An inquiry into the stability of Islamic Financial Services Institutions in terms of volatility, risk and correlations: A case study of Malaysia employing M-GARCH t-DCC and MODWT Wavelet approaches

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23 July 2014

An inquiry into the stability of Islamic Financial Services Institutions in terms of volatility, risk and correlations: A case study of Malaysia employing M-GARCH t-DCC and MODWT Wavelet approaches

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Abstract

Islamic Finance as an industry in recent times has been celebrated for its stability and resilience. With the philosophy of risk sharing and strict rules governing its activities to be in line with Islamic Law (the Shariah), the industry is seen as an alternative to the conventional finance with its tainted image of profit maximizing at any cost causing the Global Financial Crisis of 2008 - 2009. Given this claim it would be interesting to investigate the stability of the Islamic Financial Services Institutions (IFSIs) in comparison to the conventional sector. The Malaysian IFSIs were chosen as a case study as the Malaysia's Islamic Finance industry developed in the world with strict Shariah screening. As such, the Malaysian IFSIs are investigated to gain insights into their performance in terms of volatility and correlations with the market and then compared to their competitors by employing an M-GARCH t-DCC and also MODWT Wavelet technique to further dissect this volatility into their contributions from the point of view of different time scales. The findings are that IFSIs are much more volatile than their competitors with seemingly independent spikes in volatility unique to themselves but are low in correlation to the market implying that IFSIs volatility may be independent of the market due to assets that require the risk taking in order to justify earnings. IFSIs may need to cooperate in developing risk management standards and practices to mitigate risk that are unique to themselves as well as review the contracts and assets that may expose the IFSIs to too much risk.

Key words: Islamic Finance, Islamic Financial Services Institutions, Volatility, Risk, Correlation, Diversification, M-GARCH t-DCC and MODWT Wavelet

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1. Introduction

Islamic Finance is unique to conventional finance in that unlike its conventional counterpart, Islamic Finance is driven by a unique philosophy other than just the maximization of shareholder wealth. Essentially, the dealings of daily life for a Muslim are dictated by the Shariah (Islamic Law) which acts as a code of conduct that reflects devotion to the Creator and the Religion (Saleem, 2012). Within that code lays the philosophy that all dealings should be fair and just and that business or financial transaction is an exchange of equivalent counter value (iwad) amongst the contracting parties (Rosley, 2006). This renders the taking of interest (riba), speculative activity intolerable and should be avoided. As such, Islamic Financial Services Institutions (IFSI) must act accordingly and are constantly screened by local authorities to make sure that they are "Shariah Compliant". Or in other words, the activities of said IFSI are not contradicting Islamic law and therefore are fit for investment from Muslim investors seeking returns or diversification from "clean" sources.

IFSI in Malaysia operate in a unique environment where the industry of Islamic Finance stands parallel to Conventional Finance. Because they do not operate in a vacuum, they are required to be competitive with conventional financial institutions or risk losing customers. Given this situation the IFSIs performance are constantly being compared to their conventional counterparts even though the IFSIs are theoretically supposed to be functioning based on different principals that render interest bearing debt based financing void and hedging opportunities limited (IFSI stability report, 2013) as compared to their conventional counterparts.

However, it is often claimed that even though IFSIs are limited in hedging opportunities, the industry as a whole is more stable than the conventional because being Shariah compliant limits the risk associated with conventional finance for returns that are more stable or less volatile (Kabir, Bacha and Masih, 2013). This view is what has drawn much attention to the Islamic Finance industry with many investors perceiving an almost "safe heaven" like feature with the potential to play an important role in the still developing Islamic world. Gheeraert(2014) provides empirical evidence that the development on Islamic Banking has strongly contributed to boosting economic growth, investment and liquidity in Muslim countries. Beck, Demirgüç-Kunt and Merrouche (2013) find that while Islamic Banks are less cost effective, they are better capitalized, have higher asset quality and are less likely to disintermediate during a financial crisis.

The focus of this paper is thus on the volatilities and risk associated with the IFSI in Malaysia as compared to the market portfolio and their conventional counterparts. Malaysia is taken as a case study due to her being one of the more developed and regulated Islamic Financial Markets as well as a developing Muslim country. Given the claims on the stability of the IFSI (IFSI stability report, 2013;2010) compared to their conventional counterparts it would be interesting to investigate empirically the validity of these claims and to shed some light on the matter concerning volatility and risk that IFSIs are exposed to.

To investigate the issue, a Multivariate GARCH (M-GARCH) by Peseran and Peseran (2009) is employed to illustrate the volatilities and correlations of the IFSI, the market portfolio of KLCI and their conventional competitors. The M-GARCH has the unique ability to illustrate the conditional volatilities and correlations. This essentially means that rather than a simple moving average, the M-GARCH considers the impact of previous observations on the observation of today. Also because the M-GARCH is multivariate the conditional volatilities and correlations of the other variables included will be captured by the model. This gives an opportunity to compare the time conditional characteristics of volatility and correlations of the variables included.

It is also worth pointing out that risk and return are time scale dependent concepts and any form of measurement must account for the different investment horizon effects (In and Kim, 2013). What this means is that risk and return in an observation must be considered to be the cumulative outcome of many different investors with different investment holding periods due to different intentions of holding shares in a company. The M-GARCH does consider time but is dependent on the data, be it high frequency (daily) observations. As a result, the M-GARCH only shows the behavior of volatilities and correlations at a single scale which is dependent on the data. If the data used is daily data then M-GARCH gives daily conditional volatilities and returns.

To deepen the investigation further the Wavelet Multiscaling Approach of Maximum Overlap Discreet Transform (MODWT) is employed to dissect the volatilities and correlations to observe their contribution from the different time scales. What will be shown is the different time scale contribution to volatility of the IFSI and at what time scale is it most correlated with the market. The findings from the Wavelet scaling ads to further understanding the volatilities and risk associated with the IFSI in Malaysia. This paper makes the following contributions of investigating the volatilities and correlations of IFSI's as compared to their conventional counterparts and the market. It also contributes to the current literature by employing the econometric techniques of M-GARCH and MODWT Wavelet in furthering an understanding of the volatilities and risk associated with IFSI's. Which the findings are that IFSI's are much more volatile than their conventional counterparts but this volatility may be seemingly independent of the market indicating that the assets and practices of the IFSI's are contributing to the high exposure to risk and fluctuation in returns for the IFSI's in Malaysia.

Following this introduction is a literature review of the various studies concerning volatility, correlations and risk. The methodology of estimation is then explained, after which an analysis of the empirical results follows. Finally, conclusion is drawn along with some policy implications as well as the limitations of this paper.

2. Literature Review

Bacha and Mirakhor (2013, p. 236 - 238) point out that there are 4 schools of thought regarding stock price behavior and thus volatility. Fundamentally, the price behavior of a stock is determined by quality of the in-house functionings of the firm. Dubbed "the rationalist", they consider factors such as quality of management of the firm in predicting the behavior of stock price movements, therefore suggesting that firm's stock price is independent of the market. This view was challenged by none other than Charles Dow, the founder/editor of the Wall Street Journal who championed the view that stock price movement was indeed a habitual thing as humans are creatures of habit. The basic assumption of the *chartist* was that history would tend to repeat itself in different cycles. This view therefore was in stark contrast to the rationalist and suggested the predictable nature of humans and therefore the stock market.

Fama (1965) provided empirical evidence against the first two by suggesting that any form of prediction is essentially flawed due to the fact that markets follow a *random walk*. In other words, he challenged the view that any meaningful stock price could be predicted on its past movements and any successive price changes are independent, identically distributed random variables. Later, Fama (1970) in the *efficient market hypothesis* reiterated *random walk* but proposed that information was the key source of market movements. Information itself is random and the speed at which it is reflected in the market depends on the level of market efficiency. It is worth pointing out that, thus far, all these studies make the assumption that investors are rational. This issue was challenged by Kahneman and Tversky (1979) with the *prospect theory*, which theoretically proposes that people underweight outcomes that are merely probable in comparison with outcomes that are obtained with certainty. In other words, people are risk adverse and do not necessarily behave rationally but instead rather inconsistently with changing preferences. This theory sets the foundation for *behavioral* school which brings human psychology and emotion into play. Akerlof and Shiller (2009) stress the importance of *Animal Spirits* in explaining the stock price movements and volatilities of the financial market today, sighting sometimes irrational and herding behavior or psychological contagion. Shiller (2000, p. 203) points out that the market is not an outcome of rational thought and careful research of experts but rather the combined effect of indifferent thinking from millions based their own emotions, random attentions and perceptions.

