International Journal of Business and Risk Management, 2018, Vol. 1, No. 1, 37-54
Available online at http://pubs.sciepub.com/ijbrm/1/1/5

DOI:10.12691/ijbrm-1-1-5

Parametric Value-at-Risk Analysis: Evidence from Islamic and Conventional Stock Market

Majoul Neila*, Hellara Slaheddine

Higher Institute of Management, Tunis University, Tunisia
*Corresponding author: m.neila@hotmail.fr

Abstract This paper examines the performance of three models (RiskMetrics, GARCH, APARCH) used with three distributions (Normal, Student-t, Skewed Student-t). The sample consists of daily data from 10 August 2007 to 26 November 2016 of Islamic and conventional stock markets indices Malaysia, Bahrain, Kuwait, Oman, Qatar, the United Arab Emirates and Indonesia). We conduct Kupiec and Engle and Manganelli tests to evaluate the performance for each model. We found that the performance of asymmetric models in estimating value at risk are superior in both in-sample and out-of-sample evaluation. We also found that the skewed student-t distribution is more preferable than normal and student-t distribution. Results show that the value of VaR is greater for conventional indices than for Islamic indices. This shows that Islamic equity indexes are less risky than conventional index. Several useful implications for policy regulation, risk assessment and hedging, stock-price forecasting and portfolio asset allocations can be drawn from the obtained results.

Keywords: *value-at-risk, GARCH models, risk, Stock market indices, Islamic finance*

Cite This Article: Majoul Neila, and Hellara Slaheddine, “Parametric Value-at-Risk Analysis: Evidence from Islamic and Conventional Stock Market.” *International Journal of Business and Risk Management*, vol. 1, no. 1 (2018): 37-54. doi: 10.12691/ijbrm-1-1-5.

1. Introduction

In recent years, effective risk management has become extremely important. Indeed, the financial crises that have occurred in recent years, as the stock market collapse in 1987, the Mexican crisis in 1995, the Asian and Russian financial crisis from 1997 to 1998, the tech bubble and the 2007 US financial crisis -2009, led to the bankruptcy of some financial institutions. All these events have increased the likelihood of financial institutions to take losses and focused for the development and adoption of specific new measures of market risk. In this context, financial regulators and financial institutions oversight committees have emphasized the need to use quantitative techniques to evaluate the risk of potential loss that financial institutions may incur [1]. This need was reinforced by an increase in financial uncertainty and increased volatility of stock returns. Such uncertainty has increased the likelihood of financial institutions to incur substantial losses due to their exposure to unpredictable market developments. These events have made investors more cautious in their investment decisions. Also, these events led to an increased need for further study of the volatility of stock market returns and the development of sophisticated models to analyze market risks.

In this context, the Basel 1 and Basel 2 agreements have introduced the first directives globally for the establishment of a regulatory framework in the financial markets following the events of the successive crises in the early nineties. These agreements recommended using a standard model for measuring market risk. Financial institutions are encouraged to develop their own internal models of risk management. The use of value at risk (VaR) has been recommended as a standard measure of market risk [2]. Indeed, the Value-at-Risk was proposed by J. P Morgan in the late 1980s and early 1990s [3]. In 1993-1994, the VaR concept was popularized when JP Morgan launched the RiskMetrics method on the market in order to promote greater transparency and establish a baseline for measuring market risk [4]. Following the approval of the proposal of the bale committee in 1993 by the European commission, VaR has become the standard tool used by financial analysts to quantify and manage market risk [5,6]. It was widely used by financial institutions and regulators [7].

VaR is defined as the maximum loss that a portfolio can suffer for a given probability and a fixed horizon. Indeed, the choice of the time horizon and the probability affect the results of the model. Similarly, the model used extensively affects the decisions. The choice between the RiskMetrics model and the symmetric and asymmetric volatility models has a significant impact on the results found.

The aim of this paper is to study the forecasting performance of RiskMetrics, GARCH and APARCH under different densities, Normal, Student- t, skewed student- t, of Islamic and conventional stocks indices. We also assess the risk from these two categories of stock indices and examine how the restrictions imposed by Islamic law affect the risk.

The paper is organized as follows. Section 2 gives an overview of Islamic indices. Section 3 presents the empirical methodology. Section 3 describes the data. Section 4 reports the empirical results and section 5 concludes the article.

2. Islamic Indices

Islamic equity indices were launched for the first time in the late 90s. Indeed, in April 1998, the index Dar al-Mal al-Islami (DMI 150) was created by two private banks (finance and Faisal Bank Vontobel) [8]. A little later, another index was created in November 1998 called SAMI (Socially Aware Muslim Index) which measures the performance of 500 companies in accordance with Islamic law. Following this, several exchanges have launched their own Islamic indexes as a new alternative for investors looking for investment opportunities in line with their beliefs and religious principles [8,9].

Indeed, in February 1999, Dow created the Dow Jones Islamic Market Index (DJIMI). Then in October 1999, FTSE launched the FTSE Shariah Global Equity Index, born of an operation of joint venture between FTSE and Yasaar consulting company. In 2006, S§P introduced S§P Shariah. In March 2007, MSCI launched its global family of Islamic MSCI Global Islamic [10,11].

The introduction of Islamic stock index is designed to filter the conventional stock indices and provide a set of solution compatible with Islamic law to meet the demands of investors in the world [11]. These Islamic indexes exclude all non-compliant securities with Islamic law. Benchmarks and criteria have been provided to reflect the Islamic investment principles. This methodology has been approved by the advisors and scholars of the Sharia Board Committee [12]. Two screens are employed by Shariah committee of MSCI Islamic. The first is business activity screen or qualitative criteria. Indeed, to determine the conformity of business sectors with Islamic law, a sectoral classification Global Industry Classification Standard (GICS) is used. Companies classified in this classification are excluded from the Islamic Index (MSCI 2011). Companies classified under le GICS are excluded from the Islamic indices (See Table 1).

Table 1. GICS classification

Sub-industries		All sub-industries of the following Industries	
Codes	Designations	Codes	Designations
20101010	Aerospace & Defense	4010	Banks
25301010	Casinos & Gaming	4020	Diversified Financials
25301020	Hotels, Resorts & Cruise Lines	4030	Insurance
25301040	Restaurants		
25401020	Broadcasting & Cable TV		
25401030	Movies & Entertainment		
30201010	Brewers		Source: MSCI 2011
30201020	Distillers & Vintners		
30203010	Tobacco		

The second screen is financial screen. This criterion comported four levels for Islamic MSCI index: Leverage Compliance (debt), Cash and Interest Bearing Items, Cash Compliance (Account Receivable + cash), Revenue from non complaint activities and total interest.

	Islamic MSCI
Leverage Compliance (debt)	$\frac{\text{debt}}{\text{total assets}} < 33\%$
Cash and Interest Bearing Items	$\frac{\text{Cash + Interest Bearing Items}}{\text{total assets}} < 33\%$
Cash Compliance (Account Receivable + cash)	$\frac{\text{Account Receivable + cash}}{\text{total assets}} < 70\%$
Revenue from noncompliant Activities and Total Interest	$\frac{\text{Revenue From Haram + Total Interest}}{\text{total assets}} < 5\%$

3. Empirical Methodology: VaR Models and Evaluation Methods

This section presents the empirical framework that we use to explore the volatility in presence of asymmetric effects and we show how evaluation criteria can be used to compare the forecasting performance of these volatility models.

3.1. Conditional Volatilities

3.1.1. RiskMetriks

Since the introduction of RiskMetrics model by JP Morgan, this model has become a reference in the risk management field. This model assumes that the error terms are normally distributed. RiskMetrics suggested using $\lambda = 0.94$ for daily data and $\lambda = 0.97$ for monthly data. It is, also, shown in the literature that $\lambda = 0.94$ provides very good volatility forecast [4-13]. The RiskMetrics model is a GARCH (1,1), which follows a conditional zero mean normal distribution with variance is expressed as a weighted exponential moving average on historical data, the parameter is specified in a pre set value λ. This model can be written as follows:

$$\sigma_t^2 = (1-\lambda)\ \varepsilon_t^2 + \lambda\sigma_{t-1}^2. \qquad (1)$$

The basic idea of this model is to vary the volatility over time, giving greater weight to the most recent data. However, it has been well documented in the literature that this model contains limitations. The yield distribution usually thicker than tail part of a normal distribution [4]. The current dynamic state characterized by volatile financial markets requires more flexible methods for capturing shocks in financial markets. There is significant evidence that significant market shocks occur more frequently than under normal distributions, which indicate the existence of a thick tail in the distribution of financial performance [14]. ARCH and GARCH models, to model the volatility varies over time, seem to be most appropriate [15].

3.1.2. GARCH Model

Developed by reference [16], the GARCH model is a generalization of the ARCH model of reference [17]. Assuming that the process of return is expressed as an autoregressive process of order k. It can be expressed as

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_j \sigma_{t-j}^{\delta} \quad (2)$$

Where $\alpha_0 > 0$, $\alpha_i \geq 0$ for i = 1 ... .q, $\beta_j \geq 0$ for j = 1 ... ip, the process is stationary if α + β <1. The GARCH model adds the moving average term, making a similar model ARMA (p, q). Although the GARCH model was considered one of the best methods for modeling financial time series, the existence of asymmetric volatility or leverage in the financial time series is a limit to this model [15]. It is heavily documented in the literature that the impact of negative shocks or bad news is more important than good news or positive impact on the financial markets. This feature cannot be captured by symmetric GARCH. This limitation is overcome by establishing asymmetric GARCH models.

3.1.3. APARCH Model

Reference [18] introduce the APARCH model. This model represents a general category ARCH model that encompasses a broader class model used in the literature. It is expressed as follows:

$$\sigma_t^{\delta} = \alpha_0 + \sum_{i=1}^{q} \alpha_i \left(\left|\varepsilon_{t-i}\right| + \gamma_i \varepsilon_{t-i}\right)^{\delta} + \sum_{i=1}^{p} \beta_j \sigma_{t-j}^{\delta} \ . \quad (3)$$

Some models can be derived and estimated from this model as:

- ARCH model of [17] when = 2 , $\gamma_i = 0$, $\beta_j = 0$
- GARCH model of [16] when = 2 , $\gamma_i = 0$
- TS-GARCH model of [19,20] and when $\delta = 1$, $\gamma_i = 0$
- GJR-GARCH of [21] when δ = 2
- T-ARCH model of [22] when $\delta = 1$
- N-ARCH model of [23] when $\gamma_i = 0$, $\beta_j = 0$
- Log-ARCH model of [24,25] when $\delta = 0$

3.2. Distributions Yields

3.2.1. The Normal Distribution

The normal distribution is the most widely used distribution in the estimation of GARCH models. The log-likelihood function of the standard normal distribution is given by:

$$L_N = -0.5 \sum_{t=1}^{T} \left[Ln(2\pi) + Ln\left(\sigma_t^2\right) + z_t^2 \right]. \quad (4)$$

Faced with the existence of fat tails in financial series, financial literature has proposed to improve forecasting methods by introducing different fat tailed distribution instead of the normal distribution. Reference [26] suggested replacing the normal distribution through the distribution of student. While reference [27] found that the distribution skewed student can properly handle two characteristics of leptokurticity and asymmetry of financial time series.

3.2.2. The Student Distribution

For a Student's t distribution, the log-likelihood is written as follows:

$$L_{St} = T\left\{ Ln\Gamma\left(\frac{\vartheta+1}{2}\right) - Ln\,\Gamma\left(\frac{\vartheta}{2}\right) - 0.5Ln\left[\pi(\vartheta-2)\right]\right\} \\ -0.5\sum_{t=1}^{T}\left[Ln\left(\sigma_t^2\right) + (1+\vartheta)\left[Ln\left[1+\left(1+\frac{Z_t^2}{\sigma_t^2(\vartheta-2)}\right)\right]\right]\right] \quad (5)$$

Where ϑ is the degree of freedom> 2, Γ (.) Is the gamma function, When $\vartheta \rightarrow \infty$ we have the normal distribution.

