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BEHAVIORAL OF ISLAMIC FINANCIAL MARKETS: THE CASE OF ASYMMETRIC BEHAVIORAL OF 17 COUNTRIES

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Abstract

Using daily closing price to investigate the asymmetric property of stock market volatility, we collected data from 17 different indexes (Abu Dhabi, Bahrain, Bangladesh, Dubai, Egypt, Indonesia, Jordan, Kuwait, Lebanon, Malaysia, Morocco, Oman, Pakistan, Qatar, Saudi Arabia, Tunisia, and Turkey) up to twenty years, aiming to cover all representative Islamic countries. Our main goal is to assess whether asymmetry is common to all markets irrespective of their specific nature or if, on the contrary, diverges across different countries, according to the distinctive behavior of their economies. GARCH, EGARCH and GJR-GARCH models estimated to capture the dependence in the variance. Motivated by the fact that the original return series exhibit fat tails features we selected a GED distribution to embody this characteristic of the data except for Qatar, Lebanon, and Bahrain; skewed student distribution employed. The GARCH indicates that the conditional variance will exhibit reasonably long persistence of volatility for all countries, for EGARCH and GJR, confirm that the stock market investors respond differently to bad news compared to good news in all countries; however, this is not statistically significant in Tunisia, Morocco, Lebanon, Bahrain and Oman only.

Key words: Asymmetric, EGARCH, GJR-GARCH, Volatility, Islamic Financial Markets

INTRODUCTION

After pioneer research of Stigler and Kindahl (1970), many researchers founded that stock returns in developed market respond asymmetrically to the arrival of unanticipated news, negative shocks presume to increase level of volatility than positive shocks of the same magnitude (such as Black, (1976), Alberg et al. (2008) Evans & McMillan (2007), Beum-Jo (2011)).

Bentes, et al, (2013) investigates NIKKEI 225, S&P 500 and STOXX 50 returns, focusing on the asymmetric property of these markets. They found, for all the three index returns, the conditional variance is an asymmetric function of the past residuals. More recent, Ning et al, (2015) examines asymmetric pattern in volatility clustering for both the stock and foreign exchange markets. They found evidence that volatility clustering is strongly asymmetric in of high volatility occur more often than clusters of low volatility.

Asymmetric information is a significant problems to fundamental and empirically market economies. Subrahmanyam and Titman (2013) conclude when the volatility of the technology shocks is large, it will reflect in real economy, suggested that will affect the validity of market efficiency theory. Asymmetric information is a vital role in characterizing price movements. Particularly, the asymmetric effect shows a negative correlation between stock returns and volatility. This involving that large negative shock is associated with a greater increase in volatility than large positive shocks.

Leverage theory might explain the asymmetric effects; if the firm's stock price fall, then debt to equity ratio will increase, resulting on increasing financial risk of the firm, create high level of volatility in its stock return. Risk premium theory might be the other explanation; if the new information released, it is expected that firm's stock price swinging up and down, generate high level of volatility in its stock return, therefore, it likely that rational investors raised the required rate of return of the particular stock that had more bad news lately, resulting enlarge the negative impact of bad news. (Black, 1976; Christie, 1982; Campbell, et al.,1992).

On the other hand, stock markets in 17 Islamic countries (Abu Dhabi, Bahrain, Bangladesh, Dubai, Egypt, Indonesia, Jordan, Kuwait, Lebanon, Malaysia, Morocco, Oman, Pakistan, Qatar, Saudi Arabia, Tunisia, and Turkey) provide an excellent case study on the asymmetric effects of emerging stock markets for several reasons. The opening of many Islamic emerging markets to foreign investors in the 1990s has provided new opportunities for diversification (see for example; MENA countries (Harrison and Moore, 2012)) , however, Bahrain, Kuwait, Oman and Saudi Arabia still have more restrictions to most foreign investors compare to others countries.

The 17 Islamic markets are quite heterogeneous; by the end of 2014, the Malaysian stock market was the largest based on its market capitalization of approximately $500,387.41 billion, while the Bahrain market was the smallest at approximately $8.55 billion. Measured by the number of listed companies, Malaysia has the biggest stock market with 909 companies listed while Bahrain is the smallest with 49 companies listed.

There are few financial cross-links among the Islamic stock markets, even though they are geographically partly close together (see for example MENA countries, Girard and Ferreira, 2004), the risk-return relationships of stocks listed on Islamic emerging markets are quite remarkable, if not anomalous. Most countries show low returns and low volatility compared to high returns and high volatility generally observed in emerging markets in Asia, Latin America, and Eastern Europe (Girard and Ferreira, 2004; Smith and Ryoo, 2003).

Al-Hajieh, et al. (2011) examine the volatility within Middle East countries, they found that the month of Ramadan (Islamic holy month) shows high level of volatility and the overall impact of Ramadan on returns is statistically significant for most Middle East countries but not profitable. Therefore, this study extends the literature investigating stock return volatility in two distinct ways. Firstly, it uses data on stock market returns of 17 Islamic countries, a market that has not been investigated together in previous researches. Secondly, it applies GARCH model, EGARCH and GJR of asymmetric models that have been used in developed countries to identify whether or not the difference models provide supporting results, making a complementary contribution to this important issue relating to the 17 Islamic markets.

