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Full Length Research Paper

Return performance and leverage effect in Islamic and socially responsible stock indices evidence from Dow Jones (DJ) and Financial Times Stock Exchange (FTSE)

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Empirical studies on stock returns and volatility have not made serious attempt to examine these two issues on the context of Islamic and socially responsible stock market indices. This paper therefore investigates the behavior of returns and volatility of three Islamic and socially responsible stock market indices, Dow Jones Islamic Market Index (DJIMI), DJSIW, Financial Times Stock Exchange Global Islamic index (FTSEGII) and Financial Times stock exchange For Good (FTSE4G) that are listed in the USA and United Kingdom, respectively. The paper examines four main issues: (i) whether there is a difference in returns among these screened stock market indices, (ii) whether there is a risk premium in each stock index, and (iii) whether these indices face the leverage effect risk. The empirical investigation is conducted by means of the Generalized ARCH- GARCH model (GARCH-M) using daily data covering the period from January1999 until October 2007. Not only does the results show no significant difference in their returns, risk premium is found to be absent in each Islamic stock index. All the screened indices reports leverage effect, indicating that bad news has more effect on price volatility than good news.

Key words: Screened index, socially responsible, Islamic indices, generalized ARCH (GARCH), exponential GARCH (EGARCH).

INTRODUCTION

Socially responsible, has grown substantially in the past three decades. It started by some investors avoiding “sinful” investment and investing in what they believed good. Socially responsible or ethical investments have emerged in the beginning of the 20th century. The purpose of these types of investments is to avoid investing in companies that produce, sell, or even contribute directly or indirectly in products or services that contradict with their values and beliefs. There are many socially responsible investments (SRI) around the world but two of the most important and studied are Dow Jones Socially responsible world index (DJSIW) and Financial Times stock exchange For Good (FTSE4G). Similarly, 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 market indices. An Islamic stock index measures the performance of a certain basket of securities that are permissible for the Muslim to invest. The two 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. Similar to conventional stock market indices, these Islamic and socially responsible stock market indices are designed to monitor the performance of many sectors of the economy, which follows closely, the tenets of Islam. DJIMI, DJSIW, FTSE4G, and FTSEGII cover wide range of countries and stock markets.

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

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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 expec-ted return than unscreened investment (Rudd, 1981; Teper, 1991; Johnson and Neave, 1996; Langbein and Posner; 1980). The low diversification benefits enjoyed by screened investment resulted in higher portfolio risk. On top of that, screened investment is also perceived to incur high administration and monitoring costs.

Past studies have concentrated on the performance of these four indices against their conventional counterparts. Lack of evidence from studies done in examining the relationship between socially responsible and Islamic investments is one of the contributions of this study. In addition, previous studies suggested that Islamic investments performed better than the non-Islamic or non-screened investments (Hussein, 2004; Hussein and Omran, 2005). However, nothing has been done to compare Islamic and socially responsible indices against their counterparts.

Another point is that the Islamic indices under Dow Jones and FTSE require companies to meet a maximum of 33% of debt to equity ratio while the socially responsible indices do not have such a screening criteria. This could lead to either over-performance or under-performance of the Islamic indices compared to the socially responsible indices. This is because the financial theory indicates that large companies tend to borrow more than small companies, and that might cause many large companies to be excluded from the Islamic indices since large companies are highly leveraged.

Moreover, to the researcher knowledge there is a shortage in studies done on volatility, risk premium and leverage effect of screened stock market indices. This is beneficial to investors since volatility is strongly related to risk and risk is one of the main characteristic to formulate a good investment portfolio.

Hussein and Omran (2005) argued that the screening process in the DJIMI removed companies six months before they eventually collapsed and lost its entire value (examples Enron, WorldCom, and Tyco). Hussien and Omaran (2005) found that DJIMI out-performed its counterparts in the bull period as well as the entire period of the study while it underperformed its counterpart in the bear period of the study.

Similarly, Hussein (2004), using raw returns and risk-adjusted returns, found that DJIMI and FTSEGII out-performed their counterparts in the entire period and in the bull period of the study, however, DJIMI and FTSEGII under-performed their counterparts in the bear period of the study.

This being said, this paper aims to investigate the following questions. First is there a significant difference in mean returns between socially responsible (SR), Islamic indices, and their counterpart indices. Second, is there a risk premium effect in socially responsible and Islamic indices? Third, is there a leverage effect in any of these indices?

LITERATURE REVIEW

The investigation of volatility is a prominent issue in financial time series analysis. Many papers have been written using different methodology and variables 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 from1995 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 et al. (2006) investigated whether there is a relationship 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 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 a 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 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 uni-directionality 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 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, UK, France, Germany and US. It was found that Brazil is affected by the lagged returns of all the markets except US, while France, US and Japan, affected turkey return. In terms 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.

DATA AND METHODOLOGY

Unlike previous studies, this paper examines the returns and volatility of four screened stock market indices in two different countries, the US and UK. DJMI and FTSE follow the same screening criteria. 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 of included companies. The second criterion is that the company must meet specific financial ratios, which 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% and 33% of total revenues for FTSEGII and DJIMI, respectively.