3.2.3. Skewed Distribution Student

The skewness and kurtosis are two important moments in financial applications. Therefore, a distribution that can model these two moments seems appropriate. Recently, reference [27] have proposed extending the density Skewed Student proposed by [28] for the GARCH framework. To normalize the distribution Skewed Student, the log-likelihood function is written as follows:

$$L_{SkSt} = T\left\{ \begin{array}{l} Ln\,\Gamma\left(\frac{\vartheta+1}{2}\right) - Ln\,\Gamma\left(\frac{\vartheta}{2}\right) \\ -0.5Ln\left[\pi(\vartheta-2)\right] + Ln\left(\frac{2}{k+\frac{1}{k}}\right) + Ln(S) \end{array} \right\} \\ -0.5\sum_{t=1}^{T}\left[\begin{array}{l} Ln\left(\sigma_t^2\right)(1+\vartheta) \\ \times \left[Ln\left[1+\left(1+\frac{\left(S\,Z_t+m\right)^2}{\vartheta-2}\right)k^{-2I_t}\right]\right] \end{array} \right] \quad (6)$$

Where k is the asymmetry parameter θ: the degree of freedom of the distribution, Γ is the gamma function (.)

$$I_t = \left\{ \begin{array}{l} 1,\ si \mid Z_t \geq \frac{m}{S} \\ -1,\ si \mid Z_t < \frac{m}{S} \end{array} \right. \quad (7)$$

$$m(k,\vartheta) = \frac{\Gamma\left(\frac{\vartheta-1}{2}\right)\sqrt{\vartheta-2}}{\sqrt{\pi}\,\Gamma\left(\frac{\vartheta}{2}\right)}\left(k-\frac{1}{k}\right) \quad (8)$$

$$S(k,\vartheta) = \sqrt{\left(k^2+\frac{1}{k^2}-1\right)-m^2} \quad (9)$$

3.3. VaR Model Accuracy and Backtesting

The accuracy of the VaR model estimates is sensitive to the relevance of volatility model used. It is therefore important to evaluate the performance of the VaR model since the preselected volatility model. Indeed, at first the VaR models have focused on calculating the VaR on the left tail of the distribution corresponds to the negative returns. This implies that it is assumed that portfolio managers have long trading positions. Thus, the buyer suffers a loss when the price falls. More recent approaches that treat VaR models included both the two negotiating positions both long and short.

In the case of a short position, the risk of loss occurs to the seller when the price of the asset increases. Thus, in this context, we model the right tail of the distribution. The short position on investment is defined as follows:

$$\Pr\left(X_t - X_{t-1} \le VaR_{t,1}\right) = 1-\alpha. \tag{10}$$

The VaR is calculated on a day:

$$VaR_{t,1,Short} = \mu + q_{1-\alpha}^{D}\sigma_t. \tag{11}$$

With μ is the average yields $q_{1-\alpha}^{D}$ shows the quantile $(1\text{-}\alpha)^{th}$ according to the statistical distribution D.

In the long position, we model the left tail of the distribution.

$$\Pr\left(X_{t-1} - X_t \le VaR_{t,1}\right) = 1-\alpha. \tag{12}$$

Under the assumption that asset returns follow a given distribution rated D, the value at risk of a long position is given by:

$$VaR_{t,1,Long} = \mu + q_{\alpha}^{D}\sigma_t. \tag{13}$$

Both approaches are discussed in the literature to model both long and short trading positions:

The first is to calculate the empirical failure rate, both to the left and right tail of the distribution of returns. The probability is 1% and 5%. The failure rate can be defined as the number of times the performance in absolute value exceeds VaR planned. If the model is correctly specified so the failure rate is equal to the specified level of VaR.

The second approach is the backtesting which is defined as an established set of statistical procedure whose purpose is to check a posteriori whether the observed losses are adequate with expected losses. Indeed, a high p-value indicates a rejection of the null hypothesis fails. This means that the model is reliable. While a p-value low (below the level of significance) selected indicates that the null hypothesis is rejected. The backtesting allows determining the most appropriate models to determine VaR. We use the unconditional coverage test Kupiec [29] and conditional coverage test Engel and Manganelli [30].

3.3.1. The Unconditional Coverage Test Kupiec

To test the accuracy and evaluate the performance estimates of the VaR model, [29] provided a likelihood ratio test LR_{uc} to examine whether the failure rate model is statistically equal to that expected.

$$I_t = \begin{cases} 1, & r_t < VaR_{t|t-1(\alpha)} \\ 0, & r_t \ge VaR_{t|t-1(\alpha)} \end{cases} \tag{14}$$

I_t is the indicator function compared to the observed returns and the VaR estimated from the information set available at t-1.

The hypothesis to test if the failure rate of the model is equal to that expected is expressed as follows: $H_0: \alpha = \alpha_0$ is the level of VaR fixed.

Thus, the appropriate statistical likelihood ratio in the presence of the null hypothesis is given by:

$$LR_{uc} = -2\log\left\{\alpha_0^N (1-\alpha_0)^{T-N}\right\} + 2\log\left\{\left(\frac{N}{T}\right)^N \left(1-\frac{N}{T}\right)^{T-N}\right\}. \tag{15}$$

Under the null hypothesis, LR_{uc} follows an asymptotic distribution $x^2(1)$. Thus, the model chosen for the prediction of the VaR should provide the property that the unconditional coverage measured by p = E (N/T) is equal to desired coverage level p_0. Where $N = \sum_{t=1}^{T} I_t$ is the number of exceptions in the sample size T.

3.3.2. The Conditional Coverage Test Engel and Manganelli

Reference [30] develops the dynamic quantile (DQ) built on a linear regression model based on the process of the violation function centered hit:

$$\delta_t^{\alpha} = HIT_t(\alpha) = I\left(y_t < -VaR_t(\alpha)\right) - \alpha. \tag{16}$$

The dynamics of the relationship function is modeled as follows:

$$\delta_{t}^{\alpha} = \theta_0 + \sum_{i=1}^{p}\theta_I \delta_{t=i}^{(\alpha)} + \sum_{\tau=1}^{m}\vartheta_i \delta_{t=i}^{(\tau)} + \mu_t \tag{17}$$

Where μ_t is an IID process. DQ test is defined under the assumption that the regressors in the preceding equation have no explanatory power.

$$H_0 = \psi = (\theta_0, \theta_0 \ldots\ldots\ldots\ldots \theta_0, \theta_0, \theta_0, \ldots\ldots\ldots \theta_0)^T = 0.$$

For backtesting, the DQ test statistic associated with the Wald statistic is as follows:

$$DQ = \frac{\widehat{\psi^T}\, X^T \hat{\psi}}{\alpha(1-\alpha)} \xrightarrow{1} x_{1+p+m}^2 \tag{18}$$

where X is the matrix of explanatory variables.

We conduct our study of long and short portfolios position on Islamic and conventional daily stock indexes in seven countries using data from 10 August 2006 to 26 November 2015. In order to take account of possible asymmetries in the behavior of stock returns we applied the APARCH model introduced by [18] to model and calculate the VaR of portfolios defined on a long position and a short position. We are conducting Kupiec and Engel and Manganelli tests to evaluate the performance of each model. Model performance APARCH in-sample and out-of-sample were compared with those of RiskMetrics and GARCH models. We examine the performance of these models with different thresholds 1% and 5% in order to compare the results provided. The estimation process was carried out on the entire sample. We used the past four years to complete the evaluation forecast out-of-sample. To perform the calculations required for this chapter, we use metrics OX software. As suggested in previous studies on AR (1) process is used, the optimization algorithm is used BFGS.

4. Data

The data used are conventional and Islamic stock indices from 7 countries: Malaysia, Bahrain, Kuwait, Oman, Qatar, the United Arab Emirates and Indonesia. These indices are extracted from the MSCI database. The market index is represented by the MSCI World global stock index. All these indexes are taken into USD. The data are daily, covers the period from August 10, 2007 to November 26, 2016 including 2425 cases for each market. The good treasure of 3months rate is used to calculate the return on risk-free asset in the conventional frame obtained based Federal Reserve Economic Data (FRED). In the Islamic context, Dow Jones Sukuk total return index (ex-reinvestment) is used to calculate sukuk.

Table 2. Descriptive statistics

	Conventional						
	Malaysia	Bahrain	Kuwait	Oman	Qatar	Emirate	Indonesia
Mean	0.015	-0.098	-0.023	-0.007	0.008	-0.007	0.026
SD	1.073	1.326	1.328	1.252	1.437	1.792	1.913
Min	-11.279	-23.435	-11.608	-17.333	-13.172	-15.499	-14.575
Max	5.784	7.835	8.714	10.867	11.258	18.334	15.042
Skewness	-0.480	-3.178	-1.126	-1.590	-0.711	-0.434	-0.244
Kurtosis(Excess)	7.681	49.039	13.239	33.935	15.943	14.177	6.963
JB	6054.2	247000	18222	117000	25886	20383	4923.4
ARCH (2)	42.97*** [0.0000]	4.7304*** [0.0089]	50.578*** [0.0000]	43.822*** [0.0000]	72.814*** [0.0000]	77.651*** [0.0000]	78.095*** [0.0000]
ARCH (5)	23.825*** [0.0000]	3.2102*** [0.0068]	67.504*** [0.0000]	31.516*** [0.0000]	50.179*** [0.0000]	42.039*** [0.0000]	53.86*** [0.0000]
ARCH (10)	12.813*** [0.0000]	2.7488*** [0.0023]	64.847*** [0.0000]	19.697*** [0.0000]	37.687*** [0.0000]	38.687*** [0.0000]	28.383*** [0.0000]
LB (5)	31.7145*** [0.0000068]	6.79955 [0.2359797]	18.3086*** [0.0025835]	41.1467*** [0.0000001]	37.3696*** [0.0000005]	50.1482*** [0.0000]	42.452*** [0.0000]
LB (10)	36.689*** [0.0000640]	14.5158*** [0.1507369]	42.8547*** [0.0000053]	47.9275*** [0.0000006]	44.7114*** [0.0000025]	55.4132*** [0.0000000]	48.8667*** [0.0000004]
LB(20)	54.0301*** [0.0000573]	52.8855*** [0.0000845]	87.3908*** [0.0000000]	95.6635*** [0.0000000]	56.5383*** [0.0000241]	77.0839*** [0.0000000]	70.3651*** [0.0000002]
LB2 (5)	156.894*** [0.0000000]	17.697*** [0.0000000]	414.836*** [0.0000000]	215.267*** [0.0000000]	323.951*** [0.0000000]	275.706*** [0.0000000]	419.359*** [0.0000000]
LB2(10)	194.02*** [0.0000000]	34.1407*** [0.0001748]	861.946*** [0.0000000]	333.673*** [0.0000000]	575.506*** [0.0000000]	559.148*** [0.0000000]	575.957*** [0.0000000]
LB2(20)	247.157*** [0.0000000]	60.4922*** [0.0000060]	1444.43*** [0.0000000]	745.597*** [0.0000000]	1176.36*** [0.0000000]	700.975*** [0.0000000]	1025.99*** [0.0000000]
ADF	-26.897***	-27.675***	-26.598***	-26.503***	-25.503***	-26.779***	-27.955***
Observations	2425	2425	2425	2425	2425	2425	2425
	Islamic						
	Malaysia	Bahrain	Kuwait	Oman	Qatar	Emirate	Indonesia
Mean	0.027	-0.102	-0.037	0.002	0.015	-0.037	0.016
SD	1.106	1.513	1.521	1.286	1.592	2.248	2.007
Min	-10.998	-15.701	-12.311	-16.902	-15.762	-21.466	-16.626
Max	5.841	11.379	11.358	11.955	11.606	19.477	16.309
Skewness	-0.463	-1.121	-0.778	-1.297	-0.431	-0.693	-0.262
Kurtosis(Excess)	7.072	14.988	11.279	29.005	15.511	13.441	7.162
JB	5140	23206	13099	85686	24386	18449	5210.3
ARCH (2)	55.629*** [0.0000]	162.87*** [0.0000]	71.453*** [0.0000]	46.21*** [0.0000]	74.827*** [0.0000]	67.637*** [0.0000]	38.39*** [0.0000]
ARCH (5)	32.164*** [0.0000]	83.33*** [0.0000]	98.251*** [0.0000]	27.213*** [0.0000]	44.515*** [0.0000]	35.046*** [0.0000]	23.58*** [0.0000]
ARCH (10)	17.544*** [0.0000]	60.21*** [0.0000]	64.731*** [0.0000]	16.344*** [0.0000]	31.155*** [0.0000]	35.909*** [0.0000]	14.206*** [0.0000]
LB (5)	28.4557*** [0.0000296]	13.6027** [0.0183399]	21.1714*** [0.0007518]	36.7395*** [0.0000007]	56.1381*** [0.0000000]	19.5503*** [0.0015173]	15.2366*** [0.0093978]
LB (10)	31.4199*** [0.0005000]	17.9949* [0.0550493]	35.4821*** [0.0001033]	42.216*** [0.0000069]	66.0853*** [0.0000000]	29.9434*** [0.0008751]	21.2261** [0.0195713]
LB(20)	56.605*** [0.0000236]	90.7979*** [0.0000000]	68.2739*** [0.0000003]	81.113*** [0.0000000]	73.9614*** [0.0000000]	43.0768*** [0.0019971]	47.2936*** [0.0005340]
LB2 (5)	201.878*** [0.0000000]	476.298*** [0.0000000]	570.947*** [0.0000000]	190.974*** [0.0000000]	285.222*** [0.0000000]	232.443*** [0.0000000]	167.955*** [0.0000000]
LB2(10)	263.078*** [0.0000000]	830.01*** [0.0000000]	944.858*** [0.0000000]	276.89*** [0.0000000]	449.414*** [0.0000000]	551.066*** [0.0000000]	261.215*** [0.0000000]
LB2(20)	352.982*** [0.0000000]	1330.66*** [0.0000000]	1558.78*** [0.0000000]	568.525*** [0.0000000]	896.408*** [0.0000000]	805.868*** [0.0000000]	598.766*** [0.0000000]
ADF	-26.811***	-27.792***	-25.846***	-27.980***	-24.825***	-26.713***	-28.406***
Observations	2425	2425	2425	2425	2425	2425	2425

