"Return performance, leverage effect, and volatility spillover in Islamic stock indices evidence from DJIMI, FTSEGII and KLSI"

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Abstract

Empirical studies on stock returns and volatility have not made serious attempt to examine these two issues on the context of Islamic stock market indexes. This paper, therefore, investigates the behavior of returns and volatility of three Islamic stock market indices − DJIMI, FTSEGII, and KLSI that are listed in the USA, the United Kingdom, and Malaysia respectively. Our paper examines four main issues: (1) whether there is a difference in returns among these Islamic stock market indices; (2) whether there is a risk premium in each stock exchange; (3) whether these indices face the leverage effect risk and lastly; (4) whether there is a volatility spillover among these three Islamic stock market indices. The empirical investigation is conducted by means of the GARCH model (GARCH-M) using daily data covering the period from January 1999 until October 2007. Not only our results show no significant difference in their returns, risk premium is found to be absent in each Islamic stock index. While KLSE reports no leverage effect, DJIMI and FTSEGII indicate otherwise. Finally, based on EGARCH and TARCH models there is a spillover from DJIMI and FTSEGII toward KLSI but not vice versa.

Keywords: Islamic index, volatility, GARCH, Spillover, DJIMI, FTSEGII, KLSI.
JEL Classification: G10, G11, G12, G15.

Introduction

Over the last twenty years there has been a continuous development in the conventional banking and finance to produce an Islamic counterpart to cater for Muslim population around the globe. One of these developments is the initiation of Islamic stock indices. An Islamic stock index measures the performance of a certain basket of securities and these securities are permissible for the Muslim to invest. The three popular Islamic stock market indices are Financial Times Stock Exchange Global Islamic index (FTSEGII) of the London Stock Market, Dow Jones Islamic Market Index (DJIMI) of the New York Stock Exchange and lastly, Kuala Lumpur Syariah Index (KLSI) of the Bursa Malaysia introduced between January 1998 and December 1999. Similar to conventional stock indices, these Islamic stock indices are designed to monitor the performance of some sectors of the financial markets, which the investment follows closely to the tenets of Islam. DJIMI and FTSEGII cover wide range of countries and stocks while KLSI covers only local listed stocks.

Past studies have concentrated on the performance of these three indices against their conventional counterparts. Theoretically, the value of any investment is determined by the present value of the investment's expected future cash flows. Subsequently, a rational investor maximizes his utility by maximizing his wealth and minimizing risk. A rational investor who wants to maximize his utility will choose the highest possible return for a given level of risk that can be achieved by constructing a well-

diversified portfolio. This applies to all portfolio investment decisions including screened investment funds such as the Islamic Mutual Funds. Given that not all stocks listed on the stock exchanges are permissible for the Muslims to invest, every fund manager of Islamic Mutual Funds has to obtain the approval from his company's Shariah Board before purchasing any new shares. The stricter screening criteria in screened investment as observed in the Islamic Mutual Funds have been argued as one of the reasons why screened investment in general brings lower expected return than unscreened investment (Rudd, 1981; Teper, 1991; Johnson and Neave, 1996; and Langbein and Posner, 1980). The low diversification benefits by screened investment resulted to in higher portfolio risk. On top of that, screened investment is also perceived to incur high administration and monitoring costs.

Following the work by Abdul Rahim, Ahmad and Ahmad (2009) that explores the volatility of Islamic indices in Malaysia and Indonesia, in this paper we examine the stock returns and volatilities in three Islamic stock market indices namely, FTSEGII, DJIMI and KLSI. This study is different from Abdul Rahim et al. (2009) study is four folds. First, this study uses three different stock market indices while Abdul Rahim et al. (2009) is studying two closely related markets Malaysia and Indonesia. Second difference is that Indonesian Islamic market index is rather small. It contains 30 listed companies while DJIMI and FTSEGII indices contain more than 1000 listed companies from many countries. Third, KLSI is list companies from Malaysia while FTSEGII and DJIMI include local and international firms from different countries and regions. Forth, the Islamic stock indices in these three markets have dis-

tinctive screening criteria. Having different screening criteria might lead to difference in returns. Therefore, the first question of this study is whether there is a significant difference between the three Islamic stock market indices.

Besides comparing their returns and volatility, we also examine the leverage effect of a fall in the security prices listed in DJIMI, FTSEGII and KLSI. According to Black (1976), volatilities and asset returns can be negatively correlated and this relationship is popularly known as the leverage effect. Brooks (2008) explains that leverage effect happens when a fall in the price of a firm's stock causes the firm's debt to equity ratio to increase. When the large decline in the equity price is not matched by the decline in the value of debt, the firm's debt to equity ratio will rise together with the financial risk of the firm's investors. Because of the higher risk, investors would expect the volatility of the stock return to rise also. Cheung and Ng (1992), Poon and Taylor (1992), Koutmos (1996) Koutmos and Booth (1995), Booth, Martikainen and Tse (1997) found that there is a significant leverage effect and bad news (i.e., decrease in stock prices) seem to have a greater influence on stock prices than good news (i.e., increase in stock price). If the Islamic indices screen high debt to equity ratio firms such as DJIMI and FTSEGII then they should minimize the leverage effect compared to KLSI which does not have any screening act against debt to equity ratio. This is because a company having a higher than the benchmark debt to equity ratio is excluded from the DJIMI and FTSEGII. Ulrich and Marzban (2008) that both Islamic and conventional finance agree that lower debt is better than higher debt because lower debt is interpreted as a positive investment signal. Both DJIMI and FTSEGII have a screening criteria based on the level of debt. Both indices eliminate firms that have debt ratios exceeding 33%. However, KLSI does not have any criteria against debt ratio. Based on this reasoning, we postulate that leverage effect to be prominent in KLSI but not in DJIMI and FTSEGII. In addition to that, the Islamic indices that yield low returns are expected to have higher risk and will not be compensated for the extra risk incur by screening. This study also examines whether the inclusion of debt ratio screen makes any difference.