On the other hand, SR indices follow different criteria in both DJ and FTSE. DJ Sustainability World Index follows corporate sustainability criteria in order to include a company in its index. It follows integrated assessment of economic, environmental, and social criteria with a strong focus on long-term shareholder value. The methodology used can be found in their website. However, FTSE4GOOD start with excluding tobacco producers, companies manufacturing either whole, strategic parts, or platforms for nuclear weapon systems and companies manufacturing whole weapons systems. The second step is to include firms that work towards environmental sustainability, develop positive relationships with stakeholders, up-hold and support universal human rights, and ensuring good supply-chain labor standards and counter bribery.

Time series data usually exhibit three main characteristics. First, they exhibit volatility clustering or volatility pooling. In other words, periods of high volatility will be 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 peaked. 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 follow:

$$Y_t = \alpha_i + \beta_1 X_t + \varepsilon_t \tag{1}$$

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 homoskedasticity. 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 follow:

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

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, 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) indicate 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 follow:

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

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 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 et al. (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 follow:

$$Y_t = \alpha_0 + \beta_1 X_t + \theta_1 \sigma_t^2 + \varepsilon_t \tag{4}$$

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 and β_1 are the coefficients. The 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 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 under EGARCH:

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

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 non-negative. The presence of leverage effects can be tested by the hypothesis that γ < 0.

While TARCH model was introduced by Zakoian (1994) and Glosten et al. (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 follow:

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

Where d_{t-1} = 1 if ε_{t-1}^2 < 0 and 0 otherwise. In this model, good news ($\varepsilon_{t-1} > 0$) 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 $\alpha + \gamma$. If $\gamma > 0$, there is leverage effect while on the other hand, if $\gamma \neq 0$ then the news impact is asymmetric. Therefore, bad news causes more volatility in the market than 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 if there is an asymmetry in information. The data used for this study will cover four indices which are, DJIMI, FTSEGII representing Islamic indices and DJSIW and FTSE4G representing SR indices. The counterpart indices or the non-screened indices are DJ industrial average and FTSE All-World indices. The period of the study starts from January 1999 to December 2007 on daily basis. Returns are calculated using the compounded return formula. The calculation is done as follows:

$$R_{it} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \times 100 \tag{7}$$

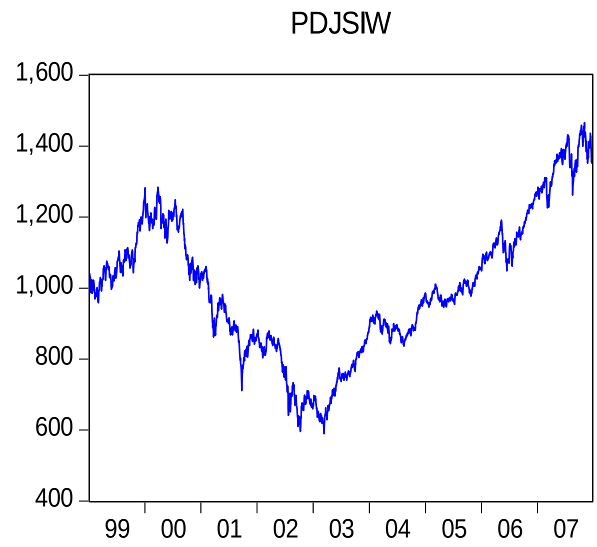
Where R_{it} is the return for index i at time t, $P_{i,t}$ is the price for index i at time t and $P_{i,t-1}$is the price of index i at time t-1.

RESULTS AND ANALYSIS

Figure 1 shows the prices and the returns of the six indices. Prices of each index in each group seem to follow each other's movements. It is evident that the prices of all the indices fell together in the second quarter of 2000 but all the indices started to gain momentum at the first quarter of 2003. 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, that is, changes in volatility, whether big or small tends to persist. It is evident that Dow Jones and FTSE stock market returns indices moves together almost during the whole period of the study. It also shows that there was a lot of volatility between 1999 and 2003.

Figure 2 plots histogram of returns for each market index against the normal distribution. It shows that returns fall beyond four standard devations which is unlikely in normal distribution. This kind of distribution is called leptokurtic. The distribution of returns in these markets show that it is also leptokurtic or has high peak. A quantile-quantile (Q-Q) plot on the other hand is a tool to check whether the two distributions are the same, that is, normal distribution against the series distibution. If both distributions are similar, the two distributions are identical, the distribution is said to be normal. However, if it is flatter or steeper, the distribution is no longer normal. In Figure 2, both distributions appear to be different. The returns deviate from the straight line and this confirms the heavy tails and high peakedness characteristic of the returns.