*** Notes: This table reports the main descriptive statistics for conventional and Islamic returns. SD:Standard deviation, Min and Max are the minimum and maximum values of the sample data, respectively, skewness and kurtosis are the estimated centralized third and fourth moments of the data. JB is the Jarque Bera test for normality, ARCH(i) is a Lagrange multiplier (LM) test of order i=2,5,10; LB (i) and LB^2 (i) are the Ljung and Box (1978) Q-statisticsfor i = 5, 10, 20 lags of the sample autocorrelation function of r_t and r^2_t , testing for autocorrelation and heteroscedasticity, respectively; * significance level at 10%, ** significance level at 5%, significance level at 1%, Numbers in square brackets [ ] indicate p-values; ADF is the augmented Dickey and Fuller (1981) test

The Daily returns were calculated as the first difference of the natural logarithm of each index and expressed as percentages:

$$R_{it} = \text{Log}\left(\frac{P_{it}}{P_{it-1}}\right)*100. \quad (19)$$

Descriptive statistics of daily logarithmic conventional and Islamic returns are presented in Table 2.

Conventional stock indexes are asymmetrically negative and have high kurtosis. The skewness, kurtosis and Jarque bera test show that all stock indices return series do not follow the normal distribution. This result encourages the most sophisticated performance distribution application as the normal distribution that takes into account different return characteristics. Ljung Box statistics (LB and LB^2) on the 5th, 10th, 20^{th} lags of the sample autocorrelation series in levels and squares indicate significant serial correlation. The Engel (1982) test for conditional heteroscedasticity and the Ljung Box test show strong evidence of ARCH effect in conditional variance of returns. These results indicate that GARCH modeling should considered the VaR estimates. The ADF test indicates that all series are stationary. The statistics describing the daily returns of the Islamic indices shows that Islamic equity indices appear to have similar statistical properties for the third and fourth time those conventional stock indices. In particular, those stock indexes are asymmetrically negative and have high kurtosis. Islamic equity indices are not normally distributed. The conditional heteroscedasticity test shows evidence of ARCH effect in conditional variance of returns. The ADF test indicates that all series are stationary. All these results show that Islamic equity indices have the same stylized facts those conventional stock indices. These results are consistent with results found by [31,32,33].

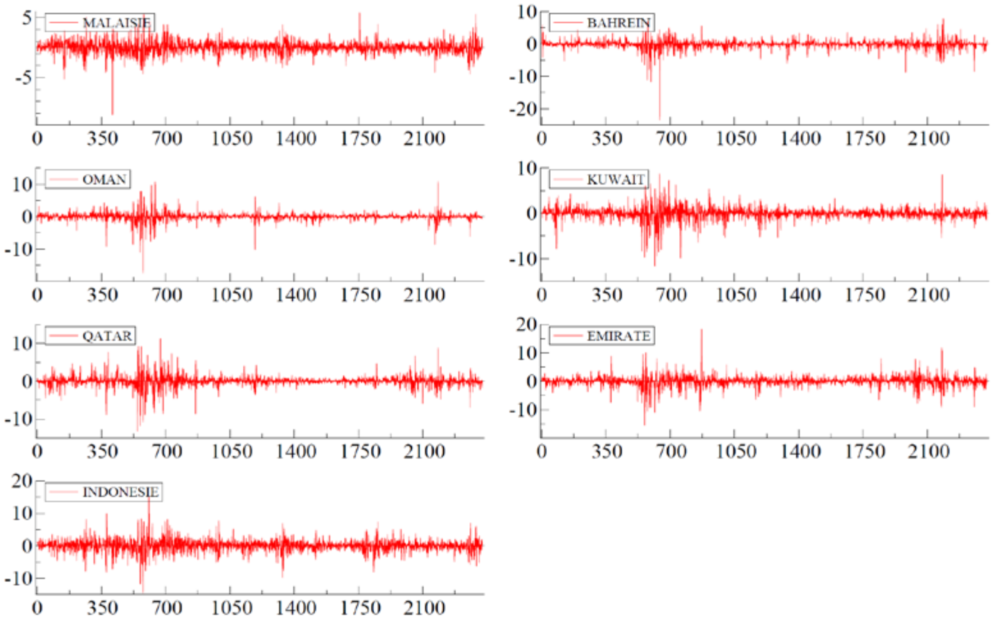

Figure 1. Conventional Daily returns of indices

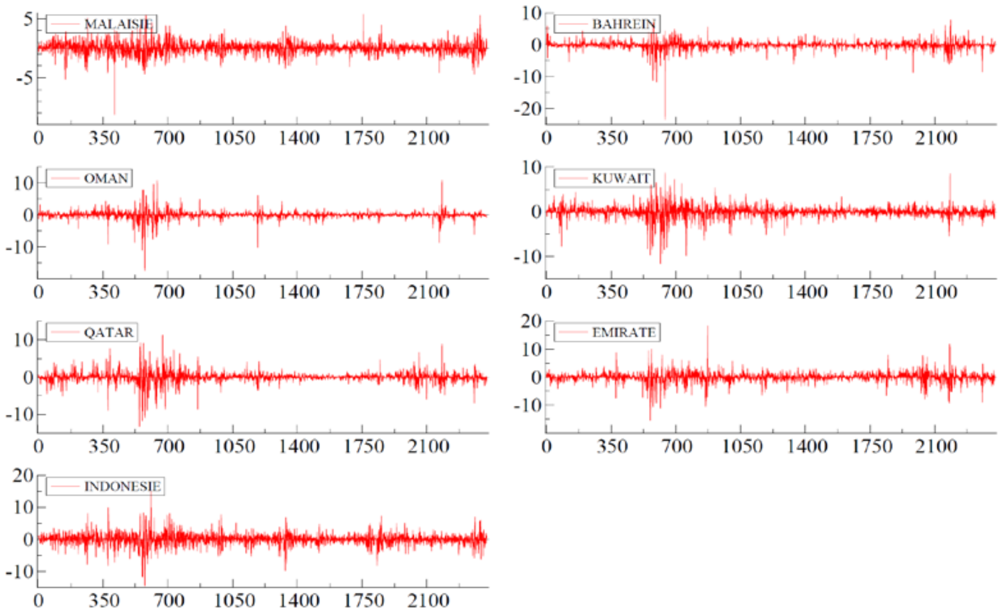

Figure 2. Islamic Daily returns of indices

Graphs of daily returns of conventional indices are illustrated in Figure 1. Indeed, the volatility clustering phenomenon "Clustering Volatility" is evident in the graphs of daily yields. The fluctuations are followed by strong variations and small changes are followed by small variations. This is mainly due to correlations of financial series. This led us also to reject the hypothesis that the returns are independent and identically distributed. Therefore, the combination of volatility will be quantified by volatility models autoregressive conditional heteroscedasticity. We model the volatility using GARCH models (1,1).

Graphs of daily returns of Islamic equity indices are illustrated in Figure 2. The evolution of Islamic stock index returns indicates that the series are highly volatile and almost identical to conventional stock indices. Similarly, the evolution of Islamic and conventional stock indexes shows high volatility recorded in the period of the Subprime crisis. This indicates that the two categories of indices were affected by the subprime crisis. Based on this preliminary analysis, we said that Islamic equity indexes capture the same stylized facts that conventional stock indexes in terms of asymmetry, not distribution normality, stationarity and leverage effect

Table 3.

	Malaysia						
	RM	**GARCH-N**	**GARCH-T**	**GARCH-SkT**	**APARCH-N**	**APARCH-T**	**APARCH-SkT**
Cst (M)	0.034 (0,247)	0.054 (0,017)	0.042 (0,014)	0.035 (0,063)	0.024 (0,275)	0.027 (0,122)	0.019 (0,336)
Cst (V)		0.033 (0,041)	0.017 (0,016)	0.017 (0,017)	0.027 (0,0317)	0.018 (0,026)	0.018 (0,0266)
AR(1)	0.104 (0)	0.117 (0)	0.096 (0)	0.094 (0)	0.108 (0)	0.097 (0)	0.095 (0)
ARCH (α_1)	0.060	0.115 (0,000)	0.098 (0)	0.097 (0)	0.092 (0)	0.089 (0)	0.088 (0)
GARCH (β_1)	0.940	0.860 (0)	0.892 (0)	0.894 (0)	0.903 (0)	0.911 (0)	0.913 (0)
APARCH (γ_1)					0.416 (0,0073)	0.337 (0,000)	0.338 (0,0002)
APARCH (δ)					1.131 (0,001)	1.361 (0)	1.351 (0)
Student			5.443 (0)	-0.029 (0,2368)		5.712 (0)	-0.033 (0,1731)
Tail				5.477 (0)			5.733 (0)
Log	-3385.6	-3334.9	-3236	-3235.4	-3314.3	-3223.6	-3222.8
Obs	2425	2425	2425	2425	2425	2425	2425
	Bahrain						
	RM	**GARCH-N**	**GARCH-T**	**GARCH-SkT**	**APARCH-N**	**APARCH-T**	**APARCH-SkT**
Cst (M)	-0.023 (0,783)	-0.055 (0,008)	-0.026 (0,001)	-0.053 (0,001)	-0.073 (0,001)	-0.024	-0.054 (0,0002)
Cst (V)		0.072 (0,000)	0.077	0.076	0.059 (0,0127)		0.091
AR(1)	0.097 (0,064)	0.068 (0,02)	0.009 (0,403)	0.009 (0,402)	0.077 (0,018)	0.008	0.012 (0,1898)
ARCH (α_1)	0.060	0.165 (0,001)	0.126 (0)	0.124 (0,00)	0.145 (0,004)		0.422 (0,0023)
GARCH (β_1)	0.940	0.812 (0)	0.831 (0)	0.833 (0)	0.850 (0)		0.906 (0)
APARCH (γ_1)					0.226 (0,1553)		0.067 (0,662)
APARCH (δ)					1.580 (0,001)		0.920 (0)
Student			2.370 (0)	-0.043 (0,005)			-0.043 (0,002)
Tail				2.367 (0)			2.021 (0)
Log		-3645.3	-2981.9	-2978.5	-3636.7		-2936.3
Obs	2425	2425	2425	2425	2425	2425	2425