Finally, Koutoms (1996) strongly suggests that studies investigating the information transmission in the first moment and second moment can be done based on returns and volatility, respectively. In addition to examining the stock market indices volatility, this study analyzes whether there is information transmission from KLSI to DJIMI and FTSEGII and

vice versa. The information transmission from one market to another has been widely reported. But majority of these studies are based on developed markets only (Antoniou, Pescetto and Violaris, 2003; Baur and Jung, 2006; Caporale, Pittis and Spagnolo, 2006; Koutoms, 1996; and Kasibhatla, Stewart, Sen and Malindretos, 2006). Only few studies examine the emerging markets (Daly, 2003; Lamba and Otchere, 2001; Shachmurove, 2005; and Soydemir, 2000).

Our paper therefore examines four main issues: (1) whether there is a difference in returns among these Islamic stock market indices, (2) whether there is a risk premium in each stock exchange, (3) whether these indices face the leverage effect risk; and lastly, (4) is there a volatility spillover among these three Islamic stock market indices. The empirical investigation is conducted by means of the GARCH model (GARCH-M) using daily data covering the period from January 1999 until October 2007. Not only our results show no significant difference in their returns, risk premium is found to be absent in each Islamic stock index. While KLSE reports no leverage effect, DJIMI and FTSEGII indicate otherwise. Finally, based on EGARCH and TARCH models for KLSI there is spillover from DJIMI and FTSEGII toward KLSI but not vice versa.

The remainder of the paper is organized as follows. Section 1 outlines the literature review while section 2 discusses the data and methodology employed. Section 3 analyzes the results and finally, the last section highlights the major conclusions and implications of the study.

1. Literature review

The investigation of volatility is a prominent issue in financial time series analysis. Many papers have been written using different methodology and variable to investigate different issues about volatility. This section will review some of these studies.

Yalama and Sevil (2008) employed seven different GARCH models to study the stock market volatility in 11 different markets using daily data from 1995 to 2007. They found that the best model to explain market volatility differ from one market to the other. Meanwhile, Yeh and Lee (2000) investigated the response of investors to unexpected returns and the information transmission in China, Hong Kong and Taiwan stock markets. Using GARCH model to analyze the asymmetric reaction of return volatility to good and bad news, they found that the impact of bad news of volatility is greater than the impact of good news in Taiwan and Hong Kong but not in China. Koulakiotis, Papasyriopoulos and Molyneux (2006) investigated whether the there is a relation-

ship between volatility and stock returns in 8 developed markets. Using weekly data and implementing GARCH-M and EGARCH-M, they found that there is a relationship between risk and returns in the GARCH-M model for the UK. Liao and Qi (2008) using daily data compared the risk and return in NYSE composite index and Shanghai stock index (SSI). They used ARCH, GARCH, TARCH, and EGARCH on both markets and found that the best model that fit SSI was EGARCH while TARCH was the best fit for NYSE composite index. In addition, they found that there is leverage effect in NYSE composite index but not in SSI. Moreover, they found that SSI volatility causes NYSE composite index but not vice versa.

A recent study by Abdul Rahim et al. (2009) uses developing countries' stock market data. They analyze the information transmission in both return and volatility between Jakarta Islamic index (JII) and Kuala Lumpur Syariah index. They report that there is information transmission that flows from KLSI to JII. However, the two stock indices are not highly correlated. The low correlation could be because these two stock exchanges do not cross list. Testing for leverage effect in both markets also proved insignificant. The unidirectionality in the transmission might be due to KLSI's higher market capitalization given that the number of shares included in KLSI is twenty times greater than JII.

Caporale et al. (2006) examined the interrelationships among the US, European and Japanese markets with the South East Asian markets by using three bivariate GARCH-BEKK models. Their findings show that South East Asian volatility depends positively on shocks from European markets and Japanese markets. Rashid and Ahmad (2008) evaluated the performance of linear and non-linear model of volatility in Karachi Stock Exchange (KSE) using daily data from 2001 to 2007. They found that GARCH-M is better than EGARCH in explaining the volatility in KSE. In addition, they found that there is risk premium or relationship between risk and returns in GARCH-M model. Regarding leverage effect in EGRACH, it was found that there is a leverage effect in KSE. Ozun (2007) examined the effect of developed stock markets on the returns of emerging markets using daily data from 2002 to 2006 and EGARCH model for volatility. The emerging markets used are Brazil and Turkey and the developed markets are Japan, the UK, France, Germany and the US. It was found that Brazil is affected by the lagged returns of all the markets except the US while France, the US and Japan, affected Turkey return. In term of leverage effect both indices have leverage effect. Kovačić (2008) investigated the leverage effect as well as the risk premium in the Macedonian Stock Exchange using daily data from 2005 to

2007. It was found that risk premium effect, is statistically weakly significant in all models with a negative sign indicating that as returns increase risk decreases. Similarly, in terms of leverage effect it was found that leverage effect is weakly significant.

Based on the above studies, this paper utilizes the models from the GARCH family. GARCH-M EGARCH-M and TARCH-M are used to test the risk premium, the mean and volatility spillover, and leverage effect in these three stock market indices. The detailed explanation of the methodology used is discussed in the next section.