Regardless of why volatilities exist there is one truism in that it does indeed exist. Ding, Granger and Engle (1993) demonstrate that volatility is changing overtime and thus any model employed should have a time varying volatility structure such as the ARCH model which takes into account autocorrelation and heteroskedascity. The limitation of ARCH however is that it is univariate, in that it considers its own past volatility but not that of others and therefore lacks some sophistication by not including other variables which consider the marginal contributions of different assets (Pesaran and Peseran, 2007).

One such multivariate volatility model is the M-GARCH proposed by Engle and Kroner (1995).Pesaran and Pesaran (2007) study six currency futures (Japanese Yen, Euro, British Pound, Swiss Franc, Canadian and Australian Dollars), four government bond futures (US ten year Treasury Note, 10 year government bonds issued by Germany, UK and Japan) and five equity index futures (US, UK, Germany, France and Japan) by employing the M-GARCH and compared a Dynamic Conditional Correlation (DCC) restricted to normal distribution or Gausian to the t-DCC which has a more relaxed distribution of near Gausian to find which distribution specification would better capture volatility. It was found that M-GARCH with t-DCC is better at capturing the fat tailed nature of financial market information compared to the DCC. The fat tail nature of financial market information points to systematic risk exposure arising from levels of leverage. From this they find that the futures market are becoming less volatile while both currencies and equities conditional correlations are rising implying financial integration amongst the markets studied.

Since then many studies have been done employing the M-GARCH t-DCC to investigate various issues regarding conditional volatilities and correlations, amongst these studies are Tamakoshi and Hamori (2014), Gjika and Horváth (2013),Kabir, Bacha and Masih (2013),Hammami, Jilani and Oueslati (2013), Valadkhani, Harvie, and Karunanayake(2013),Chevallier (2012), Celik (2012), Kamil, Bacha and Masih (2012), Syllignaki and Kouretas(2011) and You and Diagler (2010). All these studies found that conditional volatilities and correlations do indeed exhibit changes with time.

Tamakoshi and Hamori (2014) and Gjika and Horváth (2013) investigate the co-movements among major European exchange rates and Stock market co-movements in Central Europe respectively. In addition to their findings that conditional volatilities and correlations seem to be converging implying financial integration within Europe, they also find that there is an asymmetric reaction towards bad news. Investors tend to react worst to shocks such as financial crises causing for spikes in volatility during the period. This is empirical evidence in support of Kahneman and Tversky (1979) theory that investors are generally risk adverse and the heading behavior discussed by Akerlof and Shiller (2009). Conditional correlations also tend to be rising because investors, according to Gjika and Horváth (2013) see Europe as one market.

Valadkhani, Harvie, and Karunanayake(2013) and Celik (2012) and Syllignaki and Kouretas(2011).Investigate the issue of volatility spillover during financial crises. All find that during crises times, not only is there a spike in volatility but there also is indication of volatility spillover. Valadkhani, Harvie, and Karunanayake(2013) study comprises of 29 countries consisting of nations from the G6, ODEC, G4 (Anglo-Saxon countries) and G2 (Korea and Japan). Volatility spillover was found to be no only geographically linked but also culturally linked. This means that countries with close proximity of each other tend to go through similar cycles of boom and bust with any contagion spreading from nearby countries. In addition, countries that share commonalities in culture which plays a role enhancing cross border trade are observed to be more exposed to any contagion effect as the financial market of the countries become intertwined through cross border trade. Syllignaki and Kouretas (2011) are in support of these finding in their study which focuses on Central and Eastern European markets sighting the factor of geographical proximity and trade linkages as channels for volatility spillover. Celik (2012) study which focuses on emerging markets concurs with volatility spillover but stresses the impact of herding behavior.

Hammami, Jilani and Oueslati (2013) and Chevallier (2012) both investigate conditional volatility and correlations within a certain market. The former studies 30 Tunisian open-end mutual funds from January 2002 to December 2010, while the latter studies oil, gas and CO2 prices. Hammami, Jilani and Oueslati (2013) conclude that M-GARCH is a better predictor of alpha due to other methods being static and not taking into account conditional changes. Chevallier (2012) finds that while cross shocks (spillover) does happen, oil, gas and CO2 prices are largely dependent on its own past. This relationship could not be captured with the static estimators.

Kabir, Bacha and Masih (2013) and Kamil, Bacha and Masih (2012) both respectively investigate the global Islamic equities markets and Islamic equities in Malaysia. Kabir, Bacha and Masih (2013) support the geographical relationship with volatility findings of Valadkhani, Harvie, and Karunanayake (2013) and Celik (2012) and Syllignaki and Kouretas(2011) but continue to find that regional leaders play a large influence on volatility indicating financial integration and smaller markets are psychologically prone to follow the regional leaders. Though Kabir, Bacha and Masih (2013) find that the Islamic Equity Incises do tend to be mean reverting, which means that they return to normal after a shock, the Islamic Markets all may suffer from a lack of diversification opportunities. Although, Kamil, Bacha and Masih (2012) find that this might not necessarily be the case as they demonstrate that diversification is possible but since benefit is both time-variant and stock-specific, investors must be very shrewd in selecting the stocks to attain the same level of diversification benefit as the conventional sector. Kamil, Bacha and Masih (2012) demonstrate that this is possible and robust with the M-GARCH conditional volatilities and correlations in Malaysia and The United States. You and Diagler (2010) concur with their findings that diversification opportunities do exist but must take into account the time varying nature of volatilities and risk for a better result than static estimators.

One overarching issue still exists amongst all the studies above that employ the M-GARCH model is that they all utilize daily observations in data and are therefore representative of a single time scale that is high frequency. However, risk and return are time scale dependent concepts and any form of measurement must account for the different investment horizon effects (In and Kim, 2013). This is due to different types of investors having different investment horizons (Kim and In, 2013b; 2013c) and therefore the true dynamic stock price movements are in fact the result of cumulative interactions amongst homogenous individuals, each with unique motivations for holding a stock, with varying degrees in risk tolerance. Therefore the relationship between stock returns and risk factors is likely to vary depending on the time horizon of the investors (Masih, Alzahrani and Al-Titi, 2010).

To address this issue, studies such as In and Kim (2013b; 2013c), Najeeb and Masih (2013), Saiti, Dewandaru and Masih (2013), Madaleno and Pinho (2012),Khalfaoui, Boutahar (2011), Masih, Alzahrani, and Al-Titi (2010), Fernandez (2006), Gencay, Selcuk, and Whitcher, (2005). All employ Wavelet Multiscaling to dissect the stock return data into different time scales which reveal that the true dynamic of stock returns does indeed come from different time scales and does vary amongst them.

Khalfaoui, Boutahar (2011), Masih, Alzahrani, and Al-Titi (2010), Fernandez (2006), Gencay, Selcuk, and Whitcher, (2005) all investigate risk at the different time scales and find evidence that risk is multiscale in nature. By dividing risk into systematic and unsystematic components, all authors find consistent evidence that systematic or un-diversifiable risk is different depending on the time scale in which it is measured at. Therefore different investors would have different expectations of *beta* or how much a stock correlates with the market. This finding communicates very important information to investors as it has strong implications for diversification strategy depending on the stock holding period of the investor. All authors also measure the Value at Risk (VaR) at different time scales and find that risk, as a whole, tends to be concentrated in the low time scale or high frequency. However *beta* of each stock has a stronger relationship with the market at the higher time scale. In other words, systematic risk plays more of a role in explaining stock price movements in the long run. This means that long term investors are exposed more to volatilities from the market. What all these studies employing Wavelet ultimately show, is strong evidence that the study of volatility and correlations cannot be limited to a single time scale as it does not tell the complete story about the why these volatilities and correlations are so. As such, this term paper attempts to study volatilities and correlations of the IFSI's by employing both M-GARCH t-DCC and MODWT Wavelets to hopefully ascertain a better understanding.

3. Methodology

3.1 Description of the Data

For the data, 11 financial services companies listed on the FTSE Bursa Malaysia EMAS Shariah Index were considered. However for the period of 2004 to 2014 on 2 IFSI have been consistently within the requirement of the Malaysian Securities Commission Shariah Compliance Screening with the others exhibit years that they were inconsistent with Shariah screening and others being introduced late thereby limiting the number of observations to less than 1000 daily observation causing the M-GARCH estimator to not converge.

