sample period. U and L denote the upper and lower limits for a 95% two-sided confidence interval. The wavelet correlation shows evidence of the pattern for ETF returns for the variables under study. The wavelet correlation shows positive dependence in all time scales. There is also significant increase in wavelet correlation in the period under study. This support the analysis earlier on the interdependence of some of the ETF returns.

This study also analyse cross-correlation between the selected ETF returns. To explore lead-lag patterns in depth and capture cross-correlation coefficients for long leads and lags, the time delay between the two ETF returns was chosen to be ±30. By computing the wavelet cross-correlation between the ETF returns for different time scales we can check if there is any lag effect in the ETF returns relationship. Figures 7-10 depicts the selected wavelet cross-correlation analysis.

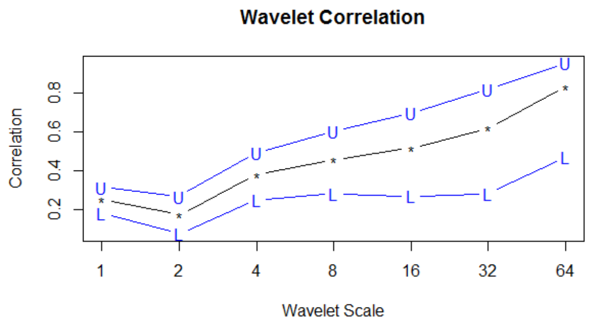
Figure 6: Wavelet Correlation between selected ETF returns