2. Data and methodology

Rosly (2005) indicated that there are four main methods of screening. The first method is production approach where the activities of the company are the focus of the screening. The second method is the capital structure approach where the modes of finance of the company will be under Shariah screening. The third method is the income approach where the income of the company is scrutinized. The last method is the asset approach where company's assets are to be screened. Most of the Islamic indices do not follow a single method but a mixture of almost all of them. The difference is only in the extent of the focus. Some indices focus more on income and production but might be flexible in modes of finance. Others might emphasis more on the production than on income.

Unlike the previous studies, this paper examines the returns and volatility of three Islamic stock market indices in three different countries, the US, the UK and Malaysia. While the DJMI and FTSE screened indices follow the same screening criteria, KLSI in Malaysia follows different screening criteria. DJ and FTSE screened indices focus more on the income approach than the activity approach while KLSI tend to give greater weight on the activities of the company rather than their incomes. Therefore, it is not surprising that DJ Islamic market index and FTSE Islamic Global index follow the same set of screening criteria[1]. The first criterion is that the company's primary business must be permissible according to Islamic laws. Therefore, companies that engage in gambling, alcohol, armaments, tobacco, pornography, or pork are excluded from the list. Second criterion is that the company must meet specific financial constraints that include a debt ratio of equal or less than 33%, account receivables equals or less than 45% for FTSEGII and 33% for DJIMI. Finally, the company's interest income must be less than 5% for FTSEGII and 33% for DJIMI of its total revenue.

On the other hand, the screening criteria for Malaysia's KLSI excludes companies that have non-permissible

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[1] http://www.djindexes.com/mdsidx/downloads/rulebooks/imi_rulebook.pdf.

activities under Islamic laws such as gambling, gaming, alcohol, interest, etc. For companies with activities comprising both permissible and non-permissible elements, the Syariah Advisory Council (SAC) considers two additional criteria. First, the public perception or image of the company must be good. Second, the core activities of the company are important and considered beneficial to Muslims and the country, and the non-permissible element is very small and involves matters such as common plight, custom and the rights of the non-Muslim community. To determine the tolerable level of mixed contributions from permissible and non-permissible activities, the SAC has established several benchmarks based on reasoning from qualified Syariah scholars. If the contributions from non-permissible activities exceed the benchmark, the company is classified as non-Syariah compliant[1].

Time series data usually exhibit three main characteristics. First, they exhibit volatility clustering or volatility pooling. In other words, periods of high volatility is followed by periods of high volatility and the same applies for periods of low volatility. Second, their distribution is leptokurtosis, which mean that the distribution is fat-tailed. Third characteristic is the leverage effect. The leverage effect is the fact that bad news affects returns more than good news. In other words, changes in the prices tend to be negatively correlated with changes in volatility. Therefore modeling such series needs to be extended using other models. The first two characteristics have been successfully modeled using ARCH (Autoregressive Conditional Heteroscedasticity) by Engle (1982) and GARCH (Generalized Autoregressive Conditional Heteroscedasticity) developed by Bollerslev (1986). The idea of ARCH and GARCH is to model the variance of the error term from the mean equation on the previous squared error terms. If the mean equation is as follows.

$$Y_t = \alpha_i + \beta_1 X_t + \varepsilon_t, \qquad (1)$$

where Y_t is the dependent variable or returns in this case, X_t is the independent variable and ε_t is the error term and α_i and β_1 are the coefficients. The error term $\varepsilon_t \sim N(0, \sigma^2)$ is assumed to have zero mean and a constant variance or homoscedastic. However, it is unlikely in the financial time series that the variance of the error term be homoscedastic. Ignoring the fact that the variance of the error term is heteroskedastic will result in either over/under

estimation of the standard error and therefore bias inferences. To overcome this problem ARCH model is used. The arch model is as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2, \qquad (2)$$

where σ_t^2 is the conditional variance, ε_{t-1}^2 is the lagged term of the squared error term from the mean equation, and ω and α_i are the coefficients.

This model indicates that the variance of the error term is dependent on the lagged squared error term. Such model is referred to as ARCH (q), where q indicates the lag order of the squared error term in the variance equation.

Although ARCH model is capable of eliminating the heteroscedasticity in the mean equation, it still has some drawbacks that led to the development of GARCH model. GARCH model was developed by Bollerslev (1986) who indicated that a GARCH model with smaller number of terms can perform as well as or even better than ARCH model with many lags. The idea of the GARCH model is simply to include the lagged value of the variance in the variance equation. The GARCH model is as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_j \sigma_{t-j}^2, \qquad (3)$$

The first term in the right hand side is the ARCH term explained earlier, while the second term is the lagged variance that is GARCH. This model is referred to as GARCH (p,q) where (q) is the lagged ARCH term and (p) is the GARCH lagged term. The above model indicate that ω is the long-term average variance, α_i is the information about the volatility in the previous period, and the beta is the coefficient of the lagged conditional variance.

Although GARCH model is better than ARCH specification since it is more parsimonious and less likely to breach the non-negative constraint it is still does not account for the leverage effect in the apparent in financial time series and does not allow for any direct feedback between the conditional variance and the conditional mean.