Nevertheless, several Islamic markets, such as Morocco, Oman and Tunisia, are largely absent from the literature on the volatility of emerging markets. Of the few published studies of which we are aware, the findings on the asymmetric volatility in Islamic markets are thus far inconclusive.

The structure of the research proceeds as follows. Section 1 provided introduction and background of this research; whereas methodology used is described in Section 2, this is followed by preliminary data analysis in Section 3. Section 4 provided the empirical results of testing market efficiency, volatility and information asymmetric; finally, Section 5 concludes of this research.

METHODOLOGY

Financial time series seem to exhibit properties such as leptokurtosis, skewness and time-varying volatilities, in most empirical research, a conditional heteroskedasticity models used to account for the temporal dependencies of stock market volatility. The ARCH/GARCH approach is the most widely spread out.

ARCH model of Engle's (1982) measuring the current volatility as a function of the past squared residuals, that is not enough, as volatility has to depends on the past squared residuals as well as on the lagged values of the variance itself, therefore, Bollerslev (1986) proposed GARCH models to formulate the volatility, especially with clustering characteristics. Even though that Bollerslev (1986) reduces the number of estimated parameters from infinity in ARCH model to two parameters in GARCH model, it is not capable to capture asymmetries since it assumes that only the magnitude of the shock but not the sign affects price oscillations.

This is so because ARCH/GARCH models enforce a symmetric response of volatility to positive and negative shocks. Nelson (1991) proposed Exponential GARCH (EGARCH) model to deal with asymmetric, as well as Glosten et al. (1993) proposed GJR model to capture asymmetric.

ARCH/GARCH Models

The ARCH model introduced by Engle (1982) allows the variance of the error term to vary over time, Bollerslev (1986) generalized the ARCH process by allowing for a lag structure for the variance, since stock returns are highly fluctuating, the generalized ARCH models, the GARCH models allows the conditional variance to be a function of the lag's squared errors as well as of its past conditional variances; the equation below presents GARCH(p, q):

$$\sigma_t^2 = \alpha_0 + \alpha_1\epsilon_{t-1}^2 + \cdots + \alpha_q\epsilon_{t-q}^2 + \beta_1\sigma_{t-1}^2 + \cdots + \beta_p\sigma_{t-p}^2 = \alpha_0 + \sum_{i=1}^{q}\alpha_i\epsilon_{t-i}^2 + \sum_{i=1}^{p}\beta_i\sigma_{t-i}^2$$

EGARCH Model

The GARCH model imposes symmetry on the conditional variance structure that may not be appropriate for modelling the behaviour of stock returns, if downward movements in volatility in financial markets are followed by higher volatilities than upward movements of the same magnitude; therefore, Nelson (1991) proposes the exponential GARCH or EGARCH model. The specification for the higher order conditional variance is:

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

The left-hand side of the equation is the log of the conditional variance. This implies that the asymmetric effect is exponential, rather than quadratic, and that forecasts of the conditional variance are generated to be non-negative. The presence of leverage effects can be tested by the hypothesis that $\gamma < 0$. The impact is asymmetric if $\gamma \neq 0$.

GJR/ Model

This popular model is proposed by Glosten, Jagannathan, and Runkle (1993). Its generalized version is given by:

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

where S_t^- is a dummy variable that take the value 1 when γ_i is negative and 0 when it is positive. A nice feature of the GJR model is that the null hypothesis of no leverage effect is easy to test. Indeed, $\gamma_1 = \ldots = \gamma_q = 0$ implies that the news impact curve is symmetric, i.e. past positive shocks have the same impact on today's volatility as past negative shocks.

Another issue should be consider when applying GARCH models to financial time series, that GARCH models do not always fully embrace the thick tails property. To overcome this weakness Bollerslev (1986) used the Student's t-distribution. Similarly to capture skewness Liu and Brorsen (1995) used an asymmetric stable density. To model both skewness and kurtosis Fernandez and Steel (1998) used the skewed Student's t-distribution which was later extended to the GARCH framework by Lambert and Laurent (2000, 2001). To improve the fit of the GARCH and EGARCH models into international equity markets, Harris et al. (2004) used the skewed generalized Student's t-distribution to capture the skewness and leverage effects of daily returns.

ANALYSIS

Preliminary Data Analysis

In order to investigate the asymmetric property of stock market volatility we collected data from 17 different indexes (Abu Dhabi, Bahrain, Bangladesh, Dubai, Egypt, Indonesia, Jordan, Kuwait, Lebanon, Malaysia, Morocco, Oman, Pakistan, Qatar, Saudi Arabia, Tunisia, and Turkey) aiming to cover all representative Islamic countries. Our main goal is to assess whether asymmetry is common to all markets irrespective of their specific nature or if, on the contrary, diverges across different countries, according to the distinctive behavior of their economies.