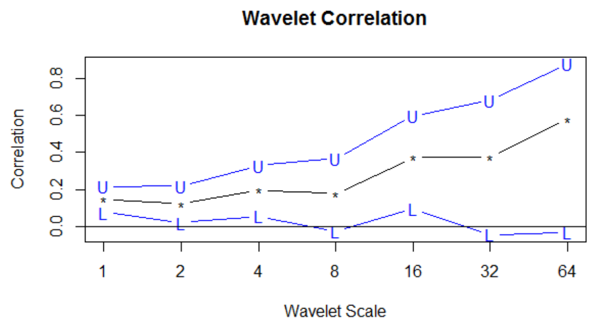
Correlation between MYETF & DAIWA



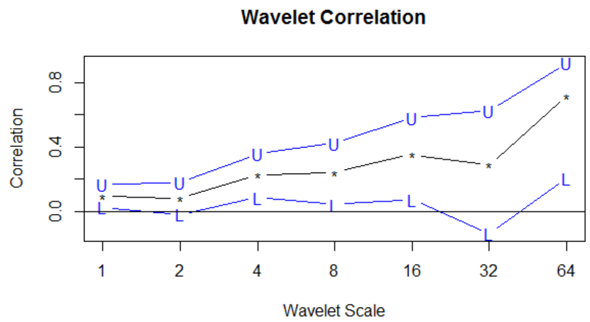
Correlation between MYETF & EASYETF



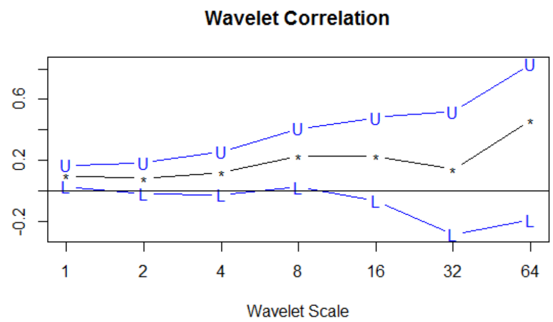
Correlation between MYETF & IFEMRG



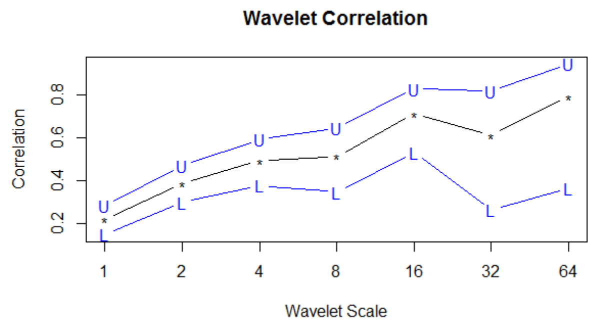
Correlation between MYETF & IFUS



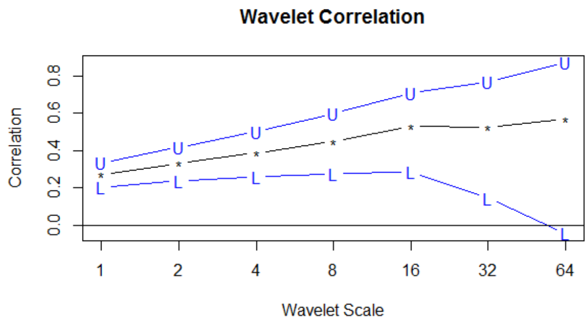
Correlation between DAIWA & IFEMRG



Correlation between DAIWA & IFUS



Correlation between EASYETF & IFEMRG



Correlation between EASYETF & IFUS

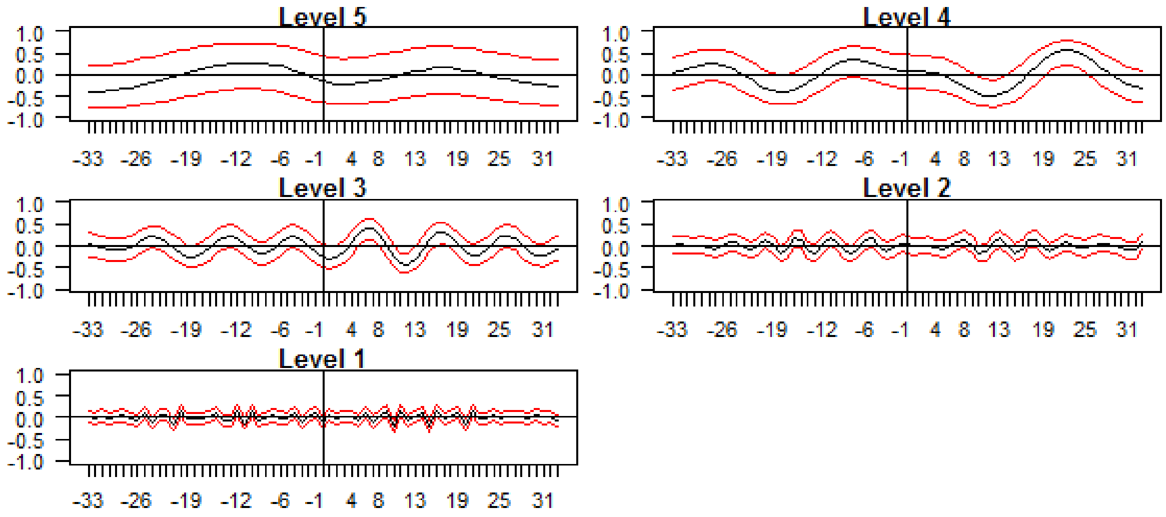


Figure 7a: Cross-Correlation MYETF & DAIWA (Jun 2008 – Dec 2009)