Another extension of GARCH by Engle, Lilien and Robins (1987) is GARCH-M where either the standard deviation or the variance is included in the mean equation in order to test whether there is a risk premium or a tradeoff between risk and returns. This model is represented as follows:

$$Y_t = \alpha_0 + \beta_1 X_t + \theta_1 \sigma_t^2 + \varepsilon_t, \qquad (4)$$

where Y_t is the dependent variable or returns in this case, X_t is the independent variable, σ_t^2 is the conditional variance or the risk premium, and ε_t is the error term and α_0, θ_1 and β_1 are the coefficients. The

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[1] (1) The five-percent benchmark is used to assess the level of mixed contributions from the activities that are clearly prohibited such as Riba, gambling, liquor and pork. (2) The 10-percent benchmark is used to assess the level of mixed contributions from the activities that involve the element of common plight which is a prohibited element affecting most people and difficult to avoid. (3) The 25-percent benchmark is used to assess the level of mixed contributions from the activities that are generally permissible according to Syariah and have an element of benefit to the public, but there are other elements that may affect the Syariah status of these activities.

GARCH-M model allows time-varying volatility to be related to expected returns. An increase in risk, given by the conditional standard deviation leads to a rise in the mean return. The value of θ gives the increase in returns needed to compensate for a give increase in risk. Therefore, it is a measure of risk aversion.

One of the problems in GARCH is that it treats any shocks to the volatility as symmetrical. That is good news and bad news has the same effect. One of the methods used to overcome these issues in GARCH is

asymmetric GARCH. However, it was argued by previous studies such as Black (1976), Christie (1982), Engle and Ng (1993) that volatility responds asymmetrically to news especially bad news. Therefore, asymmetric GARCH is developed to overcome this problem. Two main models deal with asymmetric information EGARCH (Exponential GARCH) and TARCH (Threshold GARCH). Nelson (1991) developed the following equation to treat the asymmetry in the volatility:

$$\log \sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \frac{|\varepsilon_{t-i}|}{\sigma_{t-i}} + \sum_{i=1}^{q} \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{p} \beta_j \log\left(\sigma_{t-j}^2\right). \tag{5}$$

The left-hand side is the log of the conditional variance. This implies that the leverage effect is exponential, rather than quadratic, and that forecasts of the conditional variance are guaranteed to be nonnegative. The presence of leverage effects can be tested by the hypothesis that $\gamma < 0$.

While TARCH model was introduced by Zakoian (1994) and Glosten, Jagannathan and Runkle (1993). This model is designed to test whether there is asymmetric impact of news and whether there is a leverage effect. The specification of the TARCH model is as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} + \sum_{i=1}^{q} \beta_j \sigma_{t-j}^2 = 1 \beta_j \sigma_{t-j}^2, \tag{6}$$

where $d_{t-1} = 1$ if $\varepsilon_{t-1}^2 < 0$ and 0 otherwise. In this model, good news $\varepsilon_1(t-1)$, < 0, and bad news is ($\varepsilon_{t-1} < 0$), have different impact on the conditional variance whereby good news has the impact of α, while bad news has the impact of $\alpha + \gamma$, for the leverage effect if $\gamma > 0$ there is leverage effect on the other hand if $\gamma \neq 0$ then the news impact is asymmetric. Therefore, bad news causes more volatility in the market then good news.

In this paper, the EGARCH and TARCH are used to test whether there is any leverage effect in the three screened market. That is with there is an asymmetry in information.

The data used for this study will cover three Islamic indices namely, DJIMI, FTSEGII, and KLSI. The period of the study start from April 1999 to November 2007 on daily basis. Returns are calculated

using the compounded return formula. The calculation is done as follows:

$$R_{it} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right), \tag{7}$$

where R_{it} is the return for index i at time t, $P_{i,t}$ is the price for index i a time t and $P_{i,t-1}$ is the price of index i at time $t-1$.

Therefore, four equations will be tested here to answer this paper questions. First equation is the mean returns equation where each market returns will be regressed on its own lag and the other two market returns lags. Second equation is a GARCH-M (1,1) to test whether there is any trade off between risk and returns and the effec of the volatility of each index on itself. The third and forth equations are two different methods of test the leverage effect in each stock market indices. The equation is as follows:

$$r_{DJIMI,t} = \alpha_0 + \sum_{i=1}^{t} \beta_i r_{DJIMI,t-1} + \varphi \sigma_t^2 + \delta_1 \varepsilon_{KLSI-DJIMI,t}^2 + \varepsilon_t, \tag{8}$$

$$\sigma_{DJIMI,t}^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_i \sigma_{t-j}^2 + \delta_1 \varepsilon_{KLSI-DJIMI,t-1}^2, \tag{9}$$

$$\log\left(\sigma_{DJIMI,t}^2\right) = \omega + \sum_{i=1}^{q} \alpha_i \frac{|\varepsilon_{t-i}|}{\sigma_{t-i}} + \sum_{i=1}^{q} \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{p} \beta_j \log\left(\sigma_{t-j}^2\right) + \delta_1 \varepsilon_{KLSI-DJIMI,t-1}^2, \tag{10}$$

$$\sigma_{DJIMI,t}^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \delta_1 \varepsilon_{KLSI-DJIMI,t-1}^2, \tag{11}$$

Equation (8) is the return equation where r is the daily return for DJIMI regressed on its lagged, σ_t^2 is the variance of DJIMI index, which represent the risk and return trade off, and ε_t^2 is the error term. Equation (9) is the variance equation where σ_t^2 is the conditional variance, ε_{t-i}^2 is the lagged term of the squared error term from the mean equation, σ_{t-j}^2 is the lagged conditional variance, and ω, α_j, and β_i, are the coefficients as in equation (3). Equations (10) and (11) are EGARCH and TARCH models that are used in this study. The same four equations will be run for each market.