Tables 1and 2 display the descriptive properties of the stock market returns indices of DJIMI, DJINA, DJSIW, FTSEGII, FTSEW, and FTSE4G from April 1999 to December 2007. Total observations in this study are 2340 observations for each index. The mean return of all the indices is positive. DJIMI and DJINA have the highest return of 0.016 while DJSIW has lower returns at 0.0131. In contrast, FTSEW has the highest return of 0.017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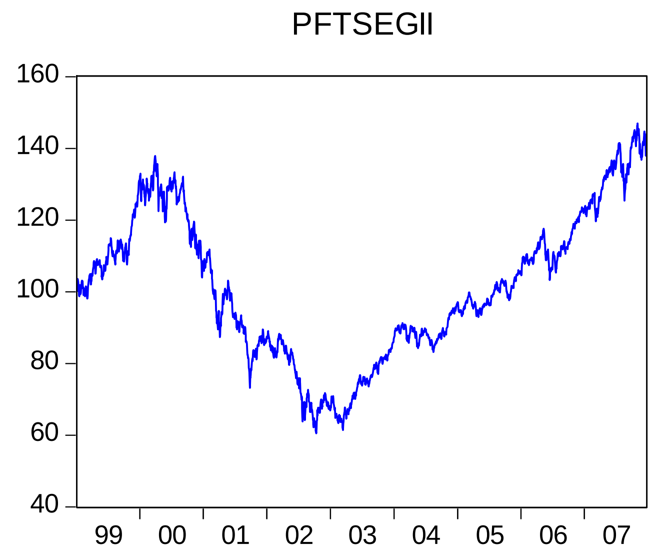
1,200
1,000
800
600
400
99 00 01 02 03 04 05 06 07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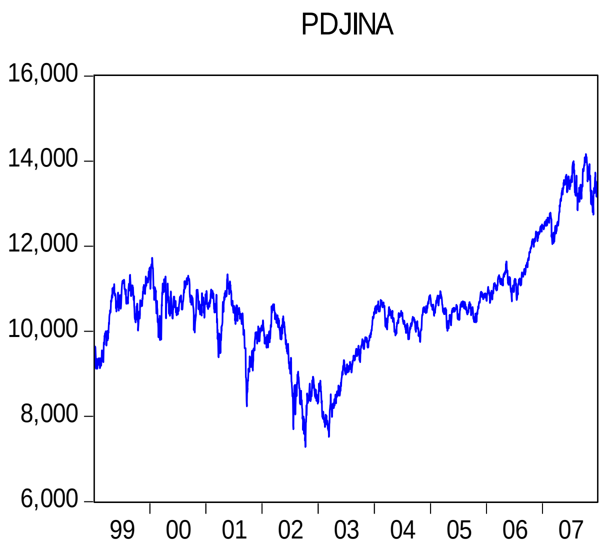
140
120
100
80
60
40
99 00 01 02 03 04 05 06 07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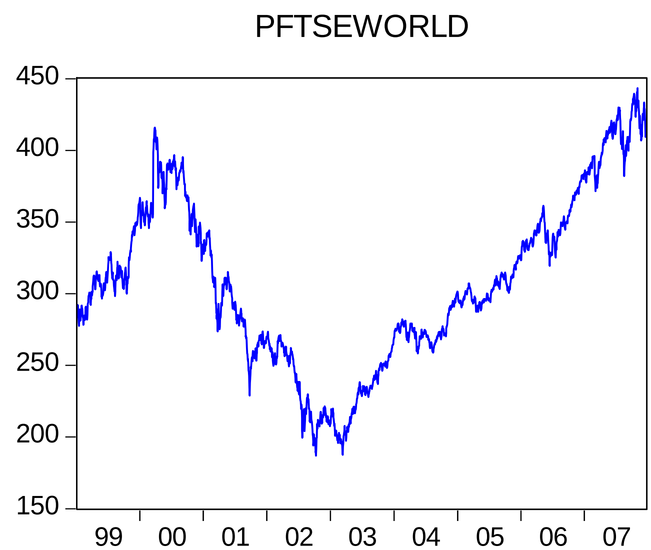
6,000
99 00 01 02 03 04 05 06 07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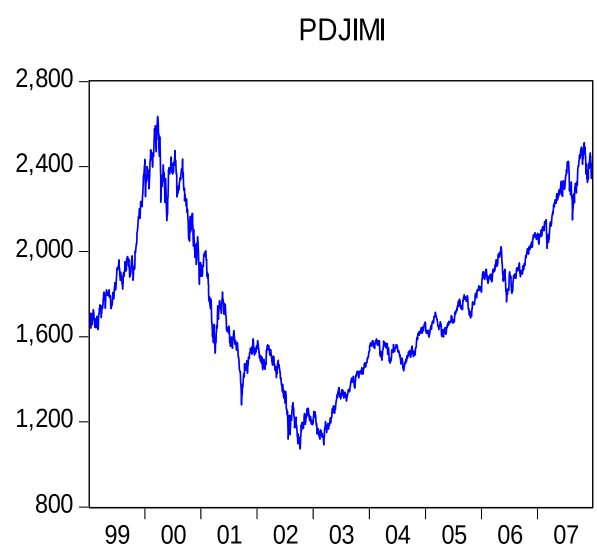
250
200
150
99 00 01 02 03 04 05 06 07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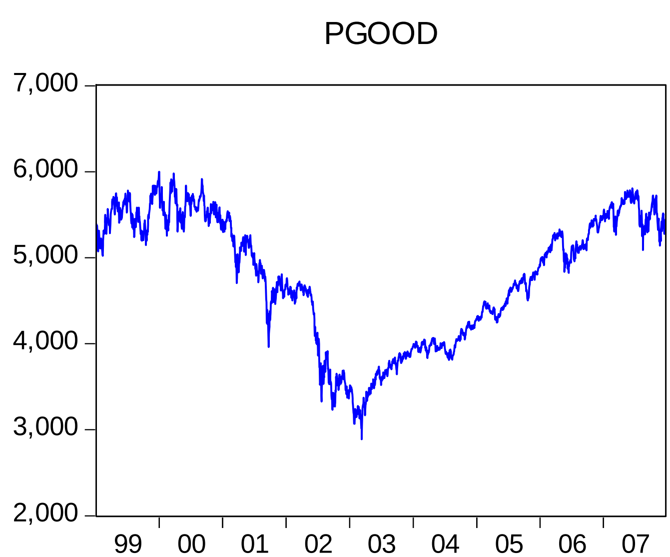
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5,000
4,000
3,000
2,000
99 00 01 02 03 04 05 06 07