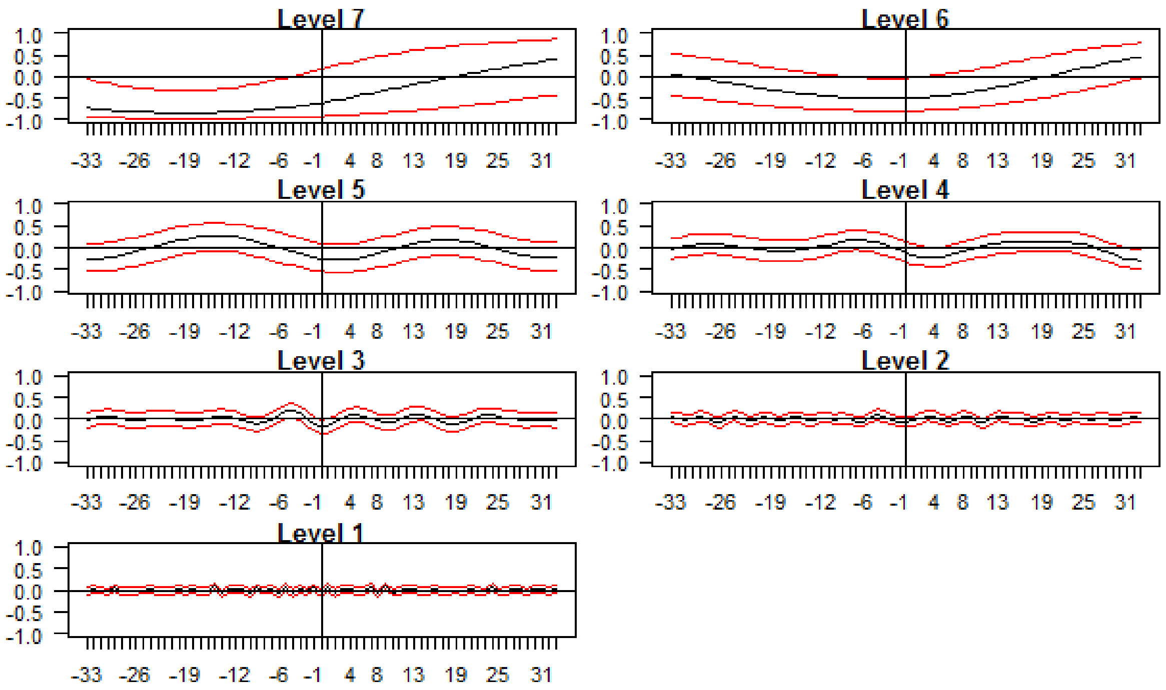


Figure 7b: Cross-Correlation MYETF & DAIWA (Jan 2010 – Mar 2014)

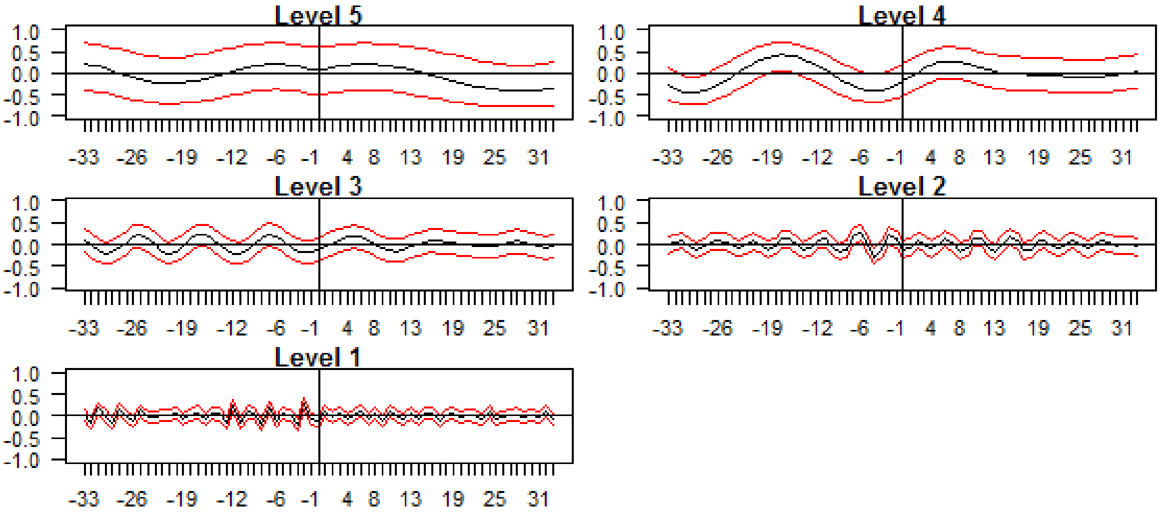


Figure 8a: Cross-Correlation DAIWA & IFUS (Jun 2008 – Dec 2009)