For consistency, only Bank Islam Malaysia Bhd (BIMB) and Syarikat Takaful Malaysia Bhd (SKYT) were chosen for investigation as they passed the securities commission Shariah Screening for the period of 2004 to 2014 and therefore are considered to operate in line with Shariah restrictions on assets of interest bearing debt and derivatives for hedging. For comparison purposes their competitors of Maybank Bhd (MALY) and LPI Capital (LPAC) were chosen due to Maybank Bhd being the largest local bank and LPI Capital being a locally listed company which deals with mainly insurance unlike the other local insurance companies which deal with a wide array of services. The market index is KLCI. All data was extracted form *Thomson-Reuters DataStream* database available at the Knowledge Management Centre of INCEIF University. The data was form 22nd July 2004 to 4th April 2014 with a total of 2532 observations.

Table 1

Symbol	Description
BIMB	Bank Islamic Malaysia Bhd
SKYT	Syarikat Takaful National Bhd
MALY	MaybankBhd
LPAC	LPI Capital Bhd
KLCI	FTSE Brusa Malaysa Kuala Lumpur Composite Index KLCI

The calculation of stock indices return is differences of the logarithmic daily closing prices of indices$\{\ln(P_t) - \ln(P_{t-1})\}$ where P is an index value.

3.2 M-GARCH

The M-GARCH is adopted as in Pesaran and Pesaran (2009). As did Pesaran and Pesaran (2009) the normal distribution is tested against the student t distribution to see which would better fit the model. To fully appreciate the dynamism of conditional volatilities and correlations, M-GARCH is computed with the following equations:

$$\textit{Mean equations}: r_t = \mu + \gamma_1 r_{t-1} + \gamma_2 r_{t-1}^{us,ge,rus} \varepsilon_t, \text{ where } r_t = (r_{1,t}, r_{2,t}, \ldots\ldots, r_{7,t})', \varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t}, \ldots\ldots\ldots, \varepsilon_{7,t})' \text{ and } \varepsilon_t | I_{t-1} \sim N(0, H_t).$$

$$\textit{Variance equations}: h_{ii,t} = \omega_i + \alpha_{i,1} \varepsilon_{i,t-1}^2 + \beta_{i,1} h_{ii,t-1}, \text{for } i = 1, 2, \ldots, 7.$$

$$\textit{DCC equation}: \begin{array}{l} q_{ij,t} = \bar{\rho}_{ij}(1-a-b) + b q_{ij,t-1} + a \eta_{i,t-1} \eta_{j,t-1} \\ \rho_{ij,t} = \dfrac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}}, \text{ where } i, j = 1, 2, \ldots, 7, \text{ and } i \neq j. \end{array}$$

Source: Syllignakis and Kouretas, 2011

For brevity sake, the full details of the equations have been omitted. For full elaboration on the details of the equation and its individual components see Pesaran and Pesaran (2009) for a more in-depth and comprehensive discussion on the method.

3.3 MODWT Wavelet

A later development of the Discreet Wavelet Transform (DWT) is the Maximum Overlap Discreet Wavelet Transform (MODWT). The MODWT is a non-orthogonal transform as compared to its predecessor the DWT. Advantages of the MODWT are that:

i. Non- Dyadic sample size
ii. Shift invariant: The MODWT and scaling coefficients are shifted the same amount when the time series is shifted by an integer unit
iii. Coarser scales are provided with increased resolution

iv. MODWT produces a more asymptotically efficient wavelet variance than its predecessor the DWT

According to Percival and Walden (2000) MODWT is defined as a time series Xt , t = 1, ..., N as follows: for every possible integer of L (L which denotes the width of the integer filter) let {hl ; l = 0, . . . , L−1} and {gl ; l = 0, ..., L−1} be the respective Daubechies Wavelet scaling filters. The MODWT wavelet and scaling coefficients are the solutions of the multiresolution decomposition analysis of Mallat (1989). Because of this we have:

$$\tilde{\omega}_{jt} = \sum_{l=0}^{L_j-1} \tilde{h}_{jl} X_{t-l \bmod N}, \; t = 0, 1, \ldots, N-1,$$

$$\tilde{v}_{jt} = \sum_{l=0}^{L_j-1} \tilde{g}_{jl} X_{t-l \bmod N}, \; t = 0, 1, \ldots, N-1,$$

Source: Khalfaoui and Boutahar 2011

Where $L_j \equiv (2^j - 1)(L-1) + 1$ is the length of the wavelet filter (See Gencay (2002) for a more in-depth explanation) and where the MODWT wavelet and scaling filters $\tilde{h}_{jl}$ and $\tilde{g}_{jl}$ are calculated by rescaling the DWT filters coefficients, such that $\tilde{h}_{jl} = h_{jl}/2^{j/2}$ and $\tilde{g}_{jl} = g_{jl}/2^{j/2}$ and circularly shifting by unit intervals for all levels of the transform. Essentially, three properties are satisfied with the MODWT filter which are:

$$\sum_{l=0}^{L-1} \tilde{h}_l = 0, \sum_{l=0}^{L-1} \tilde{g}_l = 1,$$

$$\sum_{l=0}^{L-1} \tilde{h}_{jl}^2 = \sum_{l=0}^{L-1} \tilde{g}_{jl}^2 = \frac{1}{2^j},$$

$$\sum_{l=-\infty}^{\infty} \tilde{h}_l \tilde{h}_{l+2n} = \sum_{l=-\infty}^{\infty} \tilde{g}_l \tilde{g}_{l+2n} = 0.$$

Source: Khalfaoui and Boutahar 2011

MODWT Wavelet Variance

MODWT provides an opportunity to investigate the variance of deviation in returns at the different time scales. The MODWT multiscaling enables the dissection of the variance into components form different time scales. This enables the investigation into the differences of variance at each time scale as well as which time scale holds much of the contribution towards stock price variance in returns or volatility. The scale that holds the largest variance is responsible for the most fluctuations is returns and therefore where most risk is located. The total variance of a time series can be divided into its respective scales by the MODWT as

$$\|X\|^2 = \sum_{j=1}^{J} \|\tilde{\omega}_j\|^2 + \|\tilde{v}_J\|^2 .$$

Source: Khalfaoui and Boutahar 2011

For brevity sake the details of each component are omitted here. See Khalfaoui and Boutahar (2011) for a full explanation of how MODWT variance is scaled.

MODWT Wavelet Covariance and Correlation

MODWT covariance provides an opportunity to investigate the relationship between two variables at different time scales. Let Xt and Yt be two stationary discrete time series, and let $\tilde{\omega}_{X,jt}$ and $\tilde{\omega}_{Y,jt}$ be the scale λ_j of MODWT wavelet coefficients computed to the respective time series of Xt and Yt . Thus, wavelet covariance is defined as:

$$\gamma_{XY}(\lambda_j) = \frac{1}{2\lambda_j} Cov(\tilde{\omega}_{X,jt}, \tilde{\omega}_{Y,jt}) .$$

Source: Khalfaoui and Boutahar 2011

A MODWT covariance that is unbiased is given by the estimator:

$$\hat{\gamma}_{XY}(\lambda_j) = \frac{1}{M_j} \sum_{t=L_j}^{N} \tilde{\omega}_{X,jt} \tilde{\omega}_{Y,jt}$$

Source: Khalfaoui and Boutahar 2011

For an in-depth explanation see Whitcher et al (2000)

From the Wavelet covariance a Wavelet correlation can be obtained by:

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

Source :Najeeb and Masih (2013).

For further elaboration see Najeeb and Masih (2013).

MODWT Wavelet Interpretation of Time Scales

Table 2: Scaled components and their representative time scales

Scale	Component	Frequency Resolution
Scale 1	D1	Aprox 1-2 Days
Scale 2	D2	Aprox 2-4 Days
Scale 3	D3	Aprox 1 Week
Scale 4	D4	Aprox 2 Weeks
Scale 5	D5	Aprox 1 Month
Scale 6	D6	Aprox 2 Months
Scale 7	D7	Aprox 4 Months
Scale 8	D8	Aprox 1 Year

Note: Each Scale is Representative of Different Time Scales or Stock Holding Periods

4. Data Analysis and Empirical Results

4.1 Descriptive Statistics

Table 3: Descriptive Statistics

Variable(s)	BIMB	SKYT	MALY	LPAC	KLCI
Maximum:	0.29746	0.26088	0.089333	0.057398	0.042587
Minimum:	-0.15234	-0.26088	-0.073474	-0.072472	-0.099785
Mean:	4.07E-04	9.39E-04	1.16E-04	7.09E-04	3.19E-04
Std. Deviation:	0.022307	0.023431	0.012844	0.010464	0.0074703
Skewness:	1.5939	0.69057	-0.23177	-0.51449	-1.2262
Kurtosis - 3:	18.0842	25.6841	6.1899	7.2337	16.5708
Coef of Variation:	54.7786	24.9532	110.5596	14.754	23.4016

The descriptive statistics in **table 3** reveal some interesting preliminary observations. The distributions of return for the IFSI are both positively skewed as compared to their conventional counterparts and the KLCI market portfolio. In fact, BIMB seems to be very well off with the majority of returns strongly positive compared to the others. This is in contrast to Kabir, Bacha and Masih (2013) and Najeeb and Masih's (2013) findings of Islamic Markets being mostly negatively skewed meaning that Islamic Markets are usually plagued by majority of returns on the negative side of the distribution, although it is important to keep in mind that this study is at the firm level and therefore could be just representative of the Islamic Financial Sector in Malaysia and not the entire Shariah compliant family of stocks in the country. Instead, it is both conventional and the KLCI which are negatively skewed with KLCI being largest negative skew indicating that the Malaysian market as a whole does not offer positive return most of the time.