	Kuwait						
	RM	**GARCH-N**	**GARCH-T**	**GARCH-SkT**	**APARCH-N**	**APARCH-T**	**APARCH-SkT**
Cst (M)	0.000 (0,991)	0.003 (0,8633)	0.013 (0,281)	0.000 (0,9853)	-0.014 (0,45)	0.011 (0,3651)	0.019 (0,3362)
Cst (V)		0.014 (0,1302)	0.044	0.043	0.011 (0,3036)	0.051	0.018 (0,0266)
AR(1)	0.002 (0,948)	0.001 (0,9732)	-0.019 (0,313)	-0.021 (0,276)	0.004 (0,871)	-0.017 (0,338)	0.095 (0)
ARCH (α_1)	0.060	0.064 (0,0047)	0.086 (0)	0.087 (0)	0.049 (0,1006)	0.152 (0,0001)	0.088 (0)
GARCH (β_1)	0.940 (0)	0.929 (0)	0.889 (0)	0.889 (0)	0.948 (0)	0.913 (0)	0.913 (0)
APARCH (γ_1)					0.285 (0,0549)	0.420 (0,0011)	0.416 (0,0013)
APARCH (δ)					1.748 (0)	1.234 (0)	1.230 (0)
Student			2.868 (0)	-0.025 (0,1302)		2.254 (0)	-0.010 (0,533)
Tail				2.877 (0)			2.267 (0)
Log	-3612.2	-3575.3	-3272.0	-3271.2	-3558.9	-3252.8	-3252.7
Obs	2425	2425	2425	2425	2425	2425	2425
	Oman						
	RM	**GARCH-N**	**GARCH-T**	**GARCH-SkT**	**APARCH-N**	**APARCH-T**	**APARCH-SkT**
Cst (M)	-0.001 (0,9958)	0.044 (0,0205)	0.023 (0,0074)	0.030 (0,0318)	0.010 (0,5795)	0.020 (0,0139)	0.034 (0,0144)
Cst (V)		0.028 (0,006)	0.034	0.035	0.026 (0,0016)	0.057	0.058
AR(1)	0.039 (0,5538)	0.087 (0,0209)	0.090 (0)	0.090 (0)	0.110 (0,0001)	0.086 (0)	0.085 (0)
ARCH (α_1)	0.060	0.143 (0,0001)	0.125 (0)	0.125 (0)	0.117 (0)	0.272 (0)	0.282 (0)
GARCH (β_1)	0.940	0.853 (0)	0.853 (0)	0.853 (0)	0.858 (0)	0.874 (0)	0.874 (0)
APARCH (γ_1)					0.280 (0,0059)	0.174 (0,032)	0.189 (0,0229)
APARCH (δ)					2.122 (0)	1.348 (0)	1.345 (0)
Student			2.544 (0)	0.015 (0,3513)		2.168 (0)	0.026 (0,0917)
Tail				2.542 (0)			2.157 (0)
Log	-3325.2	-3137.7	-2553.6	-2553.2	-3104.1	-2535.9	<u>-2534.9</u>
Obs	2425	2425	2425	2425	2425	2425	2425
	Qatar						
	RM	**GARCH-N**	**GARCH-T**	**GARCH-SkT**	**APARCH-N**	**APARCH-T**	**APARCH-SkT**
Cst (M)	0.026 (0,3433)	0.032 (0,0985)	0.019 (0,0706)	0.018 (0,2495)	0.025 (0,1957)	0.013 (0,2804)	0.018 (0,3546)
Cst (V)		0.008	0.023	0.023	0.012	0.037	0.037
AR(1)	0.088 (0,009)	0.083 (0,0034)	0.041 (0,0161)	0.041 (0,016)	0.093 (0,0022)	0.035 (0,0572)	0.035 (0,0408)
ARCH (α_1)	0.060	0.064	0.098 (0,0166)	0.098 (0,0166)	0.068 (0,0702)	0.231 (0,0008)	0.233 (0,0008)
GARCH (β_1)	0.940	0.933	0.891 (0)	0.891 (0)	0.930 (0)	0.919 (0)	0.919 (0)
APARCH (γ_1)					0.179 (0,0632)	0.227 (0,0131)	0.231 (0,0135)
APARCH (δ)					1.791 (0,0001)	1.168 (0)	1.173 (0)
Student			2.711 (0)	-0.001 (0,9679)		2.123 (0)	0.007 (0,6861)
Tail				2.711 (0)			2.121 (0)
Log	-3664.4	-3637	-3185.2	-3185.2	-3623.1	-3155.6	<u>-3155.5</u>
Obs	2425	2425	2425	2425	2425	2425	2425

	UAE						
	RM	**GARCH-N**	**GARCH-T**	**GARCH-SkT**	**APARCH-N**	**APARCH-T**	**APARCH-SkT**
Cst (M)	0.069 (0,1547)	0.060 (0,0422)	0.055 (0,0016)	0.045 (0,0955)	0.018 (0,5955)	0.046 (0,0057)	0.043 (0,1465)
Cst (V)		0.051	0.113	0.112	0.045	0.204	1.935
AR(1)	0.087 (0,0058)	0.089 (0,0002)	0.050 (0,0032)	0.050 (0,0035)	0.100 (0)	0.049 (0,0035)	0.048 (0,0022)
ARCH (α_1)	0.060	0.074 (0)	0.104 (0)	0.104 (0)	0.080 (0)	0.248 (0,0001)	1.551 (0,5195)
GARCH (β_1)	0.940	0.910 (0)	0.860 (0)	0.861 (0)	0.915 (0)	0.857 (0)	0.817 (0)
APARCH (γ_1)					0.380 (0,0003)	0.352 (0,0022)	0.253 (0,0173)
APARCH (δ)					1.555 (0,0002)	1.418 (0)	2.182 (0)
Student			2.787 (0)	-0.011 (0,5015)		2.209 (0)	0.000 (0,9957)
Tail				2.790 (0)			2.048 (0)
Log	-4459.3	-4401.3	-4045.9	-4045.7	-4371.2	-4025.5	-4017.4
Obs	2425	2425	2425	2425	2425	2425	2425
	Indonesia						
	RM	**GARCH-N**	**GARCH-T**	**GARCH-SkT**	**APARCH-N**	**APARCH-T**	**APARCH-SkT**
Cst (M)	0.043 (0,2677)	0.053 (0,0766)	0.087 (0,0011)	0.051 (0,0781)	-0.001 (0,9812)	0.061 (0,0282)	0.008 (0,7936)
Cst (V)		0.055	0.080	0.079	0.032	0.065	0.061
AR(1)	0.062 (0,0178)	0.060 (0,0108)	0.038 (0,0691)	0.030 (0,1574)	0.068 (0,0031)	0.042 (0,0429)	0.038 (0,0665)
ARCH (α_1)	0.060	0.088 (0)	0.109 (0)	0.110 (0)	0.080 (0)	0.126	0.124
GARCH (β_1)	0.940	0.897 (0)	0.869 (0)	0.869 (0)	0.920 (0)	0.875 (0)	0.879 (0)
APARCH (γ_1)					0.362 (0,0022)	0.281 (0)	0.359 (0)
APARCH (δ)					1.552 (0)	1.683 (0)	1.382 (0)
Student			4.719 (0)	-0.077 (0,0011)		4.208 (0)	-0.097 (0,0001)
Tail				4.794 (0)			4.450 (0)
Log lik	-4673.9	-4644.9	-4541.6	-4537	-4625.9	-4528.8	-4521.1
Obs	2425	2425	2425	2425	2425	2425	2425
	Malaysia						
	RM	**GARCH-N**	**GARCH-T**	**GARCH-SkT**	**APARCH-N**	**APARCH-T**	**APARCH-SkT**
Cst (M)	0.055 (0,0331)	0.060 (0,0037)	0.048 (0,0071)	0.047 (0,0177)	0.041 (0,045)	0.036 (0,0445)	0.033 (0,0819)
Cst (V)		0.023	0.021	0.021	0.017	0.016	0.016
AR(1)	0.087 (0,0015)	0.092 (0)	0.083 (0)	0.083 (0)	0.085 (0,0003)	0.083 (0)	0.082 (0,0001)
ARCH (α_1)	0.060	0.082 (0)	0.076 (0)	0.076 (0)	0.070 (0,0007)	0.074 (0,0003)	0.072 (0,0006)
GARCH (β_1)	0.940	0.900 (0)	0.907 (0)	0.907 (0)	0.927 (0)	0.924 (0)	0.926 (0)
APARCH (γ_1)					0.278 (0,0133)	0.270 (0,0023)	0.278 (0,0032)
APARCH (δ)					1.429 (0,0001)	1.568 (0)	1.525 (0)
Student (DF)			5.156 (0)	-0.006 (0,799)		4.950 (0)	-0.013 (0,5527)
Tail				5.158 (0)			5.020 (0)
Log	-3441.9	-3413.1	-3319.1	-3319.1	-3400.9	-3310.7	-3310.6
Obs	2425	2425	2425	2425	2425	2425	2425

	Bahrain						
	RM	**GARCH-N**	**GARCH-T**	**GARCH-SkT**	**APARCH-N**	**APARCH-T**	**APARCH-SkT**
Cst (M)	-0.067 (0,513)	-0.060 (0,0086)	-0.027 (0,0007)	-0.060 (0,0002)	-0.081 (0,0003)	-0.025	-0.057 (0,0003)
Cst (V)		0.091	0.053	0.053	0.094		0.084
AR(1)	0.108 (0,0249)	0.073 (0,005)	0.004 (0,7111)	0.003 (0,7336)	0.079 (0,0035)	0.007	0.006 (0,4979)
ARCH (α_1)	0.060	0.070 (0)	0.076 (0)	0.076 (0)	0.065 (0)	0.182	0.174 (0,0003)
GARCH (β_1)	0.940	0.915 (0)	0.899 (0)	0.900 (0)	0.930 (0)	0.936	0.934 (0)
APARCH (γ_1)					0.227 (0,0241)	0.434	0.433 (0,3929)
APARCH (δ)					1.700 (0,0005)	1.075	1.057 (0)
Student (DF)			2.911 (0)	-0.030 (0,0009)		2.100 (0)	-0.024 (0,0011)
Tail				2.918 (0)			2.112 (0)
Log	-4122.2	-3931.6	-3291.7	-3287	-3920.2	-3241.5	-3237.3
Obs	2425	2425	2425	2425	2425	2425	2425
	Kuwait						
	RM	**GARCH-N**	**GARCH-T**	**GARCH-SkT**	**APARCH-N**	**APARCH-T**	**APARCH-SkT**
Cst (M)	-0.038 (0,317)	-0.021 (0,3315)	0.004 (0,8122)	-0.018 (0,43)	-0.044 (0,0559)	0.005 (0,6465)	-0.018 (0,444)
Cst (V)		0.033	0.058	0.057	0.027	0.057	0.056
AR(1)	-0.021 (0,5019)	-0.022 (0,3264)	-0.029 (0,1008)	-0.030 (0,0886)	-0.021 (0,3489)	-0.030 (0,0216)	-0.030 (0,0734)
ARCH (α_1)	0.060	0.070 (0)	0.076 (0)	0.076 (0)	0.065 (0,0001)	0.182 (0,0022)	0.174 (0,0022)
GARCH (β_1)	0.940	0.915 (0)	0.899 (0)	0.900 (0)	0.930 (0)	0.936 (0)	0.934 (0)
APARCH (γ_1)					0.227 (0,0235)	0.434 (0,0018)	0.433 (0,0018)
APARCH (δ)					1.700 (0)	1.075 (0)	1.057 (0)
Student (DF)			2.911 (0)	-0.030 (0,0546)		2.100 (0)	-0.024 (0,1388)
Tail				2.918 (0)			2.112 (0)
Log	-4050.5	-4000.8	-3721.9	-3720.7	-3989.5	-3696.3	-3695.5
Obs	2425	2425	2425	2425	2425	2425	2425
	Oman						
	RM	**GARCH-N**	**GARCH-T**	**GARCH-SkT**	**APARCH-N**	**APARCH-T**	**APARCH-SkT**
Cst (M)	-0.102 (0,3406)	-0.013 (0,5603)	0.013 (0,0887)	0.016 (0,2337)	-0.018 (0,4595)	0.014 (0,0388)	0.020 (0,1769)
Cst (V)		0.041	0.056	0.056	0.042	0.093	0.092
AR(1)	-0.022 (0,7384)	0.039 (0,2958)	0.053 (0,0005)	0.053 (0,0005)	0.039 (0,1767)	0.046 (0,0008)	0.046 (0,0008)
ARCH (α_1)	0.060	0.125 (0)	0.155 (0)	0.154 (0)	0.124 (0)	0.423 (0)	0.424 (0)
GARCH (β_1)	0.940	0.850 (0)	0.811 (0)	0.812 (0)	0.870 (0)	0.862 (0)	0.864 (0)
APARCH (γ_1)					0.078 (0,4894)	0.033 (0,7138)	0.036 (0,6866)
APARCH (δ)					1.534 (0,0002)	1.138 (0)	1.130 (0)
Student			2.452 (0)	0.006 (0,7247)		2.072 (0)	0.010 (0,5484)
Tail				2.450 (0)			2.069 (0)
Log	-3559. 3	-3337.6	-2592.1	-2592.1	-3333.6	-2564	-2563.8
Obs	2425	2425	2425	2425	2425	2425	2425