Data were gathered from Reuter's database consisting on the daily closing prices. In our study, we use the daily returns, which were computed as the log-difference of the daily stock index given by:

$$R_t = \ln P_t - \ln P_{t\ 1}.$$

Figure 1, 2, and 3 depicts the time series evolution of the 17 different indexes considered. Fig. 2 reports the fluctuations of the daily returns for the 17 indexes considered. This figure illustrates the synchronized behavior of the returns, already noticed in Fig.1. Here, however, the spikes are much more evident. Additionally, it provides a clear picture of the presence of volatility clusters.

Figure 1. Price index of 17 Islamic countries

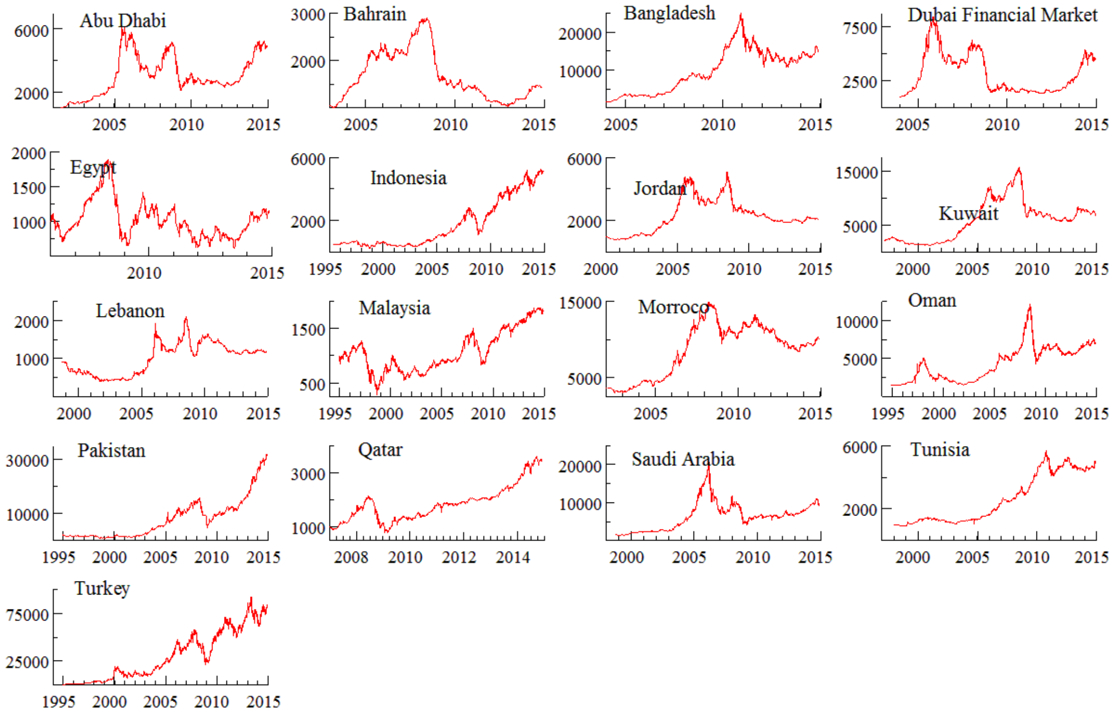


Figure 2. Daily Returns of 17 Islamic countries

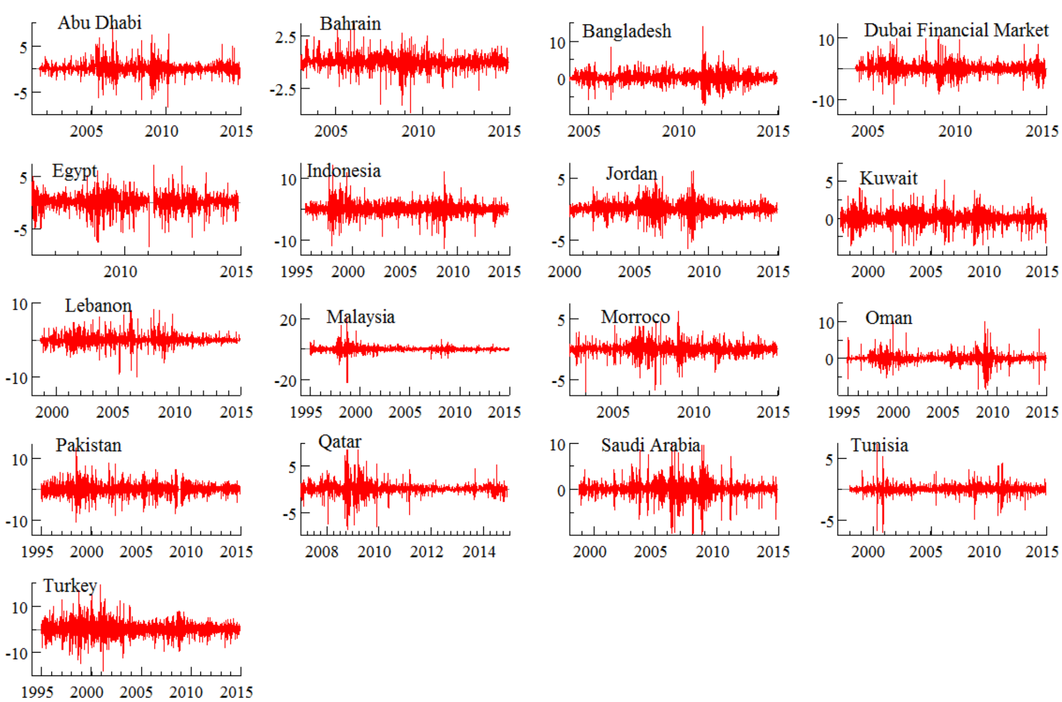
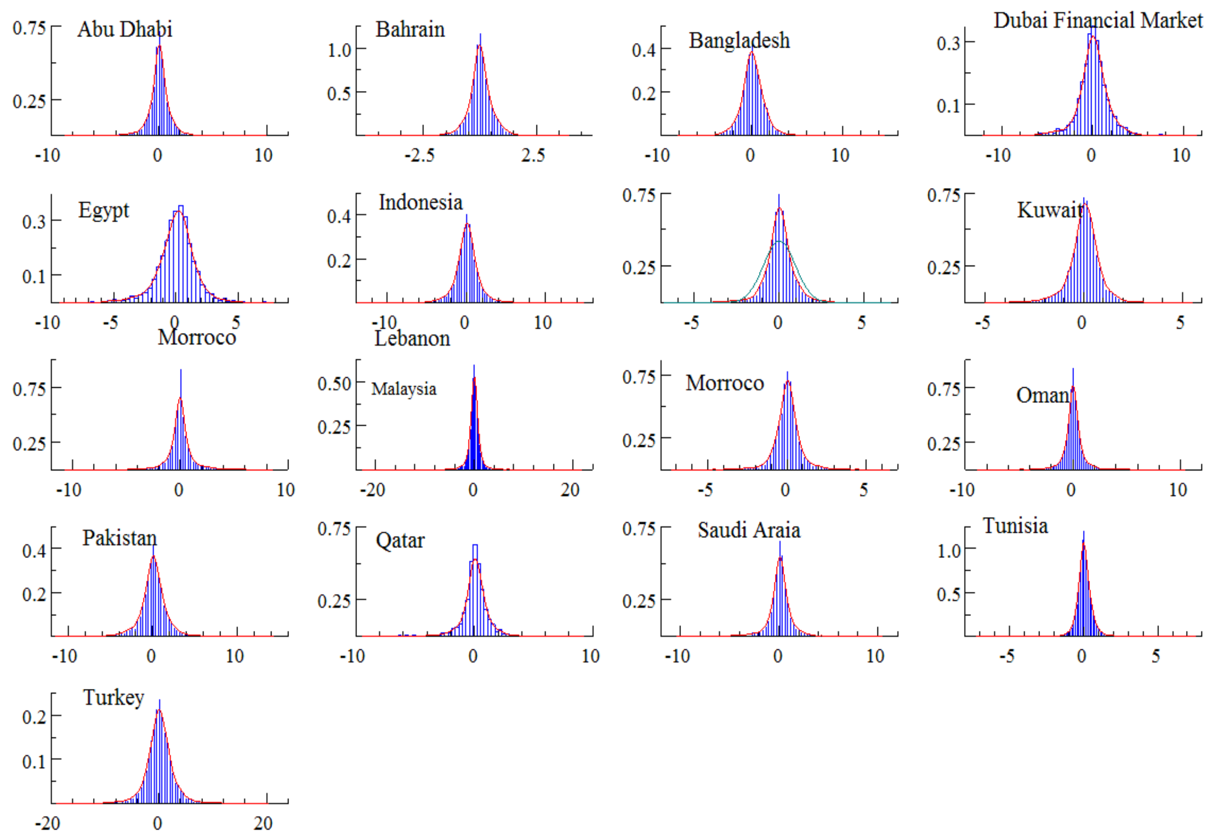


Figure 3. Histogram of Daily Returns of 17 Islamic countries



Preliminary analysis of the daily returns of 17 indexes for the whole sample period is presented in Table 1.

It shows that numbers of observation reach the highest number in Turkey (4982) and lowest number (2149) in Egypt, sample cover up to 20 years. All indexes returns demonstrate a positive close to zero mean, which is not surprising since we are dealing with returns and not with the closing prices.

Furthermore, the average daily returns are very small compared to the standard deviation. Series also display for 9 countries positive skewness. Furthermore, for all countries strong positive kurtosis, indicative of a heavier tailed distribution than the Gaussian. Consequently, unconditional normality is rejected (J-B test). The plot of the corresponding histograms (Fig. 3) corroborates this finding. Moreover, both the Ljung-Box (*Q*) and the ARCH tests reveal linear dependence excluded Turkey.