There is some cause for concern however when the level of kurtosis is taken into consideration. A kurtosis of 3 indicates normally distributed returns (In and Kim, 2013). All variables including the KLCI exhibit kurtosis in excess of 3. What is surprising is that both IFSI have kurtosis of 18.0842 and 25.6841 for BIMB and SKYT respectively while the conventional counter parts are 6.1899 and 7.2337 for MALY and LPAC respectively. What this means is that the IFSI are much more exposed to systematic risks from as a result from *fat tails,* which essentially arises from being over leveraged returns (Kabir, Bacha and Masih, 2013) as compared to their conventional counterparts. This finding is very peculiar as IFSI are expected to be highly capitalized with low levels of debt as a result from compliance with Shariah screening (Bacha and Mirakhor, 2013).

The descriptive statistics pose some interesting questions that warrant further investigation. Given the level of exposure to systematic risk the IFSI are exposed to it might be interesting to gauge their performance in terms of volatilities and correlations. Due these preliminary results, it is expected that IFIS may be more volatile than their conventional counterparts and the market portfolio of KLCI. As such, the M-GARCH and MODWT Wavelet multiscaling may reveal further information.

4.2 Investigation into Volatilities and Correlations of Islamic Financial Services Institutions

M-GARCH Normal and t- Distribution

Table 4: Estimates For Lambda 1 and 2, Delta 1 and 2 for all 5 Parameters

	M-GARCH Normal Distribution		M-GARCH t -Distribution	
Parameter	Estimate	T-Ratio[Prob]	Estimate	T-Ratio[Prob]
lambda1_BIMB	0.35341	5.4809[.000]	0.75866	18.7642[.000]
lambda1_SKYT	0.85319	78.4767[.000]	0.76745	28.5237[.000]
lambda1_MALY	0.93503	105.2995[.000]	0.95137	92.7198[.000]
lambda1_LPAC	0.7983	15.9169[.000]	0.79642	22.1400[.000]
lambda1_KLCI	0.92371	91.9860[.000]	0.94905	108.9797[.000]
lambda2_BIMB	0.20391	10.7126[.000]	0.14392	7.2153[.000]
lambda2_SKYT	0.11412	14.4251[.000]	0.19234	9.5675[.000]
lambda2_MALY	0.05538	7.8487[.000]	0.045047	5.1465[.000]
lambda2_LPAC	0.11922	5.0627[.000]	0.1451	6.4940[.000]
lambda2_KLCI	0.064057	8.2570[.000]	0.038195	6.3268[.000]
delta1	0.96624	86.2970[.000]	0.98672	189.1243[.000]
delta2	0.011261	5.1271[.000]	0.0068236	3.8533[.000]
Degrees of Freedom (df)			3.7891	40.9806[.000]
Maximized Log-Likelihood	38616.6		40050.8	

Note: Lambda 1 and 2 are decay factors for variance and covariance respectively

Following Pesaran and Pesaran (2009) it is first necessary to test which distribution will fit the M-GARCH best to provide estimates to the data. **Table 4,** summaries the Maximum Likelihood Estimates (MLE) of *Lambda 1* and *Lambda 2* for all 5 indices returns. *Delta 1* and *delta 2* are the mean reverting parameters of the indices. While all values are significant at p-value of more than 1%, it is necessary to compare the Maximized Log-Likelihood where the normal distribution (38616.6) is smaller than the t- distribution (40050.8). Also the degrees of freedom (3.7891) are less than 30. These two tests suggest that the t- distribution is more appropriate at capturing the fat tailed nature of the distribution of all indices (Kamil, Bacha and Masih, 2013).

Table 5: Test of mean reversion

Variable(s)	1 - λ(1) - λ(2)	Std. errors	t-ratio
BIMB	0.09743	0.02413	4.0380[.000]
SKYT	0.04022	0.00847	4.7466[.000]
MALY	0.00358	0.00178	2.0154[.044]
LPAC	0.05848	0.01551	3.7705[.000]
KLCI	0.01276	0.00328	3.8921[.000]

Note: $H_0 = \lambda_1 - \lambda_2 = 1$, Under H_0 mean is non-reverting

Table 5,test the mean reversion characteristics of the variables. All variables are found to be significant and mean reverting albeit very slowly. This implies that, given a shock such as a financial crisis, the returns will gradually return to their normal trend. In other words all variables' volatility will decay with time eventually dying out. The implication here is that the unconditional volatility matrix below is reliable for the long term investors as the figures are what will eventually be regardless of a shock.

4.3 M-GARCH Unconditional Volatility Matrix

Table 6: Estimated Unconditional volatility Matrix

	BIMB	SKYT	MALY	LPAC	KLCI
BIMB	0.02230	0.25654	0.21058	0.15442	0.33763
SKYT	0.25654	0.02350	0.07251	0.11196	0.17837
MALY	0.21058	0.07251	0.01284	0.25746	0.62741
LPAC	0.15442	0.11196	0.25746	0.01051	0.41073
KLCI	0.33763	0.17837	0.62741	0.41073	0.00749

Note: On diagonal values are Unconditional Volatility values while off diagonal values are Unconditional Correlations

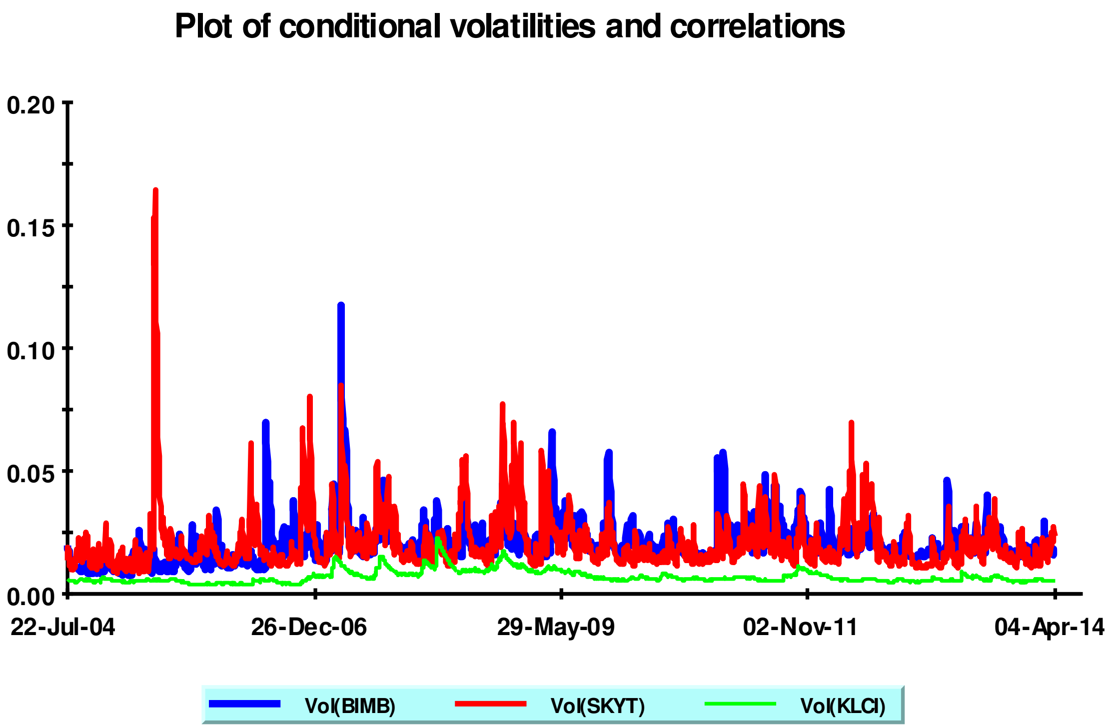
Table 6, shows the unconditional volatilities of each variable for on diagonal values while the off diagonal values are unconditional correlations. Referring to the on diagonal figures, it is observed that both IFSI are more volatile than their conventional counterparts and the market portfolio KLCI. This finding is consistent with the expectation made from observing the descriptive statistics above. KLCI appears to be the least volatile of all, although this is expected as the market portfolio benefits from the diversification effect resulting from a combination of stocks (Najeeb and Masih, 2013).