	Qatar						
	RM	**GARCH-N**	**GARCH-T**	**GARCH-SkT**	**APARCH-N**	**APARCH-T**	**APARCH-SkT**
Cst (M)	0.025 (0,3676)	0.028 (0,2129)	0.021 (0,0524)	0.024 (0,2352)	0.023 (0,2863)	0.018 (0,0564)	0.025
Cst (V)		0.010	0.017	0.016	0.010	0.041	0.040
AR(1)	0.078 (0,0328)	0.071 (0,0281)	0.015 (0,359)	0.015 (0,3805)	0.072 (0,0277)	0.006 (0,7058)	0.005 (0,7534)
ARCH (α_1)	0.060	0.075 (0,0027)	0.076 (0,3005)	0.075 (0,337)	0.072 (0,0223)	0.291 (0,0013)	0.296 (0,0012)
GARCH (β_1)	0.940	0.921 (0)	0.917 (0)	0.919 (0)	0.921 (0)	0.931 (0)	0.932 (0)
APARCH (γ_1)					0.084 (0,2849)	0.208 (0,0512)	0.214 (0,0451)
APARCH (δ)					2.069 (0)	1.146 (0)	1.152 (0)
Student			2.595 (0)	0.005 (0,82)		2.057 (0)	0.011 (0,4085)
Tail				2.594 (0)			2.056 (0)
Log	-3920	-3897.7	-3387.1	-3387	-3892.9	-3348.6	-3348.3
Obs	2425	2425	2425	2425	2425	2425	2425
	UAE						
	RM	**GARCH-N**	**GARCH-T**	**GARCH-SkT**	**APARCH-N**	**APARCH-T**	**APARCH-SkT**
Cst (M)	0.040 (0,5589)	0.025 (0,4869)	0.030 (0,1524)	0.012 (0,7123)	-0.014 (0,6874)	0.024 (0,2401)	0.013 (0,7064)
Cst (V)		0.076	0.133	0.133	0.060	0.208	0.206
AR(1)	0.024 (0,4573)	0.032 (0,1793)	0.011 (0,5177)	0.010 (0,5586)	0.038 (0,1136)	0.010 (0,5638)	0.010 (0,5493)
ARCH (α_1)	0.060	0.071 (0)	0.093 (0)	0.093 (0)	0.075 (0)	0.231 (0,0029)	0.229 (0,0027)
GARCH (β_1)	0.940	0.914 (0)	0.881 (0)	0.881 (0)	0.919 (0)	0.875 (0)	0.875 (0)
APARCH (γ_1)					0.236 (0,0168)	0.226 (0,0085)	0.224 (0,0095)
APARCH (δ)					1.729 (0)	1.479 (0)	1.476 (0)
Student			2.795 (0)	-0.017 (0,2859)		2.231 (0)	-0.008 (0,609)
Tail				2.798 (0)			2.234 (0)
Log	-5012.8	-4949	-4592.9	-4592.6	-4936.2	-4578.6	-4578.5
Obs	2425	2425	2425	2425	2425	2425	2425
	Indonesia						
	RM	**GARCH-N**	**GARCH-T**	**GARCH-SkT**	**APARCH-N**	**APARCH-T**	**APARCH-SkT**
Cst (M)	0.036 (0,3461)	0.042 (0,1732)	0.066 (0,0158)	0.042 (0,1539)	0.010 (0,7425)	0.047 (0,088)	0.017 (0,588)
Cst (V)		0.031	0.058	0.057	0.026	0.053	0.053
AR(1)	0.043 (0,1048)	0.041 (0,0879)	0.015 (0,4988)	0.010 (0,6607)	0.049 (0,0476)	0.017 (0,4208)	0.015 (0,5011)
ARCH (α_1)	0.060	0.070 (0)	0.097 (0,0001)	0.097 (0)	0.068 (0,0001)	0.117 (0,0004)	0.119 (0,0001)
GARCH (β_1)	0.940	0.922 (0)	0.889 (0)	0.889 (0)	0.931 (0)	0.885 (0)	0.886 (0)
APARCH (γ_1)					0.255 (0,0191)	0.200 (0,001)	0.236 (0,0021)
APARCH (δ)					1.728 (0)	1.715 (0)	1.545 (0)
Student			5.086 (0)	-0.053 (0,0225)		4.602 (0)	-0.061 (0,0106)
Tail				5.140 (0)			4.721 (0)
Log lik	-4783.6	-4767.1	-4674	-4671.8	-4756.3	-4666.8	-4663.9
Obs	2425	2425	2425	2425	2425	2425	2425

Notes: These tables report the estimation results of Risk metrics, GARCH, APARCH for conventional and Islamic indices. We consider seven countries Malaysia, Bahrain, Kuwait, Oman, Qatar, UAE, Indonesia. Const (m) and Const (v) refer to the constant terms in mean and variance equations. AR, , ARCH(α_1), GARCH(β_1), APARCH(γ_1) (δ) represent the autoregressive, ARCH, GARCH and APARCH parameters. Numbers in parentheses () indicate t-statistics of the estimated coefficients; Log-Lik is Log-Likelihood value.

5. Empirical Results

5.1. Estimates of RiskMetrics Model and Types of Models GARCH

In order to perform the VaR analysis, estimate Risk Metrics, GARCH, and APARCH model under three normal distributions, student and skewed student seems to be necessary. Table 3 report the results of estimating the parameters of the model RiskMetrics, GARCH and APARCH under the three distributions applied to return series of conventional and Islamic stock indices.

In Riskmetrics model, λ is equal to 0.94 for the series of daily yields. The log likelihood test shows that this model is not appropriate. In fact, this result is not surprising and is expected since the RiskMetrics model can only be assessed in the normal distribution. The rigidity of this model has led us to use the types of models GARCH (1,1). Indeed, several empirical studies (e.g [34]) show that the GARCH model types are more efficient and outperform several other models such as RiskMetrics to capture the combination of volatile financial performance series.

In the GARCH model, the coefficients of the conditional variance equation are significant. This implies a strong support for ARCH and GARCH effects. We observe that the stationarity condition is satisfied (the sum of α and β coefficients are lower and close to one). For each model of volatility, we have three specifications based on three error distributions namely the normal distribution, the student and law student skewed. The maximum likelihood function indicates that GARCH Skewed student provides the best solution for all conventional and Islamic stock indices.

The GARCH model used to model the volatility has number limitations. This model does not take into account the phenomenon of asymmetric volatility or leverage effects. In this context, Reference [18] introduces the APARCH model. It argued that there is an asymmetry between the effect of recent positive and negative changes in volatility. Asymmetries in the returns are negatively correlated with changes in volatility. In this sense, the good news and the bad news does not have the same impact on volatility. Volatility tends to rise in response to bad news and to decrease in response to good news.

The coefficients of APARCH model (1.1) are significant. A skewed effect exists for conventional stock indices. The APARCH model (1.1) with a skewed student distribution error is most appropriate for modeling the volatility of the two categories of Islamic and conventional indexes since it maximizes the log-likelihood function.

In summary, the use of APARCH model shows that this model outperforms the RiskMetrics model and GARCH. This can be interpreted by that this model is an asymmetric GARCH generalization. Similarly, the distribution skewed student surpasses all other distributions. The Skewed APARCH-student model provides the best results. He fully captures the stylized facts found in conventional and Islamic indices.

Table 4. Results of VaR in-sample of Risk Metrics models, GARCH and APARCH using normal distributions, student and skewed student

In sample		Long Position											
Conventional		RM			GARCH Normal			GARCH Student			GARCH Skewed ST		
Malaysia	5%	0,062	0,049	0,006	0,056	0,297	0,167	0,062	0,049	0,096	0,057	0,246	0,059
	1%	0,022	0	0	0,019	0,003	0,050	0,014	0,149	0,010	0,012	0,477	0,619
Bahain	5%	0,060	0,104	0	0,047	0,602	0	0,089	0	0	0,084	0	0
	1%	0,027	0	0	0,024	0	0	0,021	0	0	0,020	0,001	0,001
Kuwait	5%	0,060	0,082	0,001	0,049	0,879	0,009	0,084	0	0	0,081	0,000	0,000
	1%	0,026	0	0,001	0,025	0	0	0,018	0,010	0,305	0,017	0,018	0,392
Oman	5%	0,054	0,490	0,000	0,049	0,879	0,261	0,072	0,000	0,000	0,072	0,000	0,000
	1%	0,021	0,000	0,022	0,020	0,001	0,137	0,015	0,093	0,280	0,015	0,093	0,280
Qatar	5%	0,046	0,518	0,007	0,044	0,251	0,014	0,073	0,000	0,000	0,074	0,000	0,000
	1%	0,027	0,000	0,000	0,020	0,001	0,002	0,016	0,032	0,425	0,016	0,032	0,425
UAE	5%	0,056	0,297	0,567	0,048	0,783	0,537	0,075	0,000	0,008	0,071	0,001	0,009
	1%	0,022	0,000	0,006	0,021	0,000	0,032	0,018	0,010	0,273	0,015	0,093	0,382
Indonesia	5%	0,054	0,490	0,007	0,051	0,832	0,026	0,064	0,021	0,052	0,058	0,201	0,276
	1%	0,029	0	0	0,025	0,000	0,002	0,020	0,001	0,001	0,014	0,149	0,394
In sample		Long Position											
Conventional		APARCH Normal			APARCH Student			APARCH Skewed ST					
Malaysia	5%	0,055	0,354	0,325	0,059	0,131	0,403	0.055	0.354	0.403			
	1%	0,017	0,018	0,040	0,014	0,149	0,244	0.011	0.648	0.619			
Bahain	5%	0,047	0,602	0,026	0,076	0	0	0.047	0.602	0.026			
	1%	0,022	0	0,035	0,015	0,056	0,218	0.014	0.149	0.218			
Kuwait	5%	0,050	0,976	0,005	0,067	0,004	0,002	0.050	0.976	0.009			
	1%	0,022	0,000	0,001	0,008	0,538	0,987	0.009	0.736	0.993			
Oman	5%	0,042	0,160	0,302	0,068	0,003	0,018	0.049	0.879	0.302			
	1%	0,018	0,010	0,270	0,011	0,843	0,514	0.011	0.843	0.580			
Qatar	5%	0,040	0,073	0,016	0,062	0,049	0,000	0.046	0.518	0.016			
	1%	0,019	0,003	0,189	0,009	0,736	0,287	0.009	0.736	0.425			
UAE	5%	0,046	0,518	0.084	0,070	0,001	0,061	0.048	0.783	0.567			
	1%	0,018	0,010	0.273	0,008	0,538	0,987	0.008	0.538	0.987			
Indonesia	5%	0,045	0,370	0,801	0,057	0,246	0,594	0.051	0.832	0.887			
	1%	0,022	0,000	0,003	0,012	0,477	0,956	0.009	0.736	0.993			