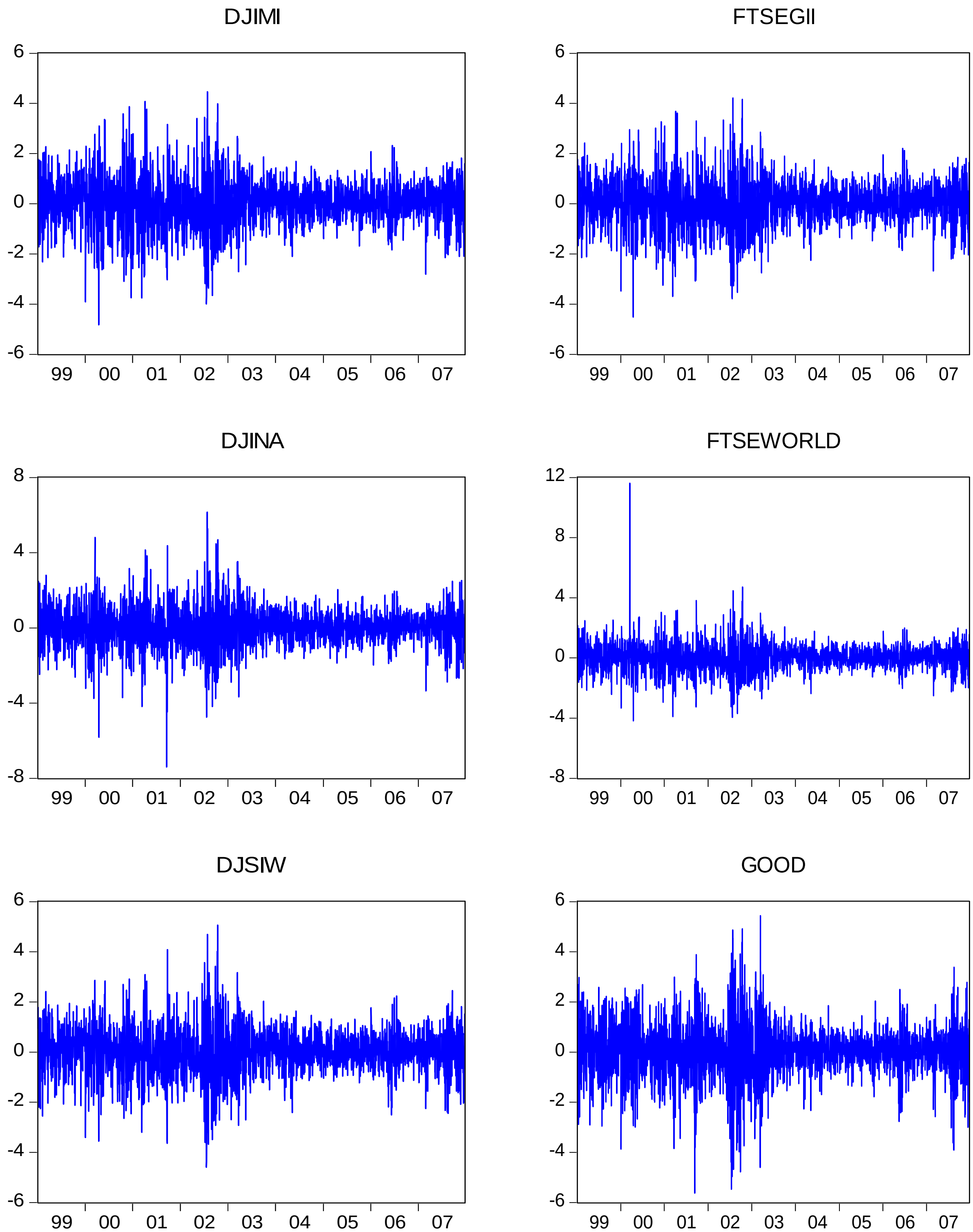