Table 1. Preliminary analysis of the daily returns of 17 Islamic countries

Countries	Starting date	Ending Date	Obs	Mean	Std. Dev	MIN	MAX	Skewness	Excess Kurtosis	Jarque-Bera	ARCH 1-10 test	Q (10)
Abu Dhabi	01/07/01	06/12/14	3504	0.050582	1.112	-8.301	9.396	0.18986	9.5286	13277**	63.509**	1301.67**
Bahrain	02/01/03	27/11/14	2939	0.013127	0.59135	-4.7505	3.6935	0.97178	4.7667	560.89**	3.902**	39.0506**
Bangladesh	01/01/04	27/11/14	2633	0.093322	1.4266	-7.4707	13.963	0.25085	7.0809	5528.3**	60.829**	1237.01**
Dubai	31/12/03	27/11/14	2854	0.068622	1.8074	-11.442	10.719	0.079314	5.1421	3147.3**	65.391**	1282.47**
Egypt	02/01/06	27/11/14	2149	0.031145	1.5521	-8.4429	7.1224	-0.64814	2.2978	198.07**	15.201**	191.867**
Indonesia	06/06/95	28/11/14	4763	0.062753	1.6528	-12.997	14.243	-0.038593	8.1541	13197**	80.471**	1679.18**
Jordan	02/01/00	27/11/14	3655	0.025463	0.94571	-6.4283	6.1978	-0.36298	6.167	5872.2**	107.97**	2571.37**
Kuwait	05/03/97	27/11/14	4377	0.02849	0.81617	-4.6649	5.1762	-0.42867	4.0235	3086.4**	78.286**	260.71**
Lebanon	07/09/98	28/11/14	3764	0.012446	1.161	-10.137	8.177	0.37184	11.498	20821**	53.119**	725.511**
Malaysia	02/12/94	28/11/14	4924	0.021488	1.3487	-22.121	21.519	1.2248	47.457	46329**	399.23**	3941.87**
Morocco	03/01/02	28/11/14	3215	0.034507	0.84927	-6.9688	6.1447	-0.42601	8.4629	9691.4**	46.176**	793.465**
Muscat	04/12/94	25/11/14	4866	0.036519	0.99597	-8.4197	10.133	0.44652	40.611	38364**	65.753**	394.104**
Pakistan	04/12/94	28/11/14	4872	0.068468	1.6007	-10.811	13.618	0.47781	1.3807	80.124**	3.4295**	38.2762**
Qatar	03/01/07	27/11/14	1984	0.070161	1.3106	-8.8077	8.6961	-0.45792	10.298	8836.6**	58.877**	1389.16**
Saudi Arabia	19/10/98	27/11/14	4343	0.050614	1.4114	-9.813	9.8458	0.080566	3.4719	374.49**	8.8048**	124.682**
Tunisia	31/12/97	28/11/14	4148	0.039627	0.59658	-7.0639	7.2998	1.599	8.3786	1856.6**	63.923**	420.051**
Turkey	02/12/94	28/11/14	4982	0.14529	2.541	-18.109	19.451	0.040445	1.2448	22.562**	1.2171	12.9833

*Note: 1. ** significant at 1%.*

2. J-B represents the statistics of the Jarque-Bera's [29] normal distribution test.

3. Q(10) is the Ljung-Box Q test for serial correlation with 10 lags. 4. ARCH test with10 lags.

Finally, Table 2 reports the ADF (Augmented Dickey-Fuller) and KPSS (Kwiatkowski, Philips, Schmidt and Shin) unit root tests. The ADF and KPSS tests examine the stationarity of the 17 countries; the null hypothesis of nonstationarity is rejected for all return series at 1%, whereas in the KPSS test the null of stationarity is not rejected at the same level of significance. The results are, therefore, consistent in both cases indicating stationarity in 17 countries index returns. Since we considered the return series and not the original prices unit root tests were performed in levels, which is equivalent to take the first differences of the price series.

Table 2. ADF and KPSS unit root tests for the 17 indexes returns

Countries	ADF Test	KBSS
Abu Dhabi	-32.4327 **	0.386665 *
Bahrain	-10.3757 **	0.248974
Bangladesh	-28.7856 **	0.503488 **
Dubai	-29.8592 **	0.66518 **
Egypt	-13.0236 **	0.365868 *
Indonesia	-38.4141 **	0.14066
Jordan	-32.8083 **	0.780422 **
Kuwait	-33.43 **	0.881295
Lebanon	-32.6222 **	0.327252
Malaysia	-38.7683 **	0.083331
Morocco	-31.2329 **	0.572264 **
Muscat	-11.4404 **	1.12004 **
Pakistan	-13.0003 **	0.25963
Qatar	-23.458 **	0.0739635 **
Saudi Arabia	-13.9444 **	0.154488
Tunisia	-10.1786 **	0.606282 **
Turkey	-9.50892 **	0.12794

Runs test and Variance ratio results

The study begins by identifying whether or not the 17 indexes returns do follow a Random Walk using Runs Test and variance ratio. This research utilizes the Wald-Wolfowitz (1940) runs test to test for the randomness of the series. Runs tests are used to examine for serial dependence in share price movements and compare the expected number of runs from a random process with the actual observed number of runs. In addition to, variance ratio test (VR) is employed to examine the predictability of equity returns. This method has the advantage of exhibiting good finite-sample properties (Lo and MacKinlay, 1989) and is sensitive to serial correlation.