In sample		Short Position											
Conventional		RM			GARCH Normal			GARCH Student			GARCH Skewed ST		
Malaysia	95%	0,952	0,783	0,965	0,955	0,370	0,631	0,953	0,602	0,985	0,950	0,976	0,999
	99%	0,987	0,229	0,859	0,990	0,947	0,994	0,996	0,013	0,073	0,994	0,070	0,525
Bahain	95%	0,961	0,055	0,165	0,961	0,055	0,084	0,921	0	0	0,917	0	0
	99%	0,987	0,003	0,042	0,981	0,003	0,191	0,985	0,093	0,547	0,981	0,003	0,191
Kuwait	95%	0,959	0,097	0,001	0,966	0,004	0,000	0,948	0,740	0	0,947	0,651	0,001
	99%	0,985	0,093	0	0,989	0,843	0,001	0,992	0,538	0	0,991	0,736	0
Oman	95%	0,953	0,602	0,029	0,958	0,160	0,591	0,926	0,000	0,001	0,928	0,000	0,002
	99%	0,981	0,003	0,046	0,985	0,093	0,985	0,988	0,477	0,956	0,988	0,477	0,956
Qatar	95%	0,952	0,783	0,097	0,020	0,001	0,002	0,928	0,000	0,000	0,930	0,001	0,000
	99%	0,979	0,000	0,106	0,986	0,149	0,582	0,987	0,229	0,613	0,987	0,337	0,917
UAE	95%	0,959	0,097	0,081	0,967	0,002	0,002	0,944	0,297	0,318	0,943	0,246	0,184
	99%	0,979	0,000	0,029	0,986	0,149	0,376	0,988	0,477	0,956	0,987	0,337	0,625
Indonesia	95%	0,961	0,055	0,027	0,967	0,002	0,010	0,963	0,020	0,060	0,953	0,602	0,357
	99%	0,985	0,093	0,689	0,990	0,947	0,994	0,993	0,232	0,902	0,992	0,538	0,987
In sample		Short Position											
Conventional		APARCH Normal			APARCH Student			APARCH Skewed ST					
Malaysia	5%	0,952	0,783	0,956	0,949	0,927	0,923	0.950	0.976	0.999			
	1%	0,988	0,477	0,616	0,996	0,013	0	0.990	0.947	0.994			
Bahain	5%	0,957	0,202	0,004	0,987	0,001	0,114	0.957	0.202	0.165			
	1%	0.979	0	0	0,991	0,736	0	0.989	0.843	0.547			
Kuwait	5%	0,964	0,014	0,000	0,951	0,879	0	0.951	0.879	0.001			
	1%	0,987	0,229	0,000	0,994	0,070	0	0.989	0.843	001			
Oman	5%	0,954	0,441	0,607	0,930	0,001	0,002	0.953	0.602	0.607			
	1%	0,982	0,005	0,047	0,991	0,736	0,287	0.991	0.736	0.956			
Qatar	5%	0,959	0,097	0,007	0,930	0,001	0,000	0.952	0.783	0.097			
	1%	0,985	0,093	0,394	0,991	0,736	0,287	0.991	0.736	0.917			
UAE	5%	0,965	0,006	0,002	0,947	0,651	0,212	0.947	0.651	0.318			
	1%	0.985	0,093	0,379	0,994	0,070	0,525	0.988	0.477	0.965			
Indonesia	5%	0,967	0,002	0,006	0,964	0,010	0,022	0.953	0.602	0.620			
	1%	0.988	0,477	0,619	0,994	0,070	0,525	0.990	0.947	0.994			
In sample		Long Position											
Islamic		RM			GARCH Normal			GARCH Student			GARCH Skewed ST		
Malaysia	5%	0,040	0,073	0,000	0,053	0,568	0,002	0,056	0,297	0,003	0,053	0,568	0,001
	1%	0,022	0,000	0,000	0,023	0,000	0,006	0,014	0,149	0,000	0,012	0,477	0,000
Bahain	5%	0,058	0,201	0,002	0,053	0,651	0,002	0,095	0,000	0,000	0,091	0,000	0,000
	1%	0,026	0,000	0,000	0,025	0,000	0,001	0,022	0,000	0,000	0,018	0,005	0,007
Kuwait	5%	0,055	0,419	0,003	0,046	0,441	0,015	0,072	0,000	0,000	0,071	0,001	0,000
	1%	0,027	0,000	0,002	0,021	0,000	0,002	0,018	0,005	0,054	0,018	0,005	0,054
Oman	5%	0,040	0,073	0,000	0,039	0,055	0,009	0,074	0,000	0,000	0,074	0,000	0,000
	1%	0,022	0,000	0,000	0,018	0,005	0,048	0,018	0,005	0,048	0,018	0,005	0,048
Qatar	5%	0,044	0,251	0,000	0,041	0,125	0,008	0,083	0,000	0,000	0,083	0,000	0,000
	1%	0,027	0,000	0,001	0,017	0,018	0,365	0,018	0,010	0,299	0,017	0,018	0,362
UAE	5%	0,055	0,354	0,041	0,045	0,370	0,080	0,074	0,000	0,000	0,067	0,004	0,000
	1%	0,029	0,000	0,003	0,023	0,000	0,046	0,018	0,010	0,305	0,016	0,032	0,488
Indonesia	5%	0,057	0,246	0,026	0,051	0,832	0,299	0,057	0,246	0,226	0,054	0,490	0,286
	1%	0,024	0,000	0,003	0,020	0,001	0,001	0,015	0,093	0,269	0,014	0,149	0,244
In sample		Long Position											
Islamic		APARCH Normal			APARCH Student			APARCH Skewed ST					
Malaysia	5%	0,051	0,832	0,029	0,055	0,354	0,065	0,053	0,568	0,001			
	1%	0,021	0,000	0,001	0,006	0,134	0,003	0.012	0.477	0.006			
Bahain	5%	0,049	0,879	0,002	0,085	0,000	0,000	0.049	0.879	0.002			
	1%	0,022	0,000	0,009	0,015	0,056	0,033	0.013	0.337	0.318			
Kuwait	5%	0,041	0,097	0,108	0,065	0,011	0,001	0.046	0.441	0.108			
	1%	0,022	0,000	0,002	0,011	0,843	0,991	0.010	0.947	0.994			
Oman	5%	0,038	0,029	0,000	0,066	0,008	0,006	0.040	0.073	0.011			
	1%	0,018	0,005	0,048	0,015	0,093	0,538	0.013	0.229	0.607			
Qatar	5%	0,039	0,055	0,005	0,069	0,001	0,000	0.044	0.251	0.008			
	1%	0,016	0,032	0,425	0,010	0,947	0,407	0.010	0.947	0.425			
UAE	5%	0,043	0,202	0,422	0,065	0,016	0,022	0.045	0.370	0.422			
	1%	0,022	0,000	0,039	0,013	0,337	0,917	0.012	0.477	0.956			
Indonesia	5%	0,046	0,441	0,873	0,051	0,927	0,780	0.051	0.927	0.873			
	1%	0,018	0,010	0,233	0,011	0,648	0,572	0.011	0.843	0.572			

In sample		Short Position											
Islamic		RM			GARCH Normal			GARCH Student			GARCH Skewed ST		
Malaysia	95%	0,943	0,246	0,002	0,949	0,927	0,816	0,949	0,927	0,890	0,947	0,568	0,521
	99%	0,975	0,000	0,000	0,985	0,056	0,589	0,992	0,367	0,965	0,990	0,947	0,994
Bahain	95%	0,958	0,160	0,374	0,961	0,040	0,059	0,922	0,000	0,000	0,916	0,000	0,000
	99%	0,979	0,000	0,032	0,981	0,003	0,191	0,980	0,001	0,154	0,978	0,000	0,022
Kuwait	95%	0,949	0,832	0,149	0,961	0,055	0,036	0,930	0,001	0,000	0,928	0,000	0,001
	99%	0,984	0,032	0,000	0,989	0,843	0,000	0,992	0,367	0,000	0,991	0,736	0,000
Oman	95%	0,943	0,246	0,002	0,961	0,055	0,026	0,922	0,000	0,000	0,922	0,000	0,000
	99%	0,975	0,000	0,000	0,987	0,337	0,625	0,987	0,337	0,625	0,987	0,337	0,625
Qatar	95%	0,952	0,783	0,033	0,955	0,370	0,487	0,923	0,000	0,000	0,923	0,000	0,000
	99%	0,974	0,000	0,001	0,979	0,000	0,106	0,981	0,003	0,192	0,980	0,001	0,155
UAE	95%	0,958	0,160	0,017	0,964	0,010	0,001	0,943	0,246	0,024	0,939	0,064	0,077
	99%	0,982	0,010	0,296	0,985	0,056	0,366	0,987	0,337	0,917	0,986	0,149	0,579
Indonesia	95%	0,958	0,160	0,193	0,961	0,040	0,117	0,954	0,518	0,472	0,952	0,691	0,458
	99%	0,985	0,056	0,033	0,989	0,648	0,580	0,992	0,367	0,965	0,992	0,538	0,987
In sample		Short Position											
Islamic		APARCH Normal			APARCH Student			APARCH Skewed ST					
Malaysia	95%	0,953	0,602	0,707	0,949	0,927	0,757	0,947	0,568	0,521			
	99%	0,985	0,093	0,540	0,993	0,232	0,902	0.990	0.947	0,994			
Bahain	95%	0,964	0,010	0,003	0,929	0,001	0,001	0.958	0.160	0.374			
	99%	0,979	0,000	0,044	0,987	0,337	0,003	0.987	0.337	0.191			
Kuwait	95%	0,961	0,055	0,007	0,928	0,000	0,001	0.949	0.832	0.149			
	99%	0,989	0,843	0,000	0,994	0,070	0,000	0.989	0.843	0.000			
Oman	95%	0,960	0,073	0,003	0,932	0,003	0,003	0.943	0.246	0.026			
	99%	0,987	0,337	0,320	0,992	0,538	0,987	0.992	0.538	0.987			
Qatar	95%	0,956	0,251	0,180	0,930	0,001	0,000	0.952	0.783	0.487			
	99%	0,978	0,000	0,028	0,985	0,093	0,000	0.986	0.149	0.192			
UAE	95%	0,964	0,010	0,001	0,948	0,740	0,081	0.948	0.740	0.099			
	99%	0,984	0,032	0,342	0,992	0,538	0,987	0.992	0.538	0.987			
Indonesia	95%	0,965	0,006	0,012	0,964	0,014	0,005	0.952	0.691	0.472			
	99%	0,987	0,229	0,000	0,994	0,134	0,760	0.989	0.648	0.987			

5.2. VaR Analysis: Estimation in Sample and Prediction out of Sample

In this subsection, we estimate VaR in sample using the AR (1). First, we calculate the failure rate for long and short positions. The failure rate for the short trading position represents the percentage of higher the expected positive return VaR. However, for long trading positions, the failure rate is the negative performance of smaller percentage of the expected VaR. If the VaR model is correctly specified, the failure rate should be equal to the predefined level of VaR. To assess the relative performance of each model, we use the Kupiec and Engel Manganelli tests. VaR levels are 0.05 and 0.01 for short positions and 0.95 and 0.99 for long positions.

Table 4 present the results of VaR in-sample of Risk Metrics models, GARCH and APARCH using normal distributions, student and skewed student. We report the failure rate and the p-value tests of Kupiec and Engel and Manganelli.

For both long and short positions, with five levels of significance, the results clearly indicate that the VaR model based on the normal distribution fails to model returns. As expected, the presence of kurtosis and skewness in the financial series leads us to reject the normal distribution. Similarly, the result of the Kupiec test for the short position confirms that the normal distribution has a poor performance compared to other models. Indeed, the model adequacy hypothesis is strongly rejected in the considerable difference between the prefix level and the failure rate. This confirms earlier empirical studies on VaR (eg [35,36]) have shown that the normal distribution-based models can not usually take full account of the properties of "fat tails" of the distribution of returns. The Student distribution slightly improves the performance of the model and remains insufficient. We also note that the Student Skewed distribution significantly improves the results of normal distributions and student for both short and long trading positions. The APARCH skewed student model works with 100% accuracy in the cases. These results provide further confirmation that the APARCH skewed student model is more reliable in the VaR estimates.

The good performance in-sample provides a good indication of the accuracy of the prediction model. This for, this result is not a prerequisite for a good performance of out-of-sample model. Accordingly, we provide out-of-sample evaluation [34,35,36,37].

Table 5 report the out-of-sample results of long and short trading positions and under different assumptions of error distribution of conventional stock indices. The error estimates are in the last four years of the sample. The out-of-sample results are similar to results in-sample. For the Kupiec and Engel and and Manganelli tests, the RiskMetrics model gives poor results. RiskMetrics may not be an appropriate model for the assessment of losses. Distribution student shows a satisfactory performance for most markets. For cons, the VaR models based on distributions skewed student GARCH and APARCH outperform all other distributions. The APARCH model shows a better performance in the out-of-sample estimation. More precisely, the APARCH Skewed Student-model provides more accurate results VaR compared with the normal distribution, the student of law and the GARCH model. Application of the Engel and Manganelli test gives similar results to the Kupiec test.

In conclusion, our results show solid, reliable evidence that the model APARCH in its distribution skewed student provides the most accurate estimates of VaR. This can be explained by the fact that this model takes into account both the main features of financial time series such as excess kurtosis, the asymmetry of returns, the volatility clustering and leverage. Therefore, our results support the use of more realistic assumptions in financial modeling. Indeed, the use of realistic assumptions can help investors and risk managers to reduce the uncertainty associated with the maximum loss to be incurred. These results are consistent with the results found in earlier works [1,38,39,40].

5.3. The Risk for Conventional and Islamic Stock Indices

Table 6 reports the results of backtesting in sample VaR according to the Kupiec test and Engel and Manganelli.

For the two levels of significance, the results show that the VaR value is greater for conventional stock indices that Islamic market index. This result indicates that Islamic equity indexes are less risky than conventional ones for all countries included in the sample.