3. Results and analysis

Figure 1 shows the returns of the three indices. From the return graphs, it is clear that the mean returns are constant, however the variance change overtime for these indices. It is evident that volatility tends to cluster, i.e., changes in volatility whether big or small tends to persist. It is evident that DJIMI and FTSEGII moves together almost during the whole period of the study which explains the strong or almost perfect correlation. It also shows that there was a lot of volatility between 1999 and 2003. On the other hand, KLSI seems not replicate the movement on those two indices however in term of volatility it has the same period of higher volatility as those two indices.
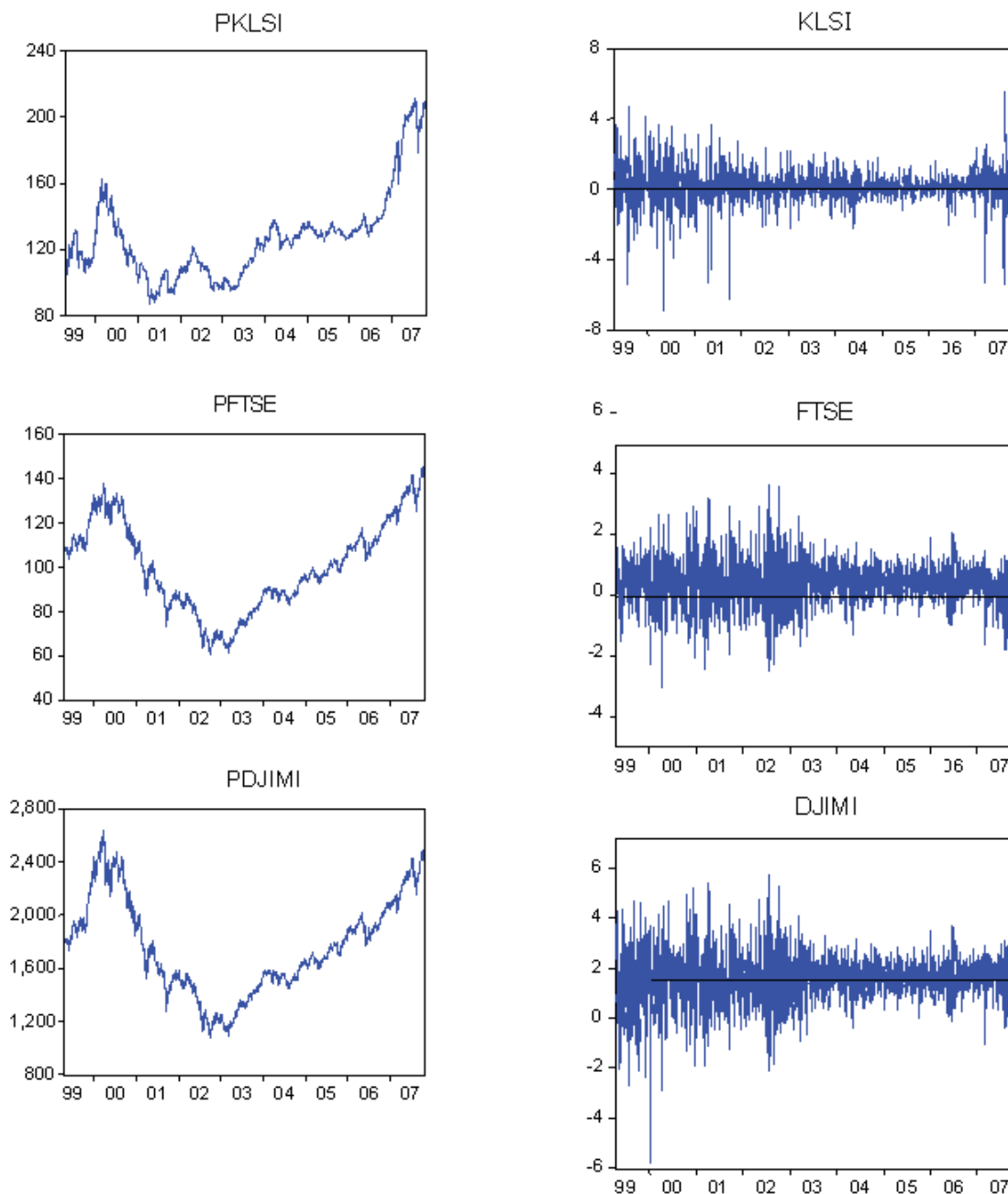