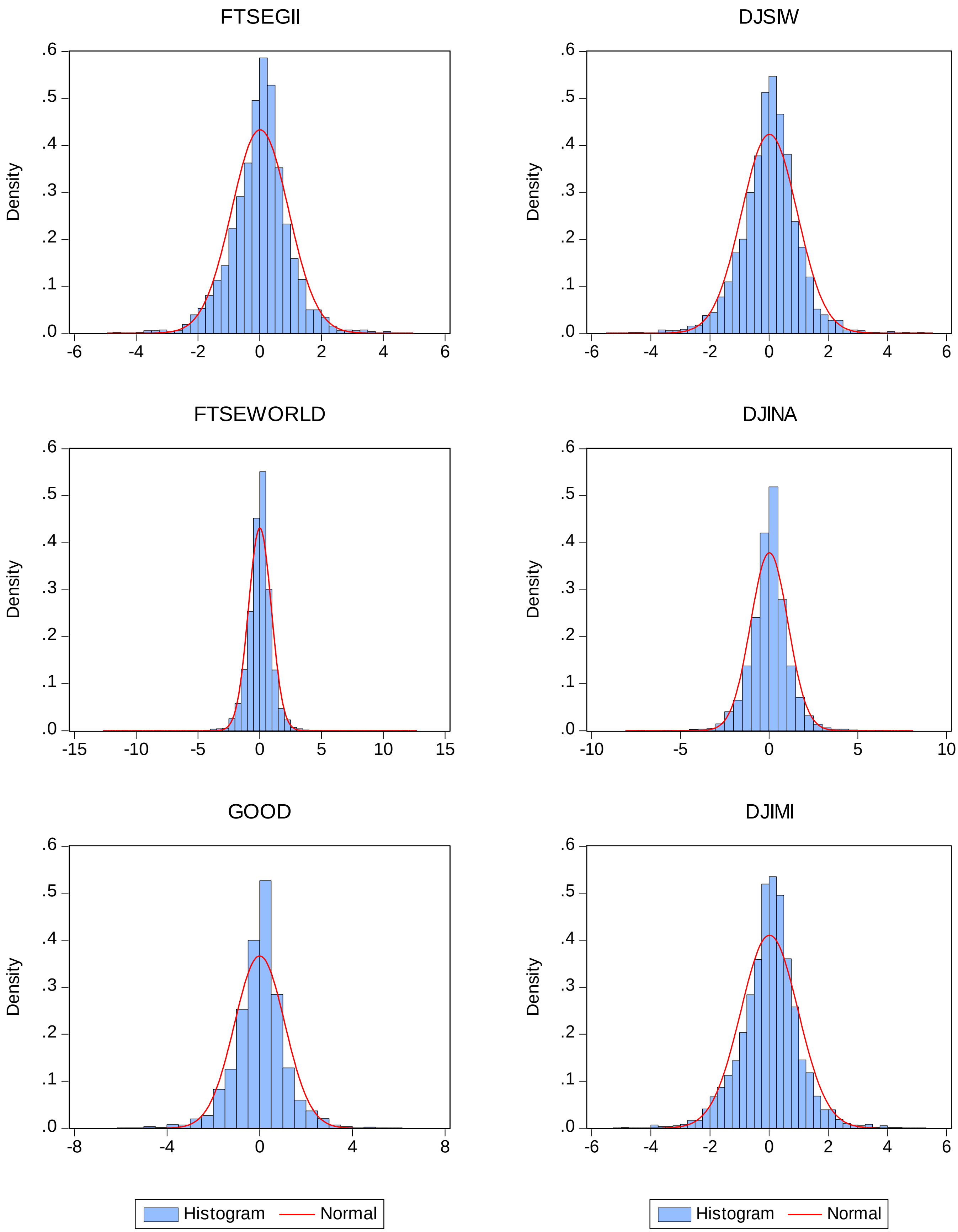