Table 5. Out of-sample VaR results of Risk Metrics models, GARCH and APARCH using normal distributions, student and skewed student

		Long Position											
Conventional		**RM**			**GARCH Normal**			**GARCH Student**			**GARCH Skewed ST**		
Malaysia	5%	0,065	0,037	0,001	0,042	0,233	0,350	0,046	0,557	0,068	0,042	0,233	0,174
	1%	0,022	0,001	0,029	0,012	0,538	0,413	0,010	1,000	0,193	0,008	0,510	0,022
Bahain	5%	0,067	0,019	0,205	0,057	0,320	0,755	0,087	0,000	0,002	0,087	0,000	0,002
	1%	0,035	0,000	0,001	0,030	0,000	0,010	0,026	0,000	0,048	0,022	0,001	0,147
Kuwait	5%	0,062	0,093	0,029	0,038	0,070	0,002	0,064	0,051	0,018	0,062	0,093	0,029
	1%	0,023	0,000	0,000	0,011	0,754	0,296	0,008	0,510	0,018	0,008	0,510	0,018
Oman	5%	0,056	0,393	0,000	0,037	0,048	0,007	0,056	0,393	0,028	0,058	0,257	0,028
	1%	0,030	0,000	0,001	0,019	0,011	0,012	0,013	0,362	0,478	0,014	0,231	0,004
Qatar	5%	0,063	0,069	0,030	0,043	0,299	0,215	0,067	0,019	0,017	0,068	0,013	0,001
	1%	0,028	0,000	0,001	0,015	0,139	0,493	0,013	0,362	0,462	0,013	0,362	0,462
UAE	5%	0,054	0,566	0,018	0,044	0,375	0,001	0,076	0,000	0,001	0,068	0,013	0,001
	1%	0,027	0,000	0,001	0,020	0,005	0,021	0,014	0,231	0,510	0,012	0,538	0,981
Indonesia	5%	0,073	0,002	0,016	0,054	0,566	0,890	0,063	0,069	0,587	0,055	0,475	0,932
	1%	0,029	0,000	0,011	0,019	0,011	0,032	0,012	0,538	0,000	0,009	0,746	0,077
Out sample		**Long Position**											
Conventional		**APARCH Normal**			**APARCH Student**			**APARCH Skewed ST**					
Malaysia	5%	0,039	0,097	0,473	0,040	0,133	0,420	0.046	0.557	0.473			
	1%	0,009	0,746	0,997	0,006	0,170	0,825	0.010	1.000	0.997			
Bahain	5%	0,056	0,393	0,658	0,089	0,000	0,001	0.056	0.393	0.755			
	1%	0,032	0,000	0,004	0,021	0,002	0,171	0.020	0.005	0.209			
Kuwait	5%	0,038	0,070	0,002	0,061	0,122	0,035	0.061	0.122	0.041			
	1%	0,010	1,000	0,178	0,004	0,030	0,167	0.010	1.000	0.296			
Oman	5%	0,037	0,048	0,007	0,056	0,393	0,006	0.056	0.393	0.028			
	1%	0,017	0,043	0,170	0,010	1,000	0,997	1.000	1.000	0.997			
Qatar	5%	0,043	0,299	0,243	0,063	0,069	0,002	0.043	0.299	0.243			
	1%	0,018	0,022	0,376	0,005	0,079	0,000	0.013	0.362	0.493			
UAE	5%	0,048	0,770	0,020	0,070	0,006	0,005	0.048	0.770	0.020			
	1%	0,019	0,011	0,318	0,008	0,510	0,991	0.012	0.538	0.991			
Indonesia	5%	0,046	0,557	0,647	0,046	0,557	0,569	0.054	0.566	0.932			
	1%	0,016	0,079	0,474	0,008	0,510	0,991	0.009	0.746	0.991			
Out sample		**Short Position**											
Conventional		**RM**			**GARCH Normal**			**GARCH Student**			**GARCH Skewed ST**		
Malaysia	95%	0,969	0,003	0,019	0,986	0,231	0,897	0,974	0,000	0,000	0,971	0,001	0,007
	99%	0,986	0,231	0,897	0,990	1,000	0,997	0,994	0,170	0,825	0,992	0,510	0,991
Bahain	95%	0,958	0,233	0,028	0,955	0,461	0,784	0,921	0,000	0,001	0,916	0,000	0,000
	99%	0,982	0,022	0,268	0,978	0,001	0,154	0,981	0,011	0,322	0,979	0,002	0,189
Kuwait	95%	0,955	0,461	0,059	0,973	0,000	0,000	0,957	0,299	0,009	0,957	0,299	0,009
	99%	0,981	0,011	0,249	0,990	1,000	0,193	0,995	0,079	0,524	0,994	0,170	0,825
Oman	95%	0,963	0,048	0,257	0,980	0,000	0,000	0,956	0,375	0,630	0,957	0,299	0,787
	99%	0,988	0,538	0,395	0,992	0,510	0,991	0,994	0,170	0,825	0,994	0,170	0,825
Qatar	95%	0,944	0,393	0,127	0,969	0,003	0,004	0,945	0,475	0,124	0,945	0,475	0,124
	99%	0,980	0,005	0,018	0,991	0,746	0,076	0,993	0,314	0,002	0,993	0,314	0,002
UAE	95%	0,935	0,037	0,279	0,948	0,773	0,378	0,922	0,000	0,002	0,920	0,000	0,001
	99%	0,972	0,000	0,016	0,985	0,139	0,493	0,992	0,510	0,991	0,992	0,510	0,991
Indonesia	95%	0,954	0,557	0,773	0,972	0,001	0,000	0,971	0,001	0,000	0,963	0,048	0,149
	99%	0,986	0,231	0,507	0,991	0,746	0,997	0,993	0,314	0,956	0,992	0,510	0,991

Out sample		Short Position											
Conventional		APARCH Normal			APARCH Student			APARCH Skewed ST					
Malaysia	95%	0,976	0,000	0,000	0,977	0,000	0,000	0.969	0.003	0.019			
	99%	0,991	0,746	0,997	0,993	0,314	0,956	0.990	1.000	0.997			
Bahain	95%	0,951	0,884	0,598	0,929	0,004	0,003	0.951	0.884	0.784			
	99%	0,977	0,000	0,034	0,987	0,362	0,465	0.987	0.362	0.497			
Kuwait	95%	0,973	0,000	0,000	0,959	0,178	0,001	0.955	0.461	0.059			
	99%	0,987	0,362	0,000	0,996	0,030	0,167	0.990	1.000	0.825			
Oman	95%	0,978	0,000	0,000	0,949	0,885	0,803	0.949	0.885	0.803			
	99%	0,991	0,746	0,997	0,995	0,079	0,524	0.991	0.746	0.997			
Qatar	95%	0,970	0,002	0,002	0,940	0,159	0,008	0.945	0.475	0.127			
	99%	0,991	0,746	0,076	0,996	0,030	0,167	0.991	0.746	0.167			
UAE	95%	0,941	0,204	0,511	0,927	0,002	0,028	0.948	0.773	0.511			
	99%	0,977	0,000	0,033	1,000	0,000	0,000	0.992	0.510	0.991			
Indonesia	95%	0,970	0,002	0,000	0,975	0,000	0,000	0.954	0.557	0.773			
	99%	0,990	1,000	0,193	0,996	0,030	0,167	0.990	1.000	0.997			
Outsample		Long Position											
Islamic		RM			GARCH Normal			GARCH Student			GARCH Skewed ST		
Malaysia	5%	0.066	0,027	0,026	0,056	0,393	0,052	0,062	0,093	0,101	0,055	0,475	0,225
	1%	0,019	0,011	0,018	0,012	0,538	0,395	0,007	0,314	0,002	0,007	0,314	0,002
Bahain	5%	0,065	0,037	0,229	0,047	0,660	0,922	0,088	0,000	0,001	0,083	0,000	0,002
	1%	0,035	0,000	0,001	0,025	0,000	0,067	0,024	0,000	0,090	0,021	0,002	0,179
Kuwait	5%	0,062	0,093	0,011	0,043	0,299	0,197	0,072	0,003	0,037	0,063	0,069	0,073
	1%	0,022	0,001	0,144	0,013	0,362	0,112	0,010	1,000	0,178	0,010	1,000	0,178
Oman	5%	0,039	0,097	0,000	0,027	0,000	0,000	0,052	0,773	0,019	0,051	0,885	0,008
	1%	0,025	0,000	0,000	0,016	0,079	0,000	0,016	0,079	0,000	0,016	0,079	0,000
Qatar	5%	0,062	0,093	0,374	0,035	0,022	0,027	0,073	0,002	0,001	0,072	0,003	0,000
	1%	0,032	0,000	0,001	0,018	0,022	0,131	0,017	0,043	0,106	0,017	0,043	0,106
UAE	5%	0,046	0,557	0,004	0,041	0,178	0,004	0,062	0,093	0,000	0,055	0,475	0,000
	1%	0,022	0,001	0,033	0,017	0,043	0,281	0,013	0,362	0,478	0,010	1,000	0,997
Indonesia	5%	0,068	0,013	0,341	0,053	0,666	0,537	0,058	0,257	0,534	0,057	0,320	0,474
	1%	0,030	0,000	0,007	0,022	0,001	0,033	0,012	0,538	0,399	0,011	0,754	0,994
Outsample		Long Position											
Islamic		APARCH Normal			APARCH Student			APARCH Skewed ST					
Malaysia	5%	0,054	0,566	0,178	0,057	0,320	0,210	0.054	0.566	0.225			
	1%	0,012	0,538	0,395	0,005	0,079	0,000	0.012	0.538	0.395			
Bahain	5%	0,045	0,461	0,639	0,090	0,000	0,000	0.047	0.660	0.922			
	1%	0,022	0,001	0,147	0,021	0,002	0,179	0.019	0.011	0.235			
Kuwait	5%	0,040	0,133	0,022	0,067	0,019	0,034	0.043	0.299	0.197			
	1%	0,013	0,362	0,112	0,005	0,079	0,524	0.010	1.000	0.524			
Oman	5%	0,033	0,009	0,000	0,061	0,122	0,006	0.051	0.885	0.019			
	1%	0,016	0,079	0,000	0,018	0,022	0,000	0.016	0.079	0.000			
Qatar	5%	0,036	0,033	0,053	0,072	0,003	0,020	0.062	0.093	0.374			
	1%	0,019	0,011	0,148	0,008	0,510	0,018	0.008	0.510	0.148			
UAE	5%	0,038	0,070	0,083	0,063	0,069	0,001	0.046	0.557	0.083			
	1%	0,016	0,079	0,480	0,008	0,510	0,991	0.010	1.000	0.997			
Indonesia	5%	0,049	0,884	0,845	0,053	0,666	0,789	0.050	1.000	0.845			
	1%	0,014	0,231	0,897	0,010	1,000	0,997	0.010	1.000	0.997			
Outsample		Short Position											
Islamic		RM			GARCH Normal			GARCH Student			GARCH Skewed ST		
Malaysia	95%	0.958	0,233	0,543	0,967	0,009	0,049	0,964	0,033	0,054	0,962	0,070	0,165
	99%	0,985	0,139	0,817	0,989	0,754	0,994	0,992	0,510	0,991	0,991	0,746	0,997
Bahain	95%	0,956	0,375	0,001	0,958	0,233	0,810	0,923	0,000	0,001	0,917	0,000	0,000
	99%	0,980	0,005	0,221	0,984	0,079	0,476	0,983	0,043	0,433	0,979	0,002	0,189
Kuwait	95%	0,947	0,666	0,682	0,967	0,009	0,020	0,950	1,000	0,100	0,946	0,566	0,050
	99%	0,979	0,002	0,025	0,985	0,139	0,001	0,993	0,314	0,002	0,993	0,314	0,002
Oman	95%	0,933	0,019	0,011	0,972	0,001	0,001	0,942	0,257	0,222	0,942	0,257	0,222
	99%	0,977	0,000	0,115	0,991	0,746	0,997	0,993	0,314	0,956	0,992	0,510	0,991
Qatar	95%	0,946	0,566	0,119	0,964	0,033	0,002	0,937	0,069	0,094	0,936	0,051	0,097
	99%	0,978	0,001	0,025	0,987	0,362	0,481	0,988	0,538	0,981	0,988	0,538	0,981
UAE	95%	0,942	0,257	0,401	0,949	0,885	0,360	0,930	0,006	0,012	0,925	0,001	0,001
	99%	0,973	0,000	0,001	0,982	0,022	0,376	0,986	0,231	0,493	0,985	0,139	0,493
Indonesia	95%	0,954	0,557	0,291	0,963	0,048	0,023	0,960	0,133	0,041	0,956	0,375	0,172
	99%	0,983	0,043	0,008	0,991	0,746	0,997	0,994	0,170	0,825	0,994	0,170	0,825