Fig. 1. Plot of closing prices and returns for DJIMI, FTSEGII and KLSI

Figure 2 plots histogram of returns for each market index against the normal distribution. It shows that various returns fall beyond four standard deviations which is unlikly in normal distribution. This kind of distribution is called to have heavy tails. The distribution of the returns in these markets show that it is also leptokurtic or has highest peak. A quantile-quantile (Q-Q) plot on the other hand is a tool to check whether two distributions are the same, i.e, normal distribution against the series distibution. If both distributions are similar, the plot is assumed to be linear. In this Figure 2, both distributins appear to be different. The returns deviate from the stringht line and this confirms the heavy tails and high peakedness characteristic of the returns.
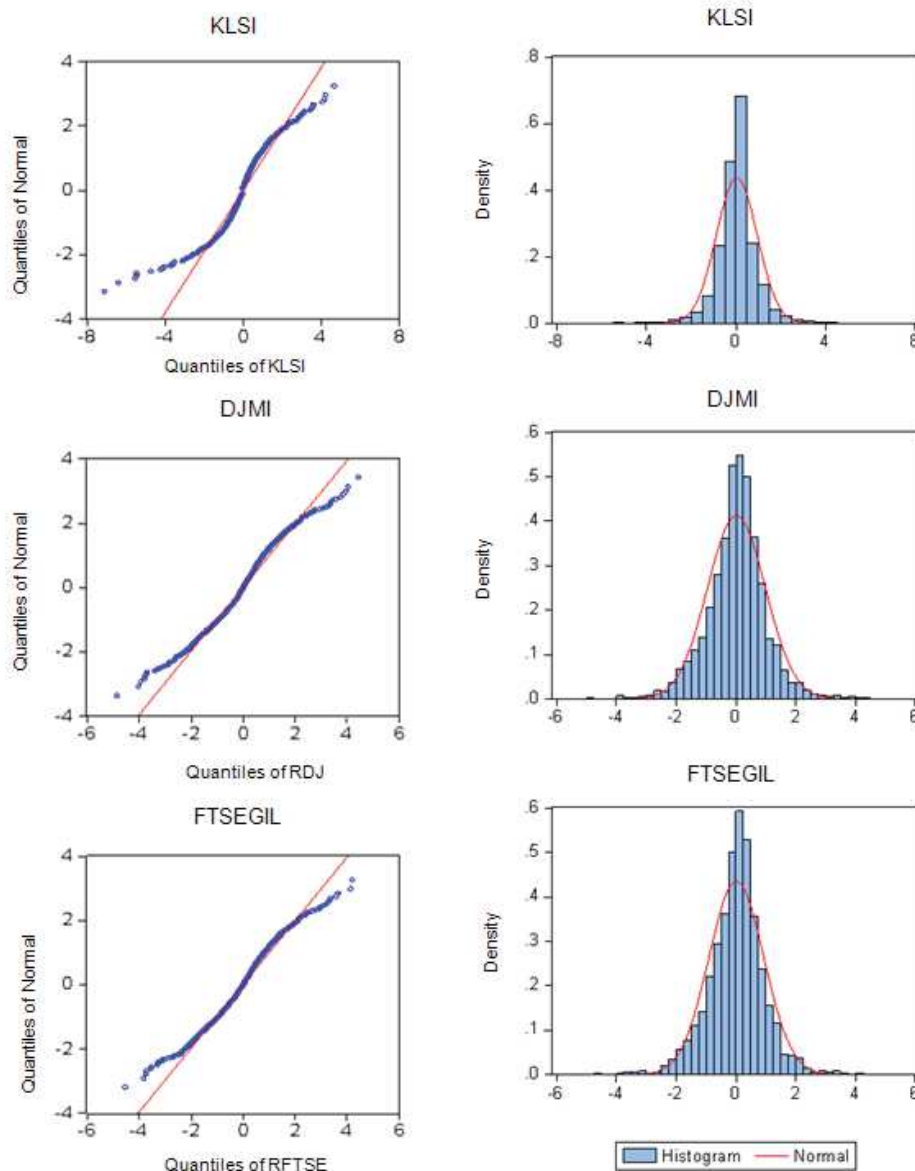

Fig. 2. Normalized returns distribution and Q-Q plot

Table 1 displays the descriptive properties of the returns of DJIMI, FTSEGII, and KLSI from April 1999 to October 2007. Total observations in this study are 2228 observations. The mean returns of the three indices are positive. The KLSI has the highest return of 0.035 (12.8% annually) while DJIMI (5.8% annually) and FTSEGII (5.1% annually) have lower returns at 0.016 and 0.0143, respectively. In term of volatility, KLSI has the lowest volatility followed by FTSEGII and finally the highest volatility is DJIMI. Although the financial theory indicates that higher volatility must be compensated by higher returns this is not the case in these three indices. KLSI has the highest returns but the lowest volatility. DJIMI seems to earn lower return than KLSI. However, the former reports higher volatility. The returns of all the three indices are negatively skewed and leptokurtic. This indicates that their returns are asymmetric. In addition, the three indices are not normally distributed based

on J-B test of normality. Meanwhile, the Ljung-Box autocorrelation test on returns and returns squared at 10 lags. It indicates that linear and non-linear dependencies exist in the first and second moment. Linear dependency might be explained as market inefficiency (Koutmos, 1996; Koutmos and Booth, 1995; and Kovačić, 2008). On the other hand, non-linear dependency might indicate the presence of GARCH effect (Kovačić, 2008).

Table 1. Descriptive statistics of DJIMI, FTSEGII and KLSI returns

	DJIMI	FTSEGII	KLSI
Mean	0.016	0.014	0.035
Std. dev.	0.968	0.918	0.913
Skewness	-0.116	-0.105	-0.590
Kurtosis	5.015	4.931	10.402
Jarque-Bera	382*	350*	5215*
LB (10)	63.97*	57.19*	89.97*
LB2 (10)	746.51*	625.18*	301.18*

Note: * Significant at 1 %.

Table 2 shows the correlation coefficient or the unconditional correlation between the three indices returns. The correlation between DJIMI and FTSEGII is the highest reaching almost one which indicate perfect correlation. However, the correlation between KLSI and each index is about 0.13 that indicate very weak but positive and significant relationship. This low correlation between DJIMI and FTSEGII can be an indication that these indices movements do not affect KLSI. This is might be because DJIMI, FTSEGII are in developed markets, while KLSI is in a developing market. Another reason could be that DJIMI and FTSEGII might have many firms that are cross-listed in both indices while KLSI does not have this characteristic. This low correlation between KLSI and both DJIMI and FTSEGII can be useful in term of diversification by investors.

Table 2. Simple correlation coefficient for the returns of DJIMI, FTSEGII and KLSI

Variable	FTSEGII	KLSI
DJIMI	0.983*	0.133*
FTSEGII	1	0.129*
KLSI	0.129	1

Note: * Significant at 1 %.