Referring to the off diagonal figures, both IFSI seem to be lower in correlation with the market portfolio (0.33763) and (0.17837) for BIMB and SKYT respectively, as compared to their conventional counterparts with (0.62741) and (0.41073) for MALY and LPAC respectively. This finding is much more in line with expectations about IFSI's due to their operational activities limiting the use of interest bearing debt and derivative instruments that tend to increase their relationship with the market. It is not surprising that Maybank Bhd is the highest correlated with the market (0.62741) considering that Maybank Bhd is the largest local bank in Malaysia (Maybank Annual Report, 2013) and therefore is likely to be providing financial services to many companies listed on the KLCI. This relationship of Maybank Bhd with KLSE is therefore expected while the relationship of LPAC with the market is perhaps due to the conventional insurance company taking positions in companies listed on the KLCI that deal with interest bearing debt an option which SKYT does not have and therefore is the least correlated with the market of all the companies studied. BIMB does have a higher correlation with the market as compared to SKYT perhaps for the similar reason of providing financial services to its customers listed on the KLCI.

It may be that the unconditional volatility and correlations holds in the long run as a result of being mean reverting. But for further understanding of the volatility and correlations of IFSI's, it would be interesting to investigate the volatility and correlations that each institution experiences through time. Since the data is inclusive of both the 2008 – 2009 global financial crisis and the late 2009 start of the European sovereign debt crisis, It will be interesting to see how the IFSI's faired compared to their conventional counter parts and the market portfolio KLCI through the period. The M-GARCH t-DCC provides an opportunity to do so by revealing the dynamic conditional volatilities and correlations.

4.4 M-GARCH Plot of Conditional Volatilities and Correlations

Figure 1: M-GARCH Conditional Volatility of BIMB v SKYT v KLCI



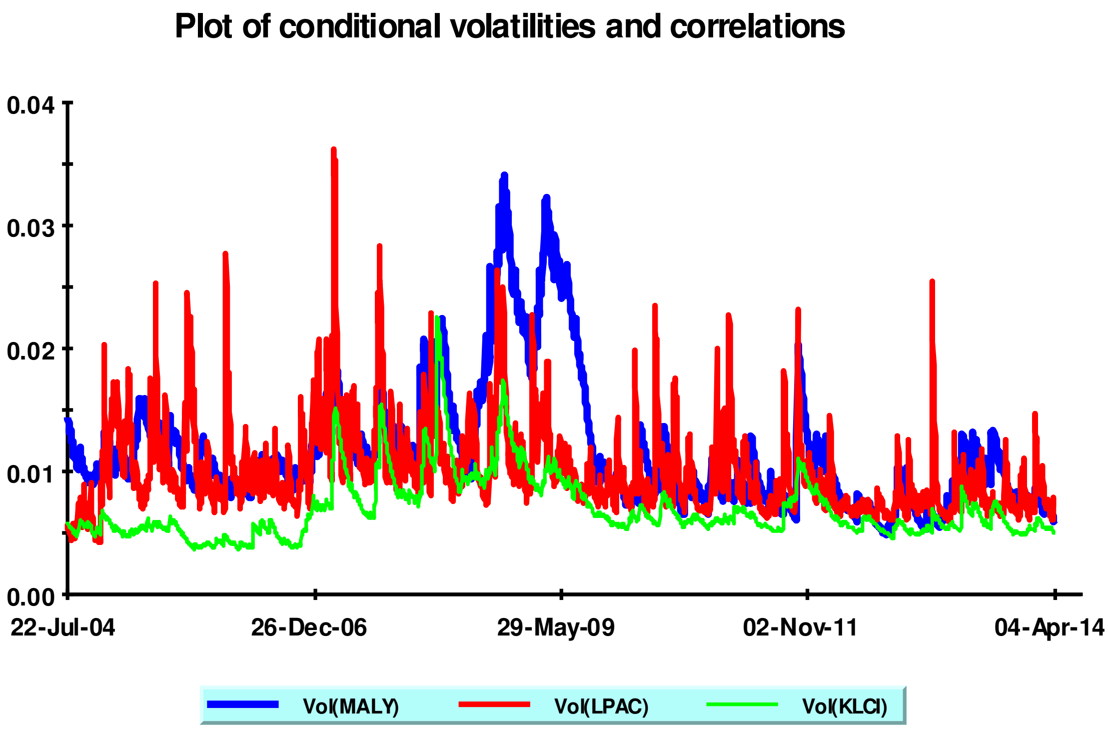
What is instantly noticeable from **Figure 1** is that both IFSI's of BIMB and SKYT are much more volatile as compared to the market with spikes in volatility that are seemingly independent of the market. While it is noticeable that the market experiences increased volatility during the global financial crisis of 2008 – 2009, the spikes in volatility relative to the market of KICI experienced by the IFSI's seem to be unique phenomena apparent before, during and after the crisis with large spikes unique to the IFSI's. Although, the IFSI's seem to have both reacted worse in late 2008 when Lehman Brothers declared bankruptcy, triggering what many believe to be the onset of the global financial crisis of 2008 – 2009. What is peculiar is that the volatility of the IFSI's did not die out following the crisis but continued in almost similar magnitude suggesting that BIMB and SKYT are somewhat independent of the market.

A possible explanation to this would be due to the asset composition of BIMB. Being an Islamic bank the contracts drawn out carries with it the unique feature of risk sharing. The implication is that any profit realized by the bank should be justified by an equivalent counter value to the counterparty (Rosley and Sanusi, 1999; Rosley, 2005). This exposes Islamic banks to some unique risk in terms of credit and operational due to not being able to shift the risk involved in financing activities to the counterparty to solely bare as it would constitute an unjust gain and therefore *riba*. This would violate the very philosophy in which Islamic banks operate on. The cost, of course, is increased exposure to credit risk, non-performing financing and counter party risk as the non-existence of compounding interest raises the incentive for default. Bacha (1997) points out to the lack of a “bonding” effect resulting from some Islamic contracts as well as the financier being responsible to bare losses from failed projects giving rise to perverse incentives from borrowers.

SKYT too suffers from almost similar volatility perhaps due to the philosophy of *tabarru'*, which according to the Bank Negara Malaysia (2003) means that the operator (SKYT) and the individual members of a group of participants agree to reciprocally guarantee each other against certain loss or damage endured by any one of them. In other words SKYT too is limited to contracts of risk sharing and may not participate in any unlawful investment activities such as purchasing conventional bonds of fixed tenure and coupons or hedging with derivatives that conventional insurance companies rely on for coverage. This exposes SKYT to some unique risk which may not be experienced by the conventional insurance companies because it has to absorb damages under the *tabarru'* concept contributing to the experienced volatility.

It seems that for the time being IFSI’s in Malaysia will continue to experience this kind of volatility in the absence of more sophisticated risk management techniques and practices that serve to mitigate the unique challenges of IFSI’s operating in an environment dominated by conventional practices.

Figure 2: M-GARCH Conditional Volatility of MALY v LPAC v KLCI



From **Figure 2** is revealed a very contrasting scenario of volatility experienced by the conventional financial services institutions of MALY and LPAC. Unlike the IFSI's both MALY and LPAC show signs of volatility that are somewhat similar in patterns, though larger in magnitude, compared to the market volatility of KLCI. This is expected due to both MALY and LPAC being much more unconditionally correlated with the market compared to the IFSI's. Also, the kurtosis levels in the descriptive statistics (**Table, 3)** above suggested that conventional financial institutions would be less volatile than IFSI's.

MALY seems to have spiked in volatility for the period of the global financial crisis of 2008 – 2009 higher than LPAC. Since MALY is a conventional bank this is anticipated and somewhat suggest that conventional banking may be more exposed during periods of crises.