The result of run test and variance ratio presented in table 3 below, the 17 indexes reject the null hypothesis that the differences between the actual runs and the expected runs have no statistical difference, with 99% confidence except for Turkey. This indicates that all Islamic financial markets do not follow a random walk except for Turkey.

The VR test has been used as an alternative to examine the predictability of stock market returns, The result shows that, for the 17 indexes, the VR (q)s have values not close to 1, leading to the rejection of the null hypothesis for the index except for Turkey. Overall, the results obtained from variance ratio tests confirm that all indexes do not follow a random walk for VR (5), at difference level of confidence except for Turkey.

Table 3. Runs test and VR test for the 17 index returns

Countries	Run Test	VR (5) test
Abu Dhabi	-10.5435**	1.3728**
Bahrain	-3.96051**	1.4707**
Bangladesh	-7.5699**	1.08931
Dubai	-2.80519**	1.11377
Egypt	-2.40191**	1.39688**
Indonesia	-4.68666**	1.16698**
Jordan	-10.6569**	1.27403**
Kuwait	-10.4258**	1.44928**
Lebanon	-3.95448**	1.32366**
Malaysia	-6.49866**	1.17167
Morocco	-5.47908**	1.34932**
Oman	-7.11877**	0.82848
Pakistan	-5.27752**	1.49987**
Qatar	-4.50541**	1.39265**
Saudi Arabia	-3.35249**	1.32613**
Tunisia	-5.03214**	2.52561**
Turkey	-1.60772	1.21865

GARCH, EGARCH and GJR-GARCH results

GARCH, EGARCH and GJR-GARCH models estimated to capture the dependence in the variance. In this study the parameters were estimated by quasi-maximum likelihood estimation process (QMLE). Motivated by the fact that the original return series exhibit fat tails features we selected a GED distribution to embody this characteristic of the data except for Qatar, Lebanon, and Bahrain; skewed student distribution employed. Model estimates during the sample period are provided in Table 4.

As shown in table 4, the constant of the mean parameter for all countries are positive and statistically significant, except for; Tunisia in EGARCH and GJR model, Jordan in EGARCH, Malaysia in GJR model. The constant of variance for all countries are positive and statistically significant, except for; EGARCH model is negative apart from Turkey, Pakistan, Lebanon, Egypt, Dubai, Indonesia and Bangladesh is positive.

The alpha coefficient of the three models in all countries is statistically significant at 99% level of confidence. This implies the existence of the ARCH process in the error term. The returns exhibit time-varying volatility clustering; this indicates that periods of volatility are followed by periods of relative calm. The alpha sign is negative as a result of not imposing restrictions on the coefficient of the EGARCH model.

The beta coefficient of the three models in all countries is statistically significant at 99% level of confidence, which indicates that the variance is dependent on its moving average. The sum of alpha and beta is close to unity, which implies that volatility shocks are quite persistent, indicates that a large positive or a large negative return will lead future forecasts of the variance to be high for an extended period. Since the sum is high, the response function to a shock is likely to die away slowly.

The GARCH coefficient (beta) is larger than the ARCH coefficient (alpha) of the three models in all countries, which indicates that the conditional variance will exhibit reasonably long persistence of volatility.

The exponential GARCH (EGARCH) model of Nelson (1991) is used to identify the possibility of leverage effects. Even if the ARCH and GARCH models are good models in estimating the volatility of the financial time series data, but both models not capable to capture leverage effects.

The EGARCH's results indicate that the stock market investors respond differently to bad news compared to good news in all countries; however, this is not statistically significant in Tunisia, Qatar, Jordan, Morocco, Lebanon, Abu Dhabi, Bahrain and Oman. Furthermore, the size effects are statistically significant at 99% level of confidence in all countries, for that reason, large positive and negative shocks will increase volatility in the stock market of all Islamic countries.

Finally, GJR's results show that the stock market investors respond differently to bad news compared to good news in all countries; however, this is not statistically significant in Tunisia, Morocco, Lebanon, Bahrain and Oman only.

Turning to the diagnostic tests of the standardized residuals, $Q^2(10)$ statistics unveils the absence of ARCH effects. Therefore, since the Ljung-Box statistic of the squared residuals is not significant in most cases all the three models seem appropriate to capture this phenomenon except for Turkey.

Similar conclusions are provided by the ARCH-LM test, which rejects the null of homocedasticity, since these models are not nested no formal tests were conducted to compare the goodness of fit.