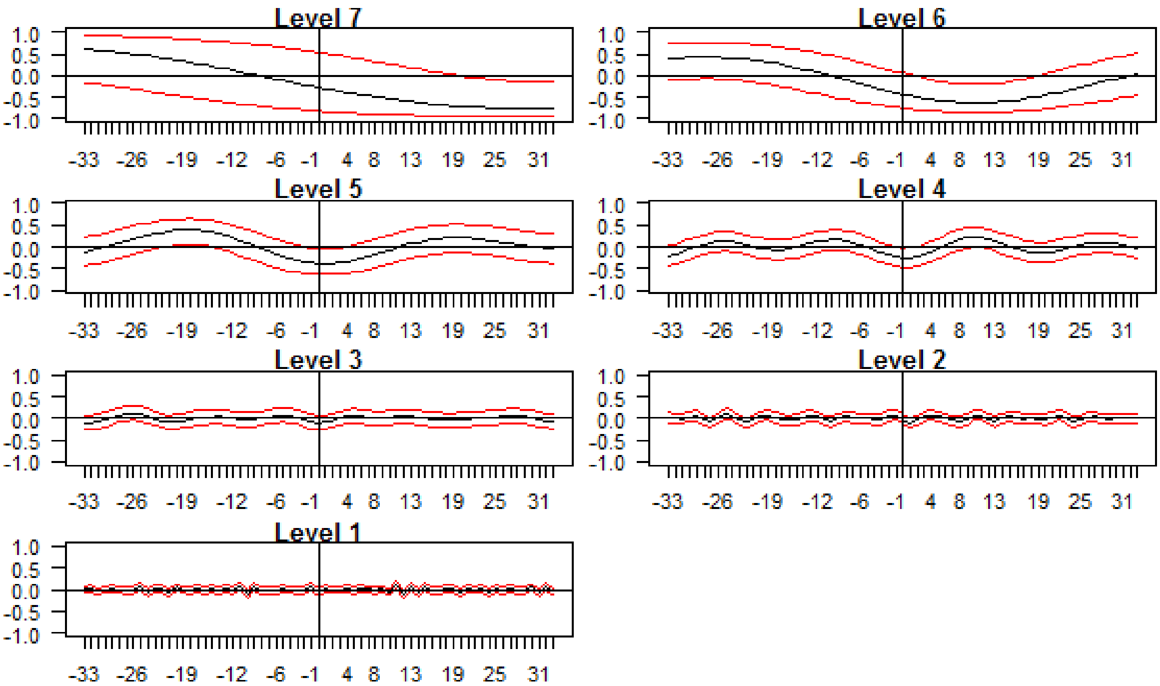


Figure 8b: Cross-Correlation DAIWA & IFUS (Jan 2010 – Mar 2014)

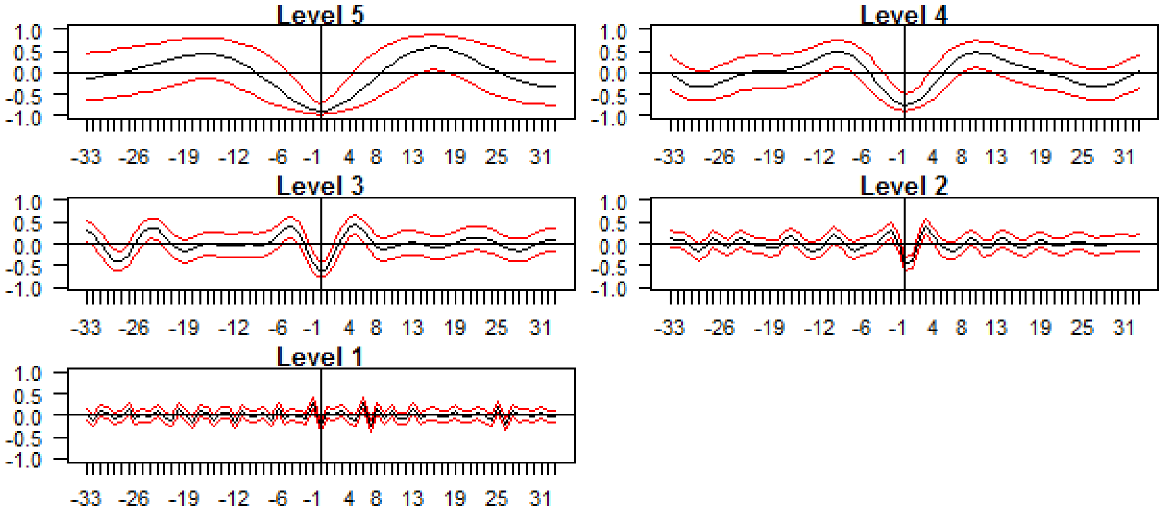


Figure 9a: Cross-Correlation EASYETF & IFEMRG (Jun 2008 – Dec 2009)