Figure 1. Plots of closing prices and returns of all the indices.

followed by FTSEGII with the average returns of 0.014 while DJSIW has lower returns at 0.002. In terms of volatility, DJSIW has the lowest volatility followed by DJIMI, and finally, the highest volatility is DJINA. On the other hand, the socially responsible index FTSE4G has the highest volatility followed by FTSEW and finally the


FTSEGII
DJSIW
FTSEWORLD
DJINA
GOOD
DJIMI
Density
.0
.1
.2
.3
.4
.5
.6
-6
-4
-2
0
2
4
6
-15
-10
-5
5
10
15
-8
8
Histogram
Normal

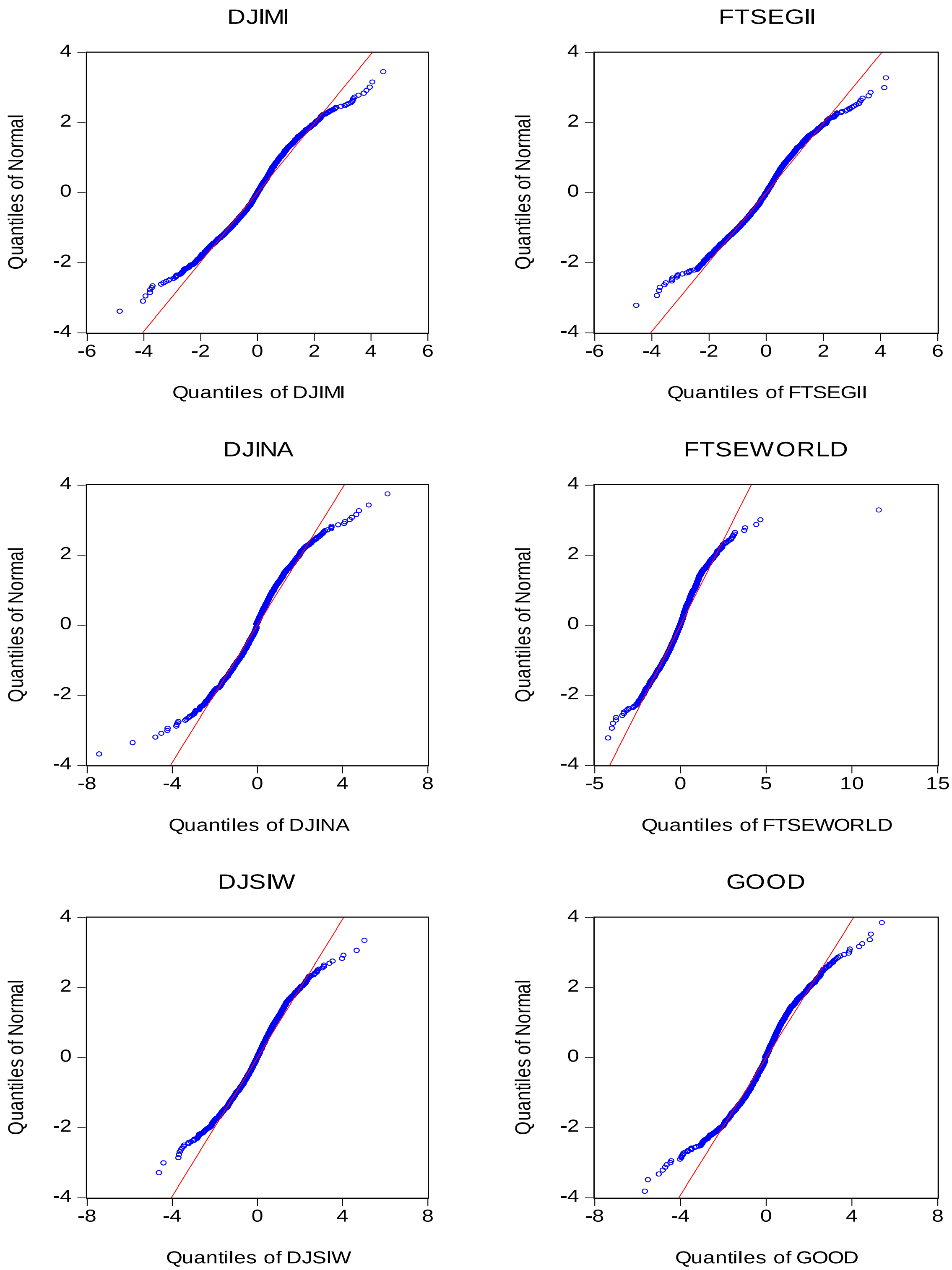


Figure 2. Normalized returns distribution and Q-Q plot.

lowest volatility is the Islamic index FTSEGII. Although the financial theory indicates that higher volatility must be compensated by higher returns, this is not the case for DJIMI and FTSE4G where the level of standard deviation is different from DJINA and FTSEW respectively. DJIMI seems to earn marginally lower return than DJINA but higher than DJSIW. All indices are negatively skewed except FTSEW, which is positively skewed. This indicates

Table 1. descriptive statistics of DJ indices returns.

Variable	DJIMI	DJINA	DJSIW
Mean	0.01589	0.01631	0.01319
Std. Dev.	0.971	1.053	0.942
Skewness	-0.113	-0.088	-0.134
Kurtosis	4.862	6.700	5.140
Jarque-Bera	342.9*	1337.8*	453.4*
LB(10)	67.4*	8.2104	78.7*
$LB^2(10)$	741.8*	621.5*	953.9*

* Significant at 1%.

Table 2. Descriptive statistics of FTSE indices returns.

Variable	FTSEGII	FTSEW	FTSE4G
Mean	0.014	0.017	0.002
Std. Dev.	0.921	0.924	1.089
Skewness	-0.101	0.759	-0.209
Kurtosis	4.801	15.086	5.865
Jarque-Bera	320.2*	14465.8*	817.2*
LB(10)	59.2*	66.7*	47.6*
$LB^2(10)$	615.3*	53.9*	1640.5*

* Significant at 1%.

that their returns are asymmetric. The negative (positive) skewness indicates that there is a greater probability of large decrease (increase) in returns than increase (decrease). All the stock market indices have kurtosis more than three, indicating leptokurtic distribution.

In addition, all the 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 indicates that linear and non-linear dependencies exist in the first and second moment for all except DJINA where the dependency is in the second moment. Linear dependency might be explained as market inefficiency (Koutmos and Booth, 1995; Kovačić, 2008). On the other hand, non-linear dependency might indicate the presence of GARCH effect (Kovačić, 2008).

Table 3 shows the correlation coefficients or the unconditional correlation between all the indices returns. Among the FTSE family of indices, the highest correlation is between FTSEGII and FTSE4G which is 0.63 while it is low between FTSEW and FTSEGII reaching 0.18 only. In contrast, among the DJ family indices the highest correlation is between DJIMI and DJSIW, that is, 0.90, while the lowest is between DJIMI and DJINA coming to only 0.14. This shows that the Islamic indices and the socially responsible indices are closely related which indicate that some of the screening criteria are common. Moving on to the cross correlations between these two families of indices, it is found that the correlation between the Islamic indices DJIMI and FTSEGII is the highest, reaching almost one which indicate perfect correlation. This is expected since both Islamic indices follow almost the same screening criteria. In contrast, the correlation between the socially responsible indices DJSIW and FTSE4G is at 0.78. On the other hand, the correlation between non-screened indices DJINA and FTSEW is strong at 0.82. Interestingly, the non-screened indices FTSEW and DJINA have a very weak but positive correlation with both Islamic indices FTSEGII and DJIMI, which might indicate that the Islamic indices are less diversified.