Table 3. GARCH, EGARCH, GJR results for the 17 index returns

Countries	Model	Cst(M)	Cst(V)	ARCH (ALPHA)	GARCH (BETA)	EGARCH (THETA1)	EGARCH (THETA2)	GJR (GAMMA)	G.E.D	Q(10)	Sig	ARCH (10)	Sig
Tunisia	**GARCH**	0.012719**	0.026693**	0.320817**	0.621873**				1.152578**	5.67	0.68	0.56	0.84
	EGARCH	0.010	-1.553902**	-0.409155**	0.93209**	0.007	0.591653 **		1.167704**	1.94	0.98	0.20	1.00
	GJR	0.012	0.026854**	0.301633**	0.620853**			0.043	1.153168**	5.54	0.70	0.55	0.85
Turkey	**GARCH**	0.146411**	0.07042**	0.099206**	0.893065**				1.380835**	20.66	0.01	1.98	0.03
	EGARCH	0.129095**	1.532056**	-0.27862**	0.984564**	-0.0364**	0.272516**		1.381372**	27.24	0.00	2.75	0.00
	GJR	0.133159**	0.07908**	0.086291**	0.88474**			0.041608**	1.380853**	18.28	0.02	1.77	0.06
Qatar	**GARCH**	0.060636**	0.019	0.194053**	0.822709**				4.11743**	13.85	0.09	1.30	0.22
	EGARCH	0.056362**	-1.485294**	-0.589571**	0.987411**	-0.043	0.559979**		4.526043**	5.60	0.69	0.54	0.87
	GJR	0.058737**	0.019	0.15491**	0.824171**			0.074171**	4.152985**	15.06	0.06	1.41	0.17
Jordan	**GARCH**	0.019753*	0.002798**	0.235401**	0.936165**				1.385897**	9.62	0.14	0.95	0.48
	EGARCH	0.017	-0.704283**	-0.276709**	0.992311**	-0.004	0.414464**		1.381707**	9.52	0.15	0.93	0.51
	GJR	0.020228*	0.00264**	0.170287**	0.940985**			0.120622**	1.394526**	9.25	0.16	0.91	0.52
Saudi Arabia	**GARCH**	0.094695**	0.025754**	0.198267**	0.807999**				1.030195**	4.62		0.48	0.90
	EGARCH	0.089281**	-0.082	-0.208871**	0.973492**	-0.067552**	0.396136**		1.049019**	3.59	0.89	0.36	0.96
	GJR	0.070246**	0.030684**	0.177066**	0.793414**			0.112473**	3.685268**	5.59	0.69	0.59	0.82
Pakistan	**GARCH**	0.102251**	0.056716**	0.188234**	0.805403**				1.269801**	8.10	0.42	0.80	0.63
	EGARCH	0.089756**	0.565097**	-0.181904**	0.954905**	-0.064047**	0.401975**		1.259488**	1.73	0.99	0.17	1.00
	GJR	0.093783**	0.062435**	0.148857**	0.800104**			0.084004**	1.272568**	7.35	0.50	0.73	0.69
Malaysia	**GARCH**	0.037597**	0.008953**	0.109908**	0.887574**				1.24769**	7.07	0.53	0.72	0.71
	EGARCH	0.032718**	-0.367	-0.480736**	0.991432**	-0.077389**	0.332159**		1.272054**	8.06	0.43	0.80	0.62
	GJR	0.029	0.008761**	0.068896**	0.893179**			0.070338**	1.25881**	6.48	0.59	0.65	0.77
Morocco	**GARCH**	0.033099**	0.042519**	0.255374**	0.704714**				1.145301**	7.96	0.44	0.82	0.61
	EGARCH	0.035016**	-0.716063**	-0.418246**	0.955509**	-0.005	0.526736**		1.174902**	5.35	0.72	0.54	0.86
	GJR	0.032971**	0.042518**	0.254312**	0.704662**			0.002	1.145396**	7.97	0.44	0.82	0.61
Lebanon	**GARCH**	-0.025339**	0.073359**	0.671232**	0.663432**				2.523411**	9.93	0.27	1.02	0.42
	EGARCH	-0.025933**	0.439	-0.454821**	0.960629**	0.015	0.88057**		2.586498**	4.41	0.82	0.45	0.92