Table 3 displays the results of the difference in mean returns t-test. The result in all cases indicates that there is no difference in mean returns among the three indices.

Table 3. T-test for difference in mean returns

Returns	T-test value
DJIMI and FTSEGII	-0.0517
DJIMI and KLSI	0.673
KLSI and FTSEGII	0.745

Table 4 reports the results of Augmented Dickey fuller (ADF) test. The purpose of this test is to find out whether these series are stationary by testing the null hypothesis that the series have unit root. From the results, it is clear that all the stock markets returns are stationary in the mean but not in the variance.

Table 4. ADF unit root test

	KLSI	DJIMI	FTSEGII
None	-39.57*	-40.55*	-41.07*
Trend & intercept	-39.63*	-40.57*	-41.12*
Intercept	-39.61*	-40.55*	-41.07*

Note: * Significant at 1%.

Table 5 reports the results of three estimations, GARCH-M, EGARCH-M, and TARCH-M as specified in equations (9), (10) and (11). These three estimations models were done for KLSI, DJIMI, and FTSEGII. Since DJIMI and FTSEGII have almost a perfect correlation between them, the estimations below were done in two markets relationship (i.e., KLSI with DJIMI without FTSEGII and KLSI with FTSEGII without DJIMI) rather than three markets to avoid biasness in the results. In the returns equation of KLSI with DJIMI and KLSI with FTSEGII, it is evident that KLSI is affected positively by its own one-day lag, one-day lag of DJIMI and one-day lag of FTSEGII. This result indicates that there is a spillover in returns from DJIMI and FTSEGII on KLSI. In addition, the coefficient of the risk returns trade off (θ) is not significant in any of the three models. In the variance equation, the coefficient α_1 and β_1 are positive and significant in all the three estimations indicating that KLSI current volatility is affected by its past volatility. The coefficient γ_1, which is supposed to test the asymmetry in the market, is not significant in any of the models indicating that there is no leverage effect. Moreover, the coefficient measuring the spillover from DJIMI to KLSI and from FTSEGII to KLSI are significant in the GARCH-M model pointing to the fact that there is spillover from DJIMI and FTSEGII towards KLSI. In other words, there is information transmission from DJIMI and FTSEGII volatilities to KLSI volatility. The half-life[1], which measure the period it takes a shock to decay into the future, for GARCH-M effect is 17.9 days for KLSI with DJIMI and 18.4 days for KLSI with FSEGII, respectively. It is clear that it takes longer for the shock in volatility to disappear in the KLSI with FTSEGII estimation than in KLSI with DJIMI estimation. To determine the best model among the three models the log likelihood criteria is used. From the table it is clear that

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[1] Half-life = In(0.5)/In($\alpha_{1+}\beta_1$).

GARCH-M model is the best fit where log likelihood is the minimum. For all the models, an ARCH test was done to test for heteroscedasticity in the three models. The results of ARCH in lag 1 and 10 suggest that there is no problem of heteroscedasticity.

Table 5. Parameter estimates of fitting GARCH (1,1), EGARCH and TARCH for KLSI from 1999-2007

Coefficient	GARCH-M		EGARCH		TARCH	
θ	0.044	0.046	0.035	0.030	0.033	0.035
C	0.008	0.006	0.008	0.012	0.007	0.006
FTSEGII (-1)		0.204*		0.197*		0.204*
DJIMI (-1)	0.194*		0.192*		0.195*	
KLSI (-1)	0.158*	0.157*	0.161*	0.161*	0.160*	0.159*
ω	0.010*	0.011**	-0.164*	-0.160*	0.011*	0.011*
α_1 (ARCH)	0.095*	0.095*	0.206*	0.200*	0.078*	0.079*
β_1 (GARCH)	0.894*	0.893*	0.977*	0.978*	0.892*	0.891*
γ_1			-0.027	-0.022	0.034	0.032
DJIMI to KLSI ($\delta \downarrow 1$)	-0.027**		-0.057***		-0.024***	
FTSEGII to KLSI ($[\delta] \downarrow 2$)		-0.028**		-0.069		-0.026***
Log likelihood	-2467	-2465	-2465	-2462	-2465	-2463
ARCH (1)	0.267	0.198	0.700	0.580	0.115	0.072
ARCH (10)	11.60	11.75	16.35	16.49	12.96	12.42

Note: *, ** and *** significant at 1%, 5%, and 10% respectively. KLSI is the dependant variable.

Table 6 reports the results for the estimation of DJIMI on KLSI. In the returns equation, the coefficient θ is not significant indicating that there is no risk premium in DJIMI. On the other hand, it is clear that DJIMI is affected positively by its own lag and negatively by KLSI lagged returns in GARCH-M model only.

In the variance equation, the coefficients for ARCH are significant in the first two estimations while GARCH coefficient is significant in all the models estimated. The coefficient γ_1 in EGARCH and TARCH models is negative and positive respectively, and significant implying that there is a leverage effect and asymmetry of news. This means that bad news has a greater effect on volatility than good news. The spillover effect coefficient from KLSI to DJIMI is not significant in all the models indicating that there is no transmission of information from KLSI volatility to DJIMI volatility. The half-life in this case is 10.8 days for half of the shock to disappear into the future. GARCH-M is the best fit based on log likelihood criteria. ARCH diagnostic test for the heteroscedasticity indicate that in lag 1 and 10 there is no problem of heteroscedasticity.