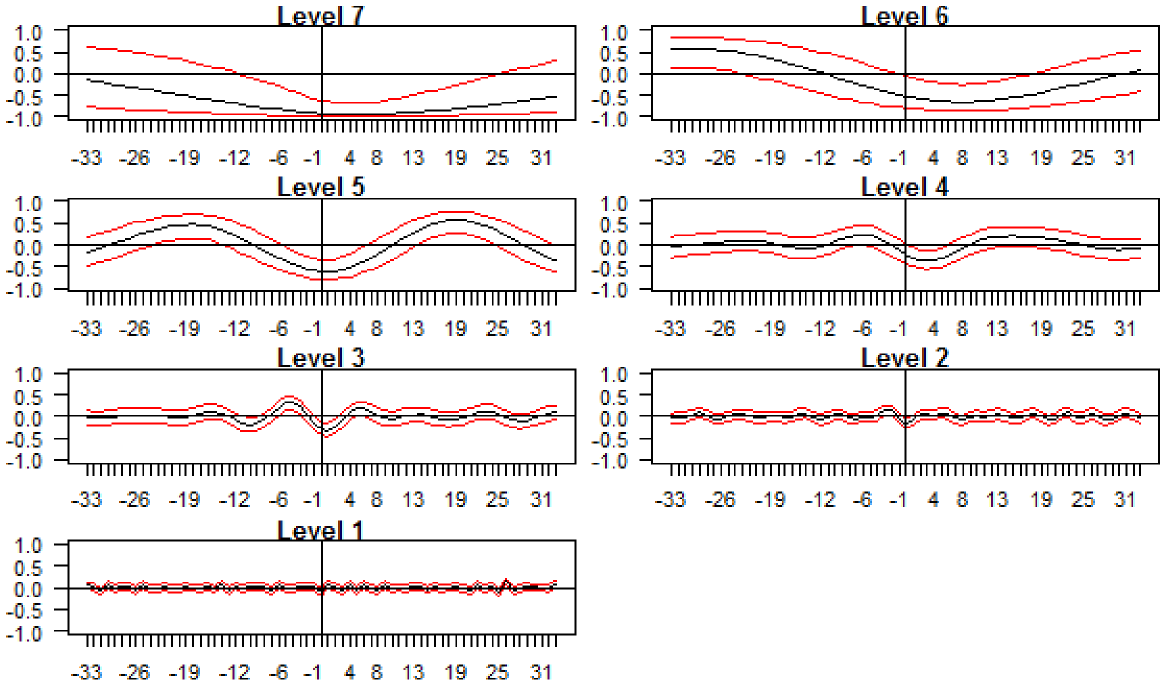


Figure 9b: Cross-Correlation EASYETF & IFEMRG (Jan 2010 – Mar 2014)

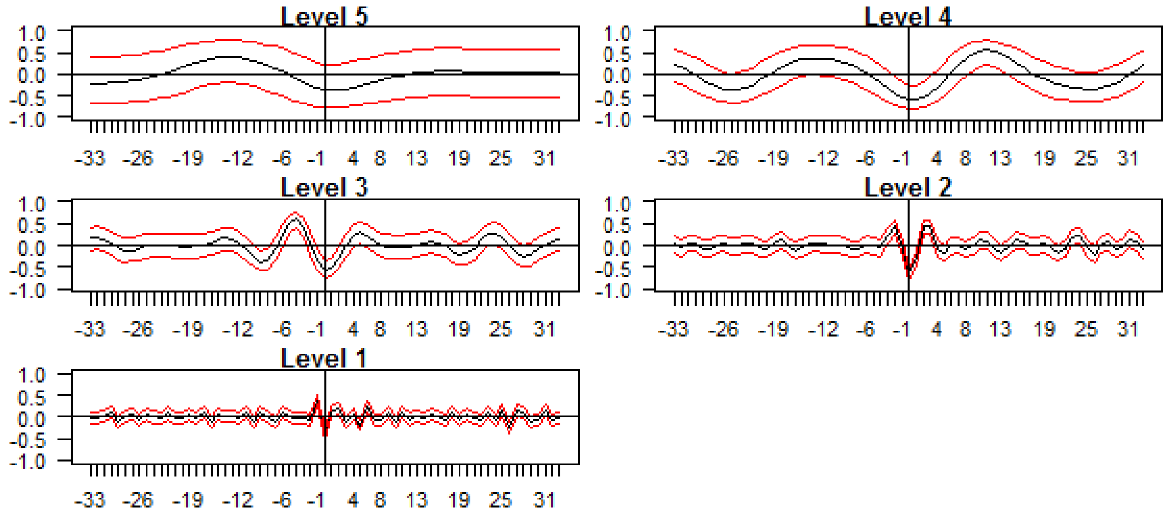


Figure 10a: Cross-Correlation IFUS & ILEMRG (Jun 2008 – Dec 2009)