	GJR	-0.02583**	0.072735**	0.648539**	0.664707**			0.040	2.52453**	9.77	0.28	1.00	0.44
Kuwait	**GARCH**	0.070186**	0.020097**	.188653**	.793248**				1.341196**	6.40	0.60	0.73	0.69
	EGARCH	0.063624**	-.807237**	-0.384926**	.959720**	-0.087177**	0.458036**		1.385015**	9.32	0.32	0.95	0.49
	GJR	0.065577**	0.022957**	0.141601**	0.78319**			0.095625**	1.360783**	7.53	0.48	0.85	0.58
Egypt	**GARCH**	0.150354**	0.083798**	0.197509**	0.781108**				1.40058**	19.32	0.01	1.84	0.05
	EGARCH	0.125119**	0.501897**	-0.386656**	0.95696**	-0.123355**	0.435186**		1.442459**	11.34	0.18	0.94	0.50
	GJR	0.132982**	0.097463**	0.113964**	0.779441**			0.134848**	1.428851**				
Dubai Financial Market	**GARCH**	0.85325**	0.109247**	0.21812**	0.764809**				1.280943**	12.14	0.15	1.22	0.27
	EGARCH	0.073511**	0.815011**	-0.416394**	0.965732**	-0.038212*	0.487307**		1.29546**	7.95	0.44	0.78	0.65
	GJR	0.075641**	0.12683**	0.184303**	0.751528**			0.084175**	1.284031**	9.64	0.29	0.97	0.46
Indonesia	**GARCH**	0.103398**	0.056219**	0.149033**	0.836421**				1.239619**	11.42	0.18	1.09	0.37
	EGARCH	0.089901**	0.543818**	-0.499732**	0.98016**	-0.084062**	0.416794**		1.262219**	8.55	0.38	0.84	0.59
	GJR	0.093018**	0.061838**	0.106982**	0.834169**			0.079049**	1.246519**	9.35	0.31	0.90	0.53
Banglad-esh	**GARCH**	0.10443**	0.040649**	0.164418**	0.825893**				1.411866**	6.06	0.64	0.61	0.81
	EGARCH	0.08891**	0.364	-0.283405**	0.966666**	-0.051035**	0.389027**		1.446105**	3.46	0.90	0.35	0.97
	GJR	0.095199**	0.047199**	0.127644**	0.821949**			0.073407**	1.4202251**	6.33	0.61	0.64	0.78
Abu Dhabi	**GARCH**	0.043999**	0.011753**	0.388509**	0.845165**				1.082829**	5.99	0.54	0.64	0.78
	EGARCH	0.040981**	-0.272	-0.293181**	0.975291**	-0.034	0.597481**		3.811533**	4.58	0.71	0.48	0.90
	GJR	0.043668**	0.012183**	0.287885**	0.842735**			0.218998**	1.086043**	5.78	0.57	0.61	0.80
Bahrain	**GARCH**	0.030565**	0.007	0.103693**	0.905228**				3.052897**	10.96	0.20	1.10	0.35
	EGARCH	0.032237**	-0.078	-0.50842**	0.982744**	0.006	0.391459**		3.115567**	10.84	0.21	1.08	0.38
	GJR	0.030493**	0.007	0.104726**	0.905048**			-0.002	3.053881**	10.87	0.21	1.09	0.36
Oman	**GARCH**	0.025215**	0.018007**	0.327328**	0.71357**				1.044231**	14.03	0.08	1.38	0.18
	EGARCH	0.033171**	-0.571	-0.503696**	0.976354**	-0.006	0.625794**		3.910453**	7.56	0.48	0.74	0.68
	GJR	0.025012**	0.018033**	0.311977**	0.713781**			0.031	1.045094**	15.43	0.05	1.52	0.12

Notes, All highlighted cell, means that the test run using skewed student distribution

CONCLUSIONS

This paper investigates the evolution of stock market efficiency, volatility and asymmetric effects in a group of 17 Islamic indexes (Abu Dhabi, Bahrain, Bangladesh, Dubai, Egypt, Indonesia, Jordan, Kuwait, Lebanon, Malaysia, Morocco, Oman , Pakistan, Qatar, Saudi Arabia, Tunisia, Turkey) aiming to cover all representative Islamic countries. The main goal is to assess whether asymmetry is common to all markets irrespective of their specific nature or if, on the contrary, diverges across different nations, according to the distinctive behavior of their economies, since the markets investigated have grown and have been subjected to reform with a view to improving their performance.

Our sample size and period extends that used by Barry Harrison and Winston Moore (2012) by some covering all Islamic countries rather than MENA countries, also sample period cover up to twenty years in many countries, A comprehensive review of the literature illustrates that even when one type of test fails to reject the null , others may actually reject it. Therefore, to help the robustness of this analysis, a series of tests are applied at that stage. These include the Wald-Wolfowitz (1940) runs test for the randomness of the series and the variance ratio (VR) of Lo and MacKinlay (1989) to tests the efficiency. The second key stage of the paper models the nature of volatility. This is undertaken using GARCH, EGARCH, GJR models to examine the structure of the volatility focusing in asymmetry effects.

Apart from turkey, the result of run test and variance ratio, all Islamic financial markets do not follow a random walk. GARCH, EGARCH and GJR-GARCH models are estimated in this paper for 17 Islamic countries. Our results show that all stock index returns exhibit asymmetry this is not statistically significant in Tunisia, Morocco, Lebanon, Bahrain and Oman only. In addition, there is also evidence of persistency in these stock markets. Finally, the diagnostic test of the residuals shows no ARCH effects indicating that these models are adequate to account for this feature of the data.

One of limitation of this research is might be the need to identify essential source of performance improvements between difference volatility specification (Such as EGARCH, GJR-GARCH, APARCH, IGARCH, FIGARCH and HYGARCH) and difference distribution assumption (Normal, student t, GED, Skewed student) within the Islamic financial markets.

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