Table 4 shows the results for a t-test for mean difference between all indices. The results indicate that there is no significant difference in returns between any of the indices. Consequently, it means that whether an investor invests in screened or non-screened index, the returns will not differ. Therefore, investors looking for more than financial returns should invest in screened investments without paying any penalty that was suggested by the traditional finance theory.

Tables 5 and 6 report the results of three estimation models, GARCH-M, EGARCH and TARCH as specified in Equations 5, 6 and 7 for DJIMI and DJSIW. In the DJIMI model, two past lagged returns are included to eliminate the autocorrelation problem in returns while in DJSIW, eight lags are included. The number of autoregressive used is based on the Aikia Information Criteria (AIC). In the returns equation, the first coefficient represents the risk premium value or the risk-returns trade off which appears to not statistically significant in all the three models for both DJIMI and DJSIW. DJIMI return is affected by one day lagged returns while DJSIW return is affected by the first and the sixth day lagged returns. It is apparent that DJIMI is more efficient in transmitting information than DJSIW. For the variance equations, almost in all models for both indices, there is a significant ARCH, GARCH, and leverage effect implying that there is an asymmetry of news. In other words, bad news has a stronger effect than good news. However, the leverage effect seems stronger for the socially responsible index DJSIW then the Islamic index DJIMI. The half-life (Half-life = $\ln(0.5)/\ln(\alpha_{1+}\ \beta_{1)})$, which measure the period it takes a shock to decay into the future, for GARCH effect is almost 12 days for DJIMI while it is 11.4 days for DJSIW. This suggests that volatility is more persistent in the Islamic index DJIMI than the socially responsible index DJSIW.

To determine the best model among the three models AIC and SC criteria are used. From the table, it is clear that either EGARCH or TARCH model are the best fit where AIC and SC are 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.

Tables 7 and 8 report the results of three estimations, GARCH-M, EGARCH and TARCH as specified in Equations 9, 10 and11 for the Islamic index FTSEGII and socially responsible index FTSE4G. In the FTSEGII model, six

Table 3. Simple correlations for the returns of all the indices.

	FTSE4G	FTSEW	FTSEGII	DJIMI	DJINA	DJSIW
FTSE4G	1					
FTSEW	0.18*	1				
FTSEGII	0.63*	0.13*	1			
DJIMI	0.62*	0.14*	0.98*	1		
DJINA	0.26*	0.82*	0.14*	0.14*	1	
DJSIW	0.78*	0.21*	0.91*	0.90*	0.26*	1

* Significant at 1%.

Table 4. T-test for difference in mean returns.

Returns difference	t-test p-value
FTSE4G - FTSEW	0.586836
FTSE4G – FTSEGII	0.502766
FTSE4G – DJIMI	0.464957
FTSE4G – DJINA	0.602026
FTSE4G – DJSIW	0.438425
FTSEW - FTSEGII	0.922612
FTSEW – DJIMI	0.970063
FTSEW – DJINA	0.964995
FTSEW – DJSIW	0.879832
FTSEGII - DJIMI	0.69343
FTSEGII – DJINA	0.943531
FTSEGII – DJSIW	0.881591
DJIMI - DJINA	0.987721
DJIMI – DJSIW	0.759808
DJINA – DJSIW	0.901285

Table 5. Parameter estimates of fitting GARCH (1, 1), EGARCH, and TARCH for DJIMI.

Model	GARCH-M	EGARCH	TARCH
DJIMI			
θ	-0.008	0.008	-0.009
C	0.053	0.0027	0.020
DJIMI(-1)	0.140*	0.139*	0.145*
ω	0.006**	-0.080*	0.008*
α1	0.053*	0.096*	0.006
β1	0.941*	0.987*	0.95*
γ1	----------------------	-0.053	0.077**
AIC/SC	2.54/2.55	2.52/2.54	2.52/2.54
ARCH(1)	0.71	0.80	1.60
ARCH(10)	9.12	8.52	6.41

*, ** and *** significant at 1, 5, and 10%, respectively.

past lagged returns are included to eliminate the autocorrelation problem in returns while in FTSE4G ten lagged returns are included. Similar to DJIMI and DJSIW the risk premium or the risk-returns trade off appears to not statistically significant in all the three models. FTSEGII return is affected by one day lagged returns as well as FTSE4G. It is apparent that both indices are equally efficient in transmitting information.

Table 6. Parameter estimates of fitting GARCH (1, 1), EGARCH and TARCH for DJSIW.

Model	GARCH-M	EGARCH	TARCH
DJSIW			
θ	-0.036	-0.072	-0.056
C	0.070	0.069	0.062
DJSIW(-1)	0.123*	0.126*	0.126*
DJSIW(-2)	-0.027	-0.022	-0.022
DJSIW(-3)	-0.027	-0.029	-0.027
DJSIW(-4)	-0.008	-0.005	-0.007
DJSIW(-5)	-0.035	-0.038	-0.031
DJSIW(-6)	-0.052**	-0.047**	-0.046**
DJSIW(-7)	-0.022	-0.012	-0.008
ω	0.007	-0.090*	0.009*
α_1	0.068*	0.109*	0.006
β_1	0.924*	0.986*	0.94*
γ_1	---------------------	-0.059*	0.085*
AIC/SC	2.48/2.51	2.47/2.51	2.46/2.50
LIKELIHOOD	-2883	-2867	-2861
ARCH(1)	0.00	0.00	0.07
ARCH(10)	4.88	8.64	8.01

*, ** and *** significant at 1, 5, and 10%, respectively.