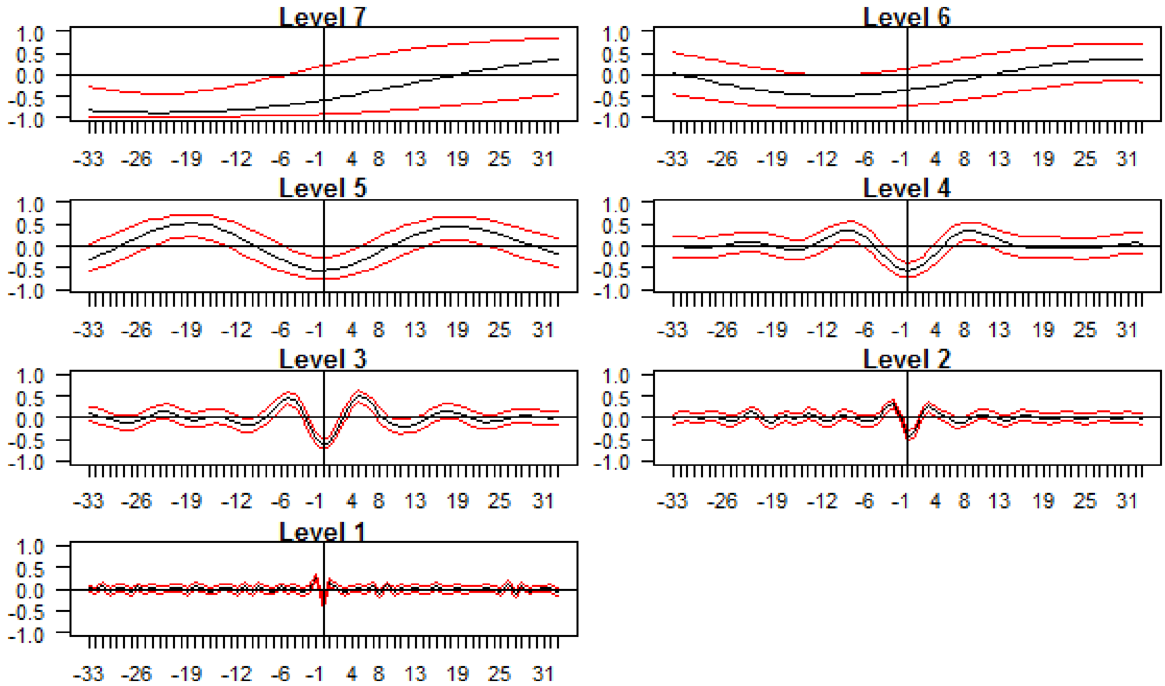


Figure 10b: Cross-Correlation IFUS & ILEMRG (Jan 2010 – Mar 2014)

In the cross-correlation analysis, all the data above were divided into two periods, namely, Jun 2008 – Dec 2009 and Jan 2010 – Mar 2014, in order to test for financial crisis contagion and interdependence on the ETF returns. In summary, we can see that there is interdependence in the cross-correlation between the ETF returns for both periods which signifies the impact of global financial crisis and Euro debt crisis. In particular, we can see in Figure 7a that during global financial crisis, there is interdependence between MYETF returns and DAIWA returns, and for level 3 and 4, there is significant positive and negative correlations in both the right and left side of the graph. This correlation behaviour was not evidence in Figure 7b, which is the post global financial crisis and at the on-set of Euro debt crisis. This behaviour is probably can be explained from the fact that as MYETF market is a developing market (Malaysia) and DAIWA is a developed market in Asia (Japan), hence we do not see any significant contagion impact on the Euro debt crisis to MYETF and DAIWA.

Examining the cross-correlation between IFUS (developed market) and ILEMRG (emerging market) also shows similar cross-correlation behaviour where in Figure 10a i.e. during global financial crisis period, the returns for level 3 and 4 shows significant positive and negative correlations in both the right and left side of the graph. This is not really the case as in Figure 10b i.e. post the global financial crisis. However, from Figure 10b, for level 5, 6, and 7, we can see there is possible IFUS returns leading to the ILEMRG returns due to the shape of the graph skewed towards the right hand side.

Overall, the wavelet cross-correlation evidence that at different levels shows some form of dynamic interactions between the ETF returns.