Table 6. Parameter estimates of fitting GARCH (1,1), EGARCH and TARCH for DJIMI from 1999-2007

DJIMI	GARCH-M (1,1)	EGARCH	TARCH
θ	-0.006	-0.004	-0.014
C	0.048	0.023	-0.032
KLSI (-1)	-0.040***	-0.037	-0.030
DJIMI(-1)	0.147*	0.147*	0.150*
ω	0.005**	-0.075*	0.006*
α_1 (ARCH)	0.053*	0.092*	0.002
β_1 (GARCH)	0.942*	0.991*	0.949*
γ_1		-0.054**	0.082*
KLSI to DJIMI ($\delta \downarrow 1$)	0.010	0.029	0.020
Log likelihood	-2789	-2772	-2767
ARCH (1)	0.468	0.432	1.32
ARCH (10)	8.93	9.49	6.89

Note: *, **, *** significant at 1%, 5%, and 10% respectively. DJIMI is the dependant variable

Table 7 reports the results for the estimation of FTSEGII on KLSI. In the return equation for there is no risk premium in this market. In addition, FTSEGII current return is affected positively and significantly by its own lagged returns and negatively by one lag of KLSI in the first model only.

In the variance equation, the coefficients for ARCH are significant in the first two estimations while GARCH coefficients are significant in all the models estimated. In addition, the leverage effect coefficient in the EGARCH and TARCH models is significant. It is negative in the EGARCH and positive in the TARCH model. This indicates that there is a leverage effect and bad news has higher impact than good news on the index volatility. The spillover effect from KLSI to FTSEGII is not significant in any of the models, which indicate that there is no information transformation from KLSI volatility towards FTSEGII volatility. The half-life in this case is 11.2 days for half of the shock to disappear in the future. Based on the log likelihood criteria it is clear that GARCH-M model is the best model. ARCH diagnostic test for the heteroscedasticity indicate that in lag 1 and 10 there is no problem of heteroscedasticity.

Table 7. Parameter estimates of fitting GARCH (1,1), EGARCH and TARCH for FTSEGII from 1999-2007

FTSEGII	GARCH-M (1,1)	EGARCH	TARCH
θ	-0.005	-0.002	-0.004
C	0.046	0.012	0.022
KLSI(-1)	-0.039***	-0.035	-0.027
FTSEGII(-1)	0.149*	0.150*	0.151*
ω	0.005**	-0.065*	0.005*
α_1 (ARCH)	0.054*	0.078*	-0.006
β_1 (GARCH)	0.941*	0.989*	0.953*
γ_1	–	-0.065*	0.091*
KLSI to FTSEGII ($\delta \downarrow 1$)	0.008	0.027	0.016
Log likelihood	-2701	-2678	-2674
ARCH (1)	1.26	1.26	2.14
ARCH (10)	11.9	14.43	10.58

Note: *, ** and *** significant at 1%, 5%, and 10% respectively. FTSEGII is the dependant variable.

To summarize, from the above models it is clear that none of the markets has risk-returns trade off. In other words, there is no relationship between the stock returns of any of these markets and their volatility. All the indices are affected positively by their own lagged returns. In addition lagged returns of DJIMI and FTSEGII are affecting KLSI returns positively indicating information transformation from these markets into KLSI. On the other hand, KLSI has a negative one-lagged effect on both DJIMI and FTSEGII in the GARCH-M model only. The variance equations indicate that the coefficient of α_1 and β_1 significant and positive in most of the cases indicating that past fluctuations has positive influence on the future volatility. In addition, β_1 is big and significant indicating that returns has long-term memory or the fluctuations are persistent. Moreover, there is leverage effect in DJIMI and FTSEGII only but not in KLSI. The leverage effect indicates that these markets become volatile when there is a large decrease in the prices (i.e., bad news). When prices of a stock fall this causes debt to equity ratio to increase leading shareholder to perceive that this stock is more risky. This is somehow perplexing. Both DJIMI and FTSEGII have strict screening criteria regarding debt ratio, which must not exceed 33%, while KLSI does not have any screen against debt ratio. In addition, there is asymmetric effect of news in these DJIMI and FTSEGII since $\gamma_1 \neq 0$. Therefore, bad news has stronger impact than good news in DJIMI and FTSEGII but not KLSI.

Lastly, in terms of spillover or information transmission, it is clear that there is evident spillover from KLSI to both DJIMI and FTSEGII but not vice versa. This means that there a transmission of information from KLSI to DJIMI and FTSEGII markets. Therefore, volatility in KLSI affects DJIMI and FTSEGII but not vice versa.

Conclusion

Our results suggest that there is no significant difference in stock market returns between the three Islamic stock market indices, KLSI, DJIMI, and FTSEGII. Therefore investing in any of them will yield the same returns. In addition, it was found that there is no risk premium in any of the three markets. Moreover, our results show that there is leverage effect risk in the case of DJIMI and FTSEGII but not KLSI. These two Islamic stock market indices seem to be affected more by bad news than good news, which could be due to their larger market capitalization than KLSI. Moreover, DJIMI and FTSEGII are international indices while KLSI is a local index. In addition, there is asymmetric impact of news on volatility, which means that bad news has a greater effect on volatilities than good news. Based on the half-life values the market that reverts to mean faster is DJIMI followed by FTSEGII and lastly KLSI. It means that KLSI take longer time to revert to it mean or for any shock in volatility to decay. This could be because both DJIMI and FTSEGII includes securities from different countries and have a larger number of stocks then KLSI which includes local stocks and is smaller compared to DJIMI and FTSEGII. Lastly, there is information transmission DJIMI and FTSEGII from toward KLSI but not vice versa. This might be a result of cross listing of some securities in KLSI at DJIMI and FTSEGII but not vice versa.

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