Outsample		Short Position											
Islamic		APARCH Normal			APARCH Student			APARCH Skewed ST					
Malaysia	95%	0,964	0,033	0,183	0,965	0,022	0,136	0.958	0.233	0.543			
	99%	0,989	0,754	0,994	0,993	0,314	0,956	0.989	0.754	0.997			
Bahain	95%	0,958	0,233	0,206	0,931	0,009	0,002	0.972	0.375	0.810			
	99%	0,986	0,231	0,897	0,988	0,538	0,399	0.992	0.538	0.897			
Kuwait	95%	0,965	0,022	0,024	0,956	0,375	0,004	0.950	1.000	0.682			
	99%	0,988	0,538	0,046	0,998	0,002	0,000	0.988	0.538	0.046			
Oman	95%	0,970	0,002	0,005	0,935	0,037	0,463	0.942	0.257	0.463			
	99%	0,990	1,000	0,997	0,992	0,510	0,018	0.990	1.000	0.997			
Qatar	95%	0,966	0,014	0,000	0,935	0,037	0,018	0.946	0.566	0.119			
	99%	0,985	0,139	0,239	0,991	0,746	0,086	0.991	0.746	0.981			
UAE	95%	0,945	0,475	0,223	0,930	0,006	0,007	0.949	0.885	0.401			
	99%	0,978	0,001	0,153	0,990	1,000	0,997	0.990	1.000	0.997			
Indonesia	95%	0,966	0,014	0,001	0,964	0,033	0,019	0.954	0.557	0.291			
	99%	0,990	1,000	0,193	0,995	0,079	0,524	0.990	1.000	0.997			

Table 6. Backtesting VaR and estimating VaR by APARCH Skewed Student

In Sample	Conventional				Islamic				In Sample	Conventional				Islamic			
Kupiec	Short position		Long position		Short position		Long position		Engel Manganelli	Short position		Long position		Short position		Long position	
	95%	99%	5%	1%	95%	99%	5%	1%		0.95	0.99	0.05	0.01	0.95	0.99	0.05	0.01
Malaisie	0.48	1.43	0.20	2.25	0.33	0.38	0.20	0.81	Malaisie	5.89	14.68	12.46	19.70	2.78	0.96	8.90	11.34
Bahrein	22.03	3.65	24.04	2.08	14.78	0.04	11.64	0.92	Bahrein	35.93	34.21	45.14	9.25	27.85	13.97	30.26	7.03
Kuwait	2.28	3.29	9.51	0.11	0.16	3.29	6.40	0.00	Kuwait	37.68	96.92	23.60	0.75	22.77	25.96	20.15	0.74
Oman	10.91	1.43	10.91	1.45	8.85	0.38	5.32	0.21	Oman	18.33	2.19	16.49	4.72	18.33	0.96	14.55	4.51
Qatar	10.20	0.11	10.91	0.11	9.51	2.08	3.87	0.00	Qatar	25.47	32.12	25.08	7.38	25.47	7.38	24.22	6.15
Emirate	1.63	0.81	6.98	0.50	0.65	0.50	3.43	0.38	Emirate	7.69	1.55	13.08	1.55	7.69	1.42	10.37	0.96
Indonesie	1.97	1.43	0.16	0.11	0.59	0.81	0.08	0.04	Indonesie	4.42	11.34	2.64	5.31	4.42	2.19	2.33	0.75
OutSample	Conventional				Islamic				Out Sample	Conventional				Islamic			
Kupiec	Short position		Long position		Short position		Long position		Engel Manganelli	Short position		Long position		Short position		Long position	
	0.95	0.99	0.05	0.01	0.95	0.99	0.05	0.01		0.95	0.99	0.05	0.01	0.95	0.99	0.05	0.01
Malaisie	12.04	1.02	3.29	4.71	2.75	0.43	0.51	3.09	Malaisie	22.53	1.55	6.43	9.12	8.20	0.84	8.65	5.16
Bahrein	18.22	1.44	22.66	7.83	19.29	1.44	21.51	6.47	Bahrein	28.67	5.38	20.44	8.42	25.04	5.38	19.76	8.05
Kuwait	3.29	9.63	4.35	4.71	0.79	9.63	2.83	3.09	Kuwait	19.16	32.09	13.16	9.12	19.30	32.09	10.60	5.16
Oman	4.92	3.09	1.28	4.09	0.54	0.43	0.73	4.09	Oman	6.94	15.26	18.13	43.35	3.37	5.16	17.90	0.54
Qatar	4.35	4.71	9.02	3.09	0.73	0.43	4.35	0.43	Qatar	20.66	14.80	19.74	47.35	15.35	9.12	15.08	15.26
Emirate	11.48	1.02	5.52	1.02	11.48	0.10	0.73	0.43	Emirate	20.57	1.55	26.88	1.55	14.10	0.74	20.79	0.84
Indonesie	11.48	0.43	1.42	1.02	3.29	0.10	0.73	1.02	Indonesie	20.57	14.81	26.88	1.55	20.40	0.74	4.94	1.55

Notes: The interpretation of the units of VaR is, using for example the first figure in the table below (0.47649), that there is a 95% chance that the loss of a portfolio will not exceed 0.47649% in a day.

Thereby the risk of Islamic index is relatively more competitive. risk reduction in the context of Islamic market indices can be explained by the specificity of each stock market. Indeed, Islamic stock markets differ from conventional stock markets in several ways [41,42,43]:

- Islamic stock markets prefer growth stocks and small cap. While conventional stock markets opt for the actions and values of average capitalization.

- Islamic finance small investments in certain sectors, considered illegal under Islamic law, such as chance games, conventional financial services based on interests ... It also restricts speculative financial transactions that do not have underlying asset real as futures and options, swaps and other transactions involving intangible elements in the property sellers.

- Contrary to conventional finance, Islamic finance is based on the profile sharing principle and losses prohibit the separation between the right to profits and the assumption of losses.

Therefore, the criteria adopted by the Islamic filtering system to eliminate non-compliant with Islamic law firms resulted in a subset of companies whose risk is reduced.

6. Conclusion

This paper evaluates the forecasting performance of several GARCH-type models (RiskMetrics, GARCH, APARCH) to estimate the market risk (the VaR) over the period 10 August 2006 to 26 November 2015, for seven conventional and Islamic stock market indices. The results show that APARCH under Skewed Student distribution provides the best results. A good assessment and risk quantification mainly depends on the chosen model and measure. Results also suggest that the value VaR is greater for conventional stock indices than the Islamic market indices. This means that Islamic indexes have a lower risk. This paper offers important implications for individual and institutional investors regarding the Islamic stock indices.

References

[1] Diamandis, P F, Drakos AA, Kouretas GP and Zarangas L: "Value-at-risk for long and short trading positions: Evidence from developed and emerging equity markets", *International Review of Financial Analysis* 20/2011, 165-176. 2011.

[2] Sinha P, Agnihotri S.: "Sensitivity of value at risk estimation to non normality of returns and market capitalization" *MPRA 56307*. 2014.

[3] Chen Q, Giles D.E and Feng H: "The Extreme-Value Dependence Between the Chinese and Other International Stock Markets" *Econometrics Working Paper* EWP1003. 2010.

[4] So M.K.P, Yu P.L.H: "Empirical analysis of GARCH models in Value at Risk estimation, *Int. Fin. Markets, Inst. and Money*,16, 180-197. 2006.

[5] Jorion, P: "Value at risk: The new benchmark for controlling market risk". Chicago: Irwin. 1997.

[6] Wilson, T: "Value at risk in Risk Management and Analysis", *C. Alexander, ed., Wiley, Chichester, England*. 1. 61-124. 1999.

[7] Dimitrakopoulos D N, Kavussanos MG, Spyrou SI.: "Value at risk models for volatile emerging markets equity portfolios". *The Quarterly Review of Economics and Finance*, 50. 515-526. 2010.

[8] El Khamlichi A, Doukkali C, Sarkar K, Arouri M, Teulon F: "Are Islamic equity indices more efficient than their conventional counterparts? Evidence from major global index families" *The Journal of Applied Business Research*, 30(4). 1137-1150. 2014.

[9] Chiadmi M.S, Ghaiti F: "Modeling Volatility of Islamic Stock Indexes: Empirical Evidence and Comparative Analysis" *IJER*, 11(2). 241-276. 2014.

[10] Ho F.C.S, AbdRahman N.A, Yusuf N.H.M, and Zamzamin Z"Performance of Global Islamic versus Conventional Share Indices: International Evidence." *Pacific-Basin Finance Journal*. 1-12. 2013.

[11] Adil, H.C.S., Isa M., Yaakub E, Khakid M.M.. «Shariah compliant screening practices of Malaysian financial institutions» *IEEE symposium on business, engineering and industrial applications*. 2013.

[12] Khatkhatay, M.H. and Nisar S.. "Shari'ah Compliant Equity Investments: An Assessment of Current Screening Norms", *Islamic Economic Studies*, 15(1). 47-76. 2007.

[13] Fleming, J., Kirby, C., Ostdiek, B.: "The economic value of volatility timing", *Journal of Finance*, 561. 329-352. 2001.

[14] Assaf, A.: "Extreme observations and risk assessment in the equity markets of MENA region: Tail measures and Value-at-Risk", *International review of Financial Analysis*, 18, 109-116. 2009.

[15] Hafezian P, Salamon H, Shitan M: "Estimating Value at risk for sukuk market using generalized autoregressive conditional heteroscedasticity models" *Energy Economics Letters*, 2(2). 8-23. 2015.

[16] Bollerslev, T.: "Generalized autoregressive conditional heteroscedasticity", *Journal of Econometrics*, 31. 307-327. 1986.

[17] Engle, R. F.: "Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation". *Econometrica*, 50(4), 987-1007. 1982.

[18] Ding, Z., Granger C.W., Engle R.F.: "A Long Memory Property of Stock Market Returns and a New Model". *Journal of Empirical Finance*, 1. 83-106. (1993).

[19] Taylor, S.: "Modeling Stochastic Volatility: A Review and Comparative Study," *Mathematical Finance*, 4, 183-204. 1994.

[20] Schwert, W.: "Stock Volatility and the Crash of '87," *Review of Financial Studies*, 3, 77-102. 1990.

[21] Glosten, L., R. Jagannathan, and D. Runkle: "On the relation between expected return on stocks," *Journal of Finance*, 48, 1779-1801. 1993.

[22] Zakoian, J.-M.: "Threshold Heteroscedastic Models," *Journal of Economic Dynamics and Control*, 18, 931-955. 1994.

[23] Higgins M. et A. Bera A.: "A class of nonlinear ARCH models", *International Economic Review*, 33,137-158. 1992.

[24] Geweke, J.: "Modeling the Persistece of Conditional Variances: A Comment," *Econometric Review*, 5, 57-61. 1986.

[25] Pentula, S.: "Modeling the Persistece of Conditional Variances: A Comment," *Econometric Review*, 5, 71-74. 1986.

[26] Bollerslev, T.: "A conditionally heteroskedastic time series model for speculative prices and rates of return", *Review of Economics and Statistic*, 69, 542-547. 1987

[27] Lambert, P. and Laurent, S.: "Modelling financial time series using GARCH-type models and a skewed density", *Universite de Liege, mimeo*.2001.

[28] Fernandez, C. Steel, M. J. F.: "On Bayesian modeling of fat tails and skewness".*Journal of the American Statistical Association*,93, 359–371. 1998

[29] Kupiec P: "Technique for verifying the accuracy of risk measurement models", *Journal of derivatives*,2, 173-184. 1995.

[30] Engle R. and Manganelli S.. "CAViaR: Conditional Auto Regressive Value-at-Risk by Regression Quantile", *Journal of Business and Economic Statistics,* 22(4), 367-381. 2004.

[31] Bekri, M., and Kim, A.): "Portfolio management with heavy-tailed distributions in Islamic Finance". *Journal of Islamic Economics, Banking and Finance (JIEBF)*,10(2). 2014.

[32] Bekri, M., Kim, A., & Rachev, S.: "