6.0 Conclusions and Policy Implications

Islamic ETF represent a significant innovation across Islamic financial market globally and in Malaysia particularly. It can provide investors with diversification benefits through one investment arrangement. One significant future of Islamic ETF is that, as stocks, they can be traded throughout the trading day, unlike mutual funds which can only be traded at the end of the day at their Net Asset Values (NAVs).

Whilst most of the empirical literature has studied performance of ETF from various perspective, this study has analysed the co-movement of 9 Islamic ETF returns and the dependence of the ETF returns in different time scales using wavelet techniques, both continuous wavelet transform (CWT) via wavelet coherence (WTC) and discrete wavelet transform (DWT) via maximal overlap discrete wavelet transform (MODWT). Using wavelet coherence method, we examine how co-movement between ETF returns evolved over time and across scale. Cross-correlation methodology is also useful in identifying differences in ETF returns relationship in several time scales and also enables changes in that relationship in different time scales to be identified. In particular, the time scale decomposition property of wavelets is useful in revealing contagion and interdependence between ETF returns in the current global financial crisis and post global financial crisis, as wavelet correlation analysis is applied on a scale-by-scale basis for reliable confidence intervals in crisis and non-crisis periods. Lead-and-lag effects of ETF returns can also be analysed for different time scales through wavelet cross-correlation.

Based on the two wavelet techniques above we can see that wavelet coherence are more user friendly and the three-dimensional results provided (time, frequency, colour code) provide an efficient way of interpreting the co-movement of the ETF returns as the colour code and the arrows can provide quick and easy way to interpret the data.

Our results from the wavelet coherence show various co-movement depending on which ETF returns we are referring to. In general, strong co-movement can be observed at the start of the sample, which is during the global financial crisis. This is evidence especially for the medium term investors (32-128 days) and also long term investor (>128 days). For low frequency investors, the co-movement seems to be strong for most of the sample period, except for certain ETF returns analysis such as MYETF against IFUS and also IFUS against ILEMRG. The main finding from cross-correlation analysis also provides similar results with certain significant and positive correlations between the ETF returns, especially during the period of global financial crisis.

As part of policy implication, risk management strategy is important for investors to protect themselves from ETF market risk and also to ensure that they make informed decision with regards to their investment. It is the role of the ETF's administrator and policy maker to educate the investors on the risk for such investment. This include knowledge on the co-movement and cross-correlation of different ETF returns globally. This practice will ensure that the Islamic ETF market is more robust and transparent in the eyes of foreign investors. This best practice will also provide sufficient information for market participants to engage in trading activity that would work to keep the market price of Islamic ETF shares close to their net asset values. The Author believe that a regulatory regime, which promotes investor confidence and market transparency, will also enable sufficient liquidity and, thereby, reduce systemic risk.

7.0 Limitations and Suggestion for Future Research

This study is the first attempt to use multiscale approach in analysing ETF returns from both developed and emerging market (IFUS, IFEMRG, IFWLD, ILUS, ILEMRG, ILWLD) and also country related ETF returns such as MYETF (Malaysia), DAIWA (Japan) and EASYETF (France). From the best of Author's knowledge, this was the first study using wavelet analysis on the returns of global ETF.

The following are some limitation of this study and hence does present opportunities for similar future research in the empirical research area of Islamic ETF. The choices of the calculation of return are somewhat arbitrary. Although this research was based on other studies using wavelet methods, nonetheless the choices on the calculation of ETF returns can be further analyse using Sharpe ratio, Sortino ratio or Treynor ratio analysis. Through Sharpe ratio, we will be able to analyse risk-adjusted ETF returns. However, some caution needs to be put in place as Sharpe ratio assume the returns are normally distributed, which not normally the case in real world for ETF returns. A variation of the Sharpe ratio is the Sortino ratio, which removes the effects of upward price movements on standard deviation to measure only return against downward price volatility. Treynor ratio on the other hand is a risk-adjusted measure of return based on systematic risk. It is similar to the Sharpe ratio, with the difference being that the Treynor ratio uses beta as the measurement of volatility.

Furthermore, many studies on the performance of ETF uses ETF tracking error against the benchmarked index as another possibility of studying the ETF performance via multiscale approach. Although the results presented above are statistically robust, it would be useful to look at other return methodologies. It would also be desirable to investigate more Islamic ETFs prices across the region in order to provide more empirical information about Islamic ETF market.

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