Figure 3: M-GARCH Conditional Volatility of BIMB v MALY v KLCI

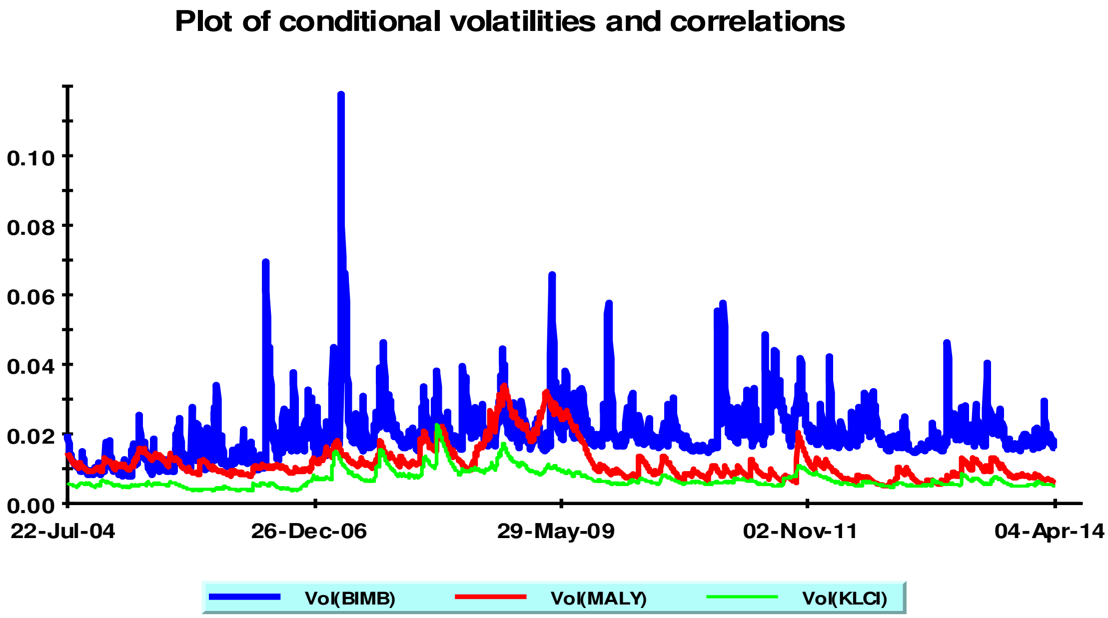


Figure 3, compares BIMB and MALY to confirm the observation of BIMB is more volatile than MALY.

Figure 4: M-GARCH Conditional Volatility of SKYT v LPAC v KLCI

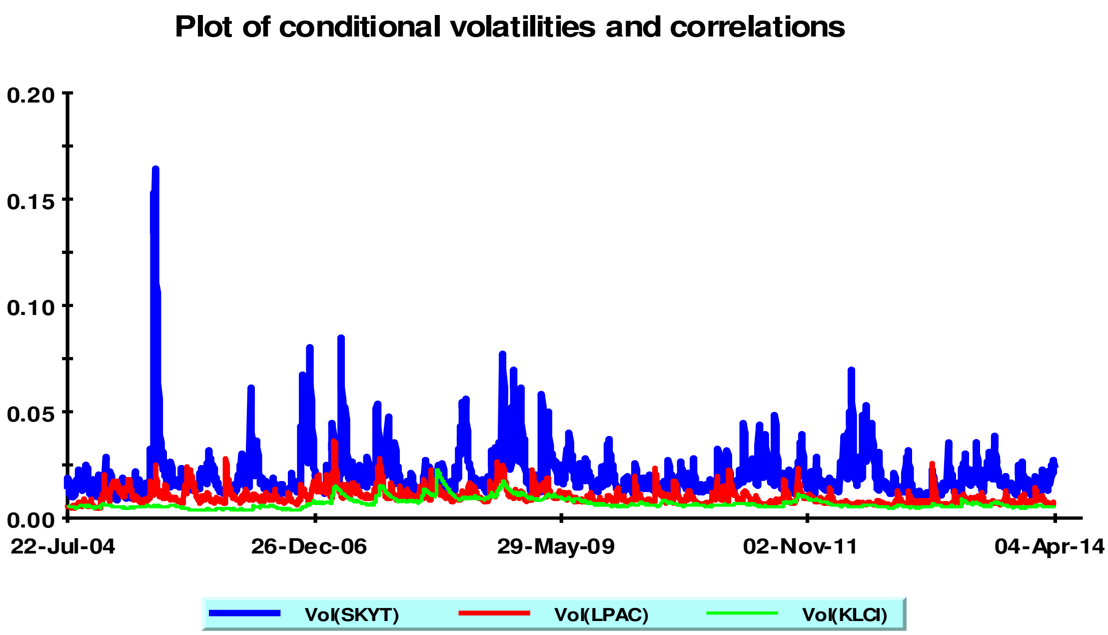


Figure 4, compares SKYT and LPAC to confirm the observation that SKYT is more volatile than LPAC.

Figure 5: M-GARCH Conditional Correlations of BIMB, SKYT, MALY, PLAC to KLCI

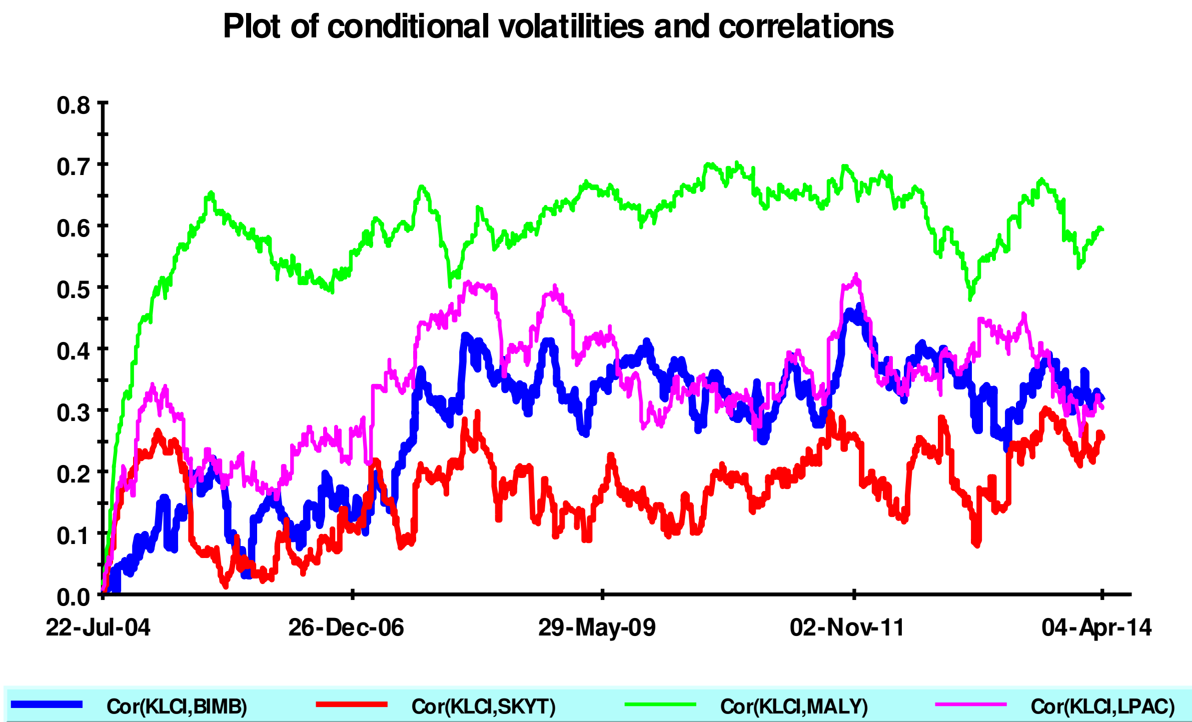


Figure 5, reveals the conditional correlations both IFSI's and their respective conventional counterpart with the market KLCI. Unsurprisingly MALY has is highly correlated with the market while LPAC and BIMB share an almost similar correlation pattern with each other. SKYT is observed to have the lowest correlation with the market however there is some evidence that this correlation is rising by observing the convergence in correlation between BIMB, SKYT and LPAC in 2014. The convergence could be a sign that the market is becoming more integrated. This may be due to BIMB and SKYT expanding their range of services to include the corporate sector and therefore raising correlations with the KLCI.

From an investor's point of view, SKYT holds the most promise for portfolio diversification due to its low correlation with the market. Although, any investor would be wise to consider the volatility as the returns of SKYT may experience large fluctuations. **Table 3,** above indicated that SKYT has the largest standard deviation in returns amongst all the variables considered here.

An important observation to point out is that both volatilities and correlations so not seem to be constant. While **Table 5,**finds evidence of mean reversion behavior, it is very slow meaning that investors may be somewhat misled should they not hold the stock long enough for it to revert to the mean where the expected returns can be realized.