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

Model	GARCH-M	EGARCH	TARCH
FTSEGII			
θ	-0.039	-0.046	-0.038
C	0.074	0.053	0.049
FTSEGII(-1)	0.145*	0.141*	0.149*
FTSEGII(-2)	-0.031	-0.022	-0.024
FTSEGII(-3)	-0.017	-0.010	-0.013
FTSEGII(-4)	-0.013	-0.016	-0.008
FTSEGII(-5)	-0.052**	-0.041	-0.039
ω	0.005**	-0.071*	0.007*
α_1	0.052*	0.085*	-0.003
β_1	0.942*	0.988*	0.951*
γ_1	----------------------	-0.057**	0.082*
AIC/SC	2.45/2.48	2.44/2.47	2.43/2.46
ARCH(1)	1.60	2.27	2.77
ARCH(10)	11.68	13.95	10.15

*, ** and *** significant at 1, 5, and 10%, respectively.

For the variance equations, almost in all models for both indices there is a significant ARCH, GARCH, and leverage effect implying that there is an asymmetry of news. In other words, bad news has a stronger effect than good news. However, the leverage effect seems stronger for the socially responsible index FTSE4G than FTSEGII. The half-life is 14 days for FTSEGII while it is 23 days for FTSE4G. It is clear that the socially responsible index take very long time to revert to it mean.

To determine the best model among the three models, AIC and SC are used. From the tables, it is clear that either EGARCH or TARCH model are the best fit since it minimizes AIC and SC criteria. 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.

To summarize, from the above models, it is clear that none of the markets has risk-returns trade off. In other

Table 8. Parameter estimates of fitting GARCH (1,1), EGARCH and TARCH for FTSE4G.

Model	GARCH-M	EGARCH	TARCH
FTSE4G			
θ	-0.05	0.111	0.129
C	0.018	-0.043	-0.048
FTSE4G (-1)	-0.071**	-0.052	-0.060**
FTSE4G (-2)	-0.017	0.000	0.000
FTSE4G (-3)	-0.019	-0.004	-0.006
FTSE4G (-4)	0.001	0.004	0.003
FTSE4G (-5)	-0.055	-0.038	-0.050
FTSE4G (-6)	-0.044	-0.017	-0.035
FTSE4G (-7)	-0.023	-0.015	-0.014
FTSE4G (-8)	-0.036	-0.022	-0.024
FTSE4G (-9)	-0.005	0.017	0.013
ω	0.019*	-0.101*	0.019*
α_1	0.101*	0.102*	0.011
β_1	0.865*	0.971*	0.895*
γ_1	----------------------	-0.109*	0.146*
AIC/SC	2.14/2.19	2.12/2.18	2.12/2.18
ARCH(1)	0.26	0.00	0.66
ARCH(10)	4.03	2.99	3.36

*, ** and *** significant at 1, 5, and 10%, respectively.

words, there is no relationship between the stock returns of any of these markets and their volatility. All the indices studied here are affected by at least one day laggedreturns. The variance equations indicate that the coef-ficient of α_1 and β_1 is significant and positive in most of the cases, indicating that past fluctuations has positive influence on the future volatility. In addition, β_1 value is large and significant, indicating that returns have long-term memory or the fluctuations are persistent. Moreover, there is leverage effect in all the indices. The leverage effect indicates that these markets become volatile when there is a large decrease in the prices. 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 for the Islamic indices (DJIMI and FTSEGII). Both DJIMI and FTSEGII have strict screening criteria regarding debt ratio, which must not exceed 33%, while the socially responsible indices do not have any screen against debt ratio. In addition, it is that there is asymmetric effect of news in these since $\gamma_1 \neq 0$. Therefore, bad news has stronger impact than good news in all the indices.

Conclusion

This study examines three main issues. The first is whether there is a significant difference between socially responsible, Islamic stock market indices and their conventional counterpart indices. The study found no significant difference in returns between the indices. The results suggest that there is no significant difference in stock market returns between the Islamic (DJIMI and FTSEGII), the socially responsible (DJSIW and FTSE4G) and the non-screened (DJINA and FTSEW) stock market indices. Therefore, investing in any of them will yield the same returns. The second issue studied in this paper is whether any of the socially responsible or Islamic indices has a risk premium effect during the period of the study and the result indicates that there is no risk-return trade-off in any of these indices. The last issue is whether there is a leverage effect in all the indices studied. It is found that in both Islamic and socially responsible indices, there is a leverage effect. This means that bad news has a stronger effect than good news. Moreover, the results show that there is the leverage effect risk in all the screened indices. However, the leverage effect is stronger in the socially responsible indices than the Islamic indices. This indicates that Islamic and socially responsible stock market indices are affected more by bad news than good news. In addition, there is asym-metric impact of news on volatility. Based on the half-life values, the markets that revert to mean faster is DJIMI and DJSIW, followed by FTSEGII and lastly FTSE4G. It means that FTSE4G takes longer time to revert to its mean or for any shock in volatility to decay.

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