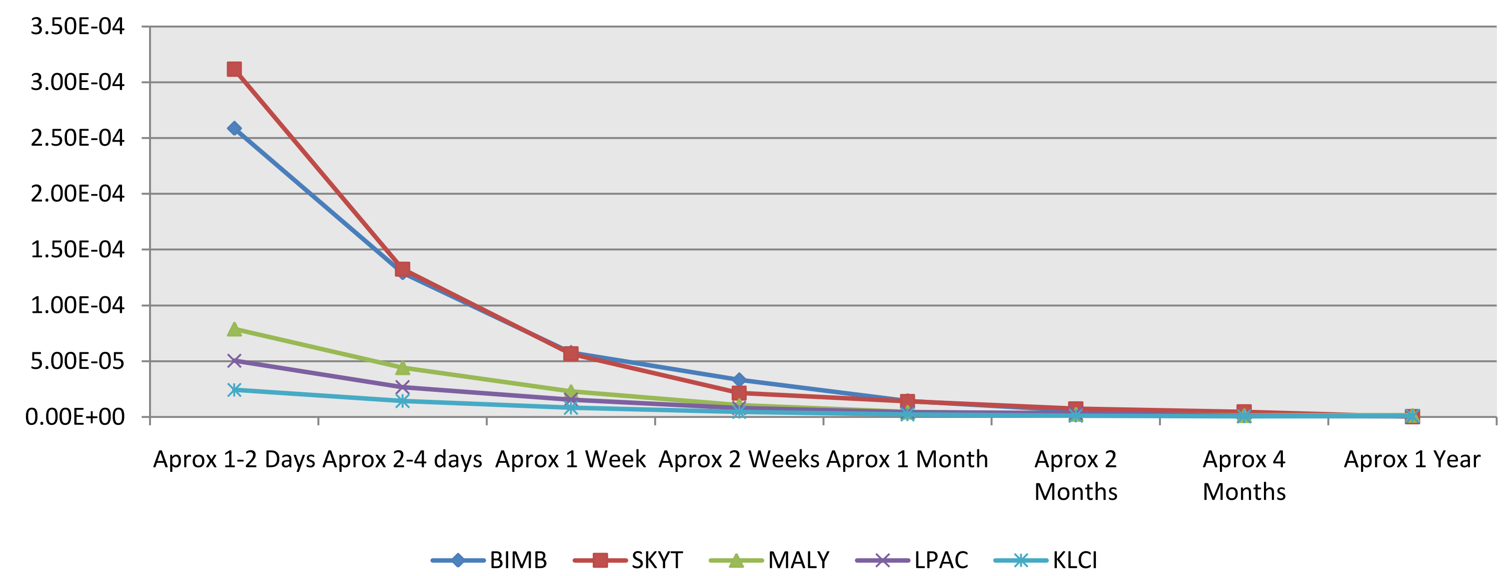
Another important issue is that all estimations above rely on daily observations. Hence the results are representative of a single time scale. However, In and Kim (2013b; 2013c), Najeeb and Masih (2013), Saiti, Dewandaru and Masih (2013), Madaleno and Pinho (2012), Khalfaoui, Boutahar (2011), Masih, Alzahrani, and Al-Titi (2010), Fernandez (2006), Gencay, Selcuk, and Whitcher (2005) all provide evidence that different investors with different stock holding periods are exposed to different variations in returns and risk.

These findings warrant further investigation to dissect volatility and correlations into different scales (stock holding periods) that enable a better understanding of how volatility and correlations of IFSI's, their conventional counterparts and the market KLCI behave.

4.5 Volatility and Correlations at Different Time Scales by MODWT Wavelet Multiscaling

MODWT Wavelet Variance and Covariance

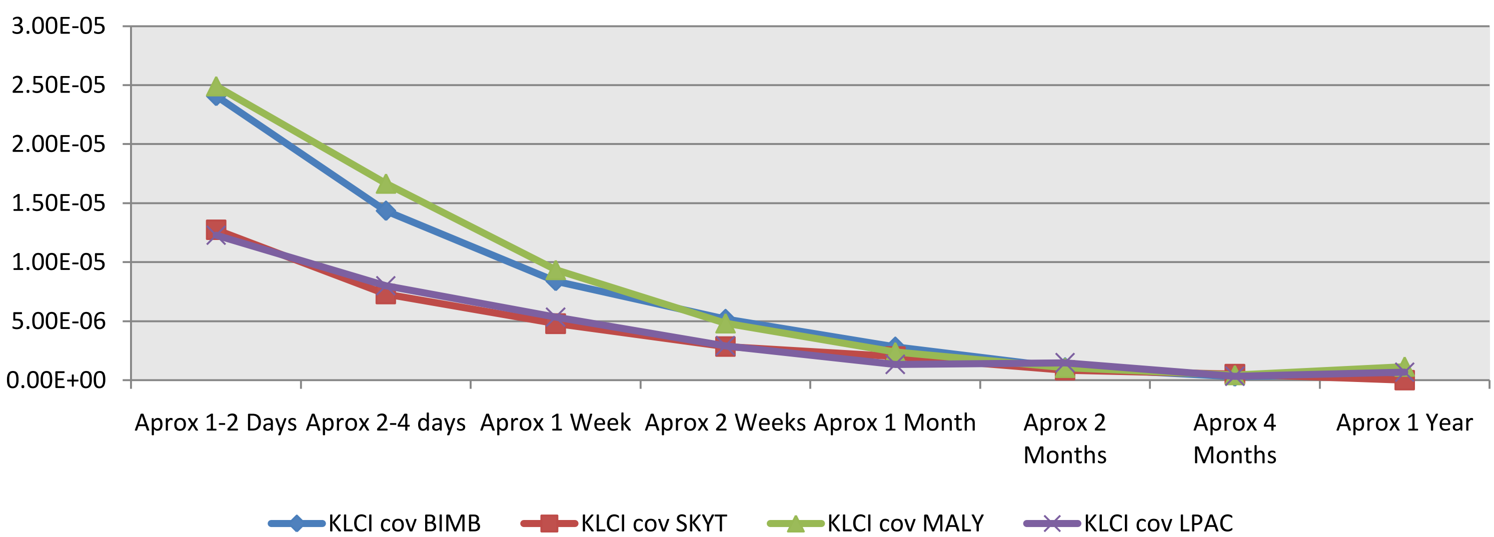
Figure 6 :MODWT Wavelet Varience of all Companies



Note: All MODWT Wavelet Variances are significant within 95% upper and lower bound limit

Figure 6, reveals theMODWT Wavelet Variance at different time scales. It is instantly observable that IFSI's experience much more variance in returns in the short time scale of 1 – 2 days and 2 – 4 days. At 1 week there is still a noticeable difference with the variance continuing to die down converging upon the conventional finance institutions of MALY and LPAC and the market KLCI at approximately 2 and 4 months. This finding indirectly acts as a robustness test in support that the volatility will be mean reverting in the long term. It would seem that the IFSI's are much more exposed to volatility in the short term compared to their conventional counterparts and the market KLCI. Short term investors and speculators would have to contend with the issue of this variance in the short term returns which implies that BIMB and SKYT are more suited to institutional investors that have longer stock holding periods such as insurance firms and pension funds.

Figure 7: MODWT Wavelet Covarience of all Companies

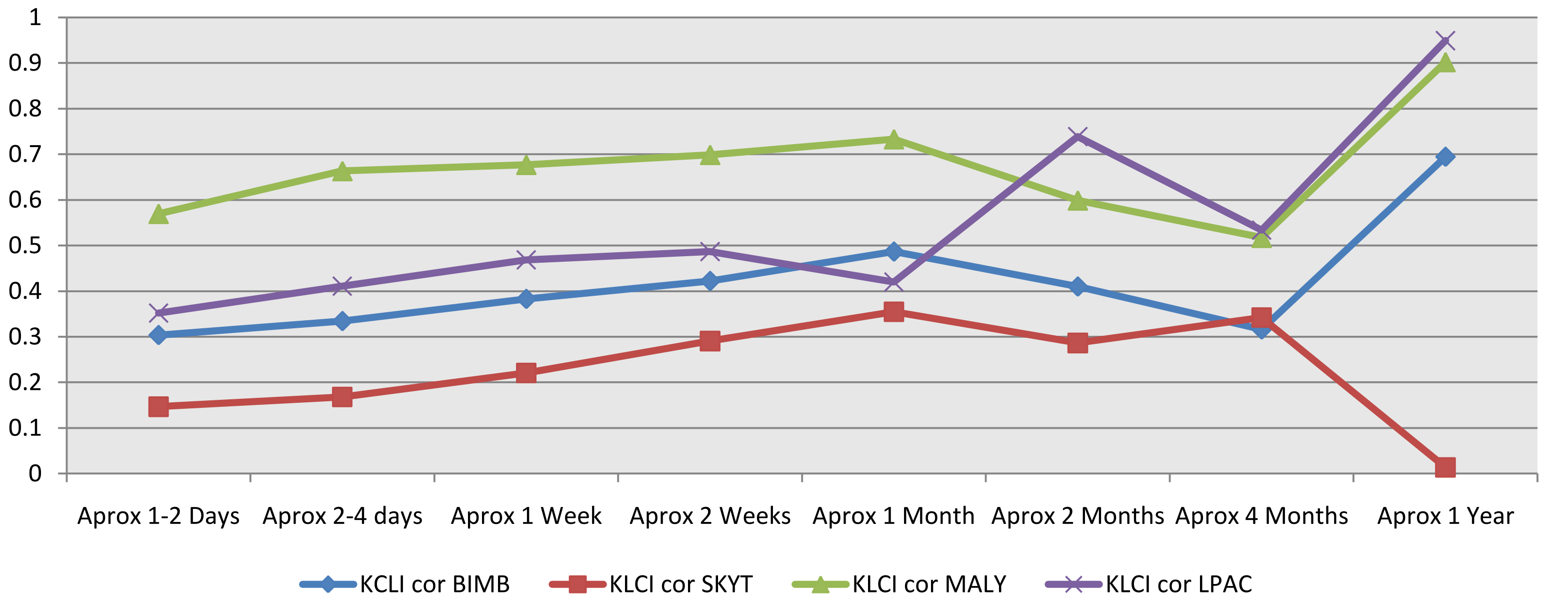


Note: All MODWT Wavelet covariance are significant within 95% upper and lower bound limit

Figure 7, reveals the MODWT covariance of IFSI's and their conventional counterparts with the market of KLCI. Both IFSI's are observed to be higher in covariance with the market in the short term as compared to their conventional counterparts. For a better understanding of the magnitude of these relationships at the different time scales it is advantages to refer to a normalized covariance enabling comparisons of the relationship of the IFSI's and their conventional counterparts with the market. This is given by the MODWT Wavelet correlation.

MODWT Wavelet Correlations

Figure 8: MODWT Wavelet Scaled Corellation of Companies with KLCI (Market Portfolio)



Note: All MODWT Wavelet correlations are significant within 95% upper and lower bound limit

Figure 8, the MODWT Wavelet correlations reveal the relationship of the IFSI's and their conventional counterparts to the market KLCI at the different time scales (stock holding periods). A positive correlation of 1 indicates perfect movement with the market while 0 indicates no relationship and a negative indicates an opposite relationship with the market. Interestingly the correlations up until approximately 2 weeks maintain a slight rising but steady trend amongst all the variables. It is interesting to note that the correlations at the first scale of 2 – 4 days are almost similar to the unconditional correlations reported in **Table 6**. The changing nature observable here rejects the use of a single correlation for the different types of investors. At approximately 1 month holding period SKYT and MALY dip in correlation to the market while LPAC experiences a rise in the 1 month holding period before dipping down in the 4 month holding period.

BIMB, MALY and LPAC all experience a sharp rise in correlation with the market for the 1 year holding period. It would seem that there is almost no diversification benefit for investors investing in MALY and LPAC for the long term as they are almost perfectly correlated in the long term. For BIMB however, the diversification benefit is significantly decreased as it too rises in the long term stopping just 0.3 short of perfectly correlated with the market. It would seem that Islamic banking may eventually in the long term be correlated with the market because of its profit rate not being able to be higher than the interest rates at which other banks charge for losing business in a dual banking system.

The greatest potential for diversification lies with SKYT. SKYT has a relatively low correlation with the market through the different stockholding periods, SKYT peaks at 1 and 4 months although still within the mid 0.3 correlated with the market. In the long term of 1 year SKYT has almost no correlation with the market making this a rare find for diversification opportunities. Investors however need to be careful because even though SKYT is the lowest correlated with the market it is the most volatile up until the 2 months holding period.

5 Conclusions and Policy Recommendations

The findings of this paper are quite surprising considering the celebrated stability of Islamic Finance. Interestingly, the IFIS's of Bank Islamic Malaysia Bhd and Syarikat Takaful National Bhd exhibit much higher volatility as compared to their conventional counter parts of Maybank Bhd and LPI Capital Bhd. Being "Shariah Compliant" which means that the IFSI's are to stay away from interest bearing assets as well as limiting the use of derivative instruments was expected to make the IFSI's theoretically more stable. However, there is evidence to the opposite here when the M-GARCH t-DCC revealed that IFSI's are indeed much more volatile than their conventional counter parts and the market while being lower in correlation with the same counterparts.

The findings imply that while IFSI's experience high levels of volatility, it is seemingly independent of the market. There is also evidence of IFSI's having many observable spikes in volatility independent of the market suggesting that this is may be due to the operations of the institution itself. A possible explanation of this peculiar finding is that IFSI's experience risks that are unique to them as a result of the Islamic Financial contracts, products and services offered. Bacha (1997) points out that there is a lack of "bonding effect" in Islamic contracts such as Mudaraba which give rise to perverse incentives. Therefore, the volatility is likely to be caused by the performance of the assets that an IFSI holds that require it to take on risk to justify any earnings.

Upon closer investigation of the volatility by the MODWT Wavelet which allows the dissecting of variance, covariance and correlations into different time scales, it is observed that much of that volatility lies in the short term up until approximately 2 months, while the MODWT correlations provide evidence that suggesting that in the long run of 1 year the conventional finance services institutions are almost perfectly correlated with the market. Only Syarikat Takaful National Bhd was found to have almost no correlation with the market in the long run of 1 year. The implication for investors is that the conventional financial institutions do not have any diversification benefit in the long run of 1 year while the benefit is limited to Bank Islam Malaysia Bhd. The Syarikat Takaful National Bhd is a rare find for diversification opportunities but short term investors need to be wary of the volatility in the short term that may cause large fluctuations in returns.

The findings of this paper may suggest some policy recommendations for IFSI's. Firstly, it may be necessary to review the performance of IFSI's assets in general to determine the level of exposure that each type of asset carries. Assets that put the IFSI's at high levels of exposure or have a track record for non-performance should be scrutinized and made apparent their flaws for any risk management strategies to be made in order to mitigate their negative effects. Second, it may be that IFSI's needed more corporation in terms of developing risk management practices and instruments such as Islamic derivatives to counter such risks. Much of the risk management practices are borrowed from the conventional standards such as Basel 2 and 3, and while both provide some allowances for risk management in IFSI's it is arguably insufficient and needs further development that incorporates an understanding of the issues of risk from the IFSI's point of view. Third, it is necessary to continue to develop the Islamic finance industry for better stability amongst the IFSI's. Currently IFSI's function in a dual environment where they must compete with conventional finance, while it may be arguable that this had led to the development of the IFSI's having to compete, it does limit the IFSI's to mimic the conventional in their services and financing activities. As such, IFSI's have a different philosophy but operate with the same style in which the conventional do. The result may be negative as IFSI's experience the continuing tensions between needing to conform but preserve the philosophy of Islamic Finance.

This may have some ramifications to the operations and assets that the IFSIs hold. The development of the Islamic Finance industry as a whole may give strength to the IFSIs to be more innovative in their own, not to mention a larger base for risk sharing type financing.

Limitations of the paper

The findings of this paper must be interpreted with a grain of salt and represent a case study rather than definitive findings. One of the limitations is that the investigation here only included 2 IFSI's of BIMB and SKYT. This is hardly a proper representation of the IFSI industry as a whole. Indeed, these 2 IFSI's could be outliers in the world of Islamic Finance and thus do not represent the whole situation. For a better understanding of the big picture, it may be necessary to extend this study to include observations from different financial markets where Shariah screening exists such as the United States with the Dow Jones Shariah Screening to ascertain the performance of the any IFSI's there for robustness.

This paper also does not separate systematic risk form unsystematic risk. As a result it still remains to be investigated how much systematic risk is contributing to the high volatility experienced by IFSI's as studies such as, Khalfaoui, Boutahar (2011), Masih, Alzahrani and Al-Titi (2010), Fernandez (2006), Gencay, Selcuk, and Whitcher (2005) have provided empirical evidence that systematic risk exposure of a company or stock is different depending on the time scale.

Recommendations for further research

It would be interesting to extend the investigation made in this paper to include IFSI's from other markets and do a comparison for robustness. In addition calculating the systematic risk exposure at the different time scales would give vital information as to whether it is the assets of the IFSIs that are causing the volatility or if it is unsystematic risk, which points to in efficient management of the IFSI's as unsystematic risk can be diversified. Following In and Kim (2013b; 2013c), a sharp ratio at the different time scales could be calculated to gauge the level of efficiency of the IFSI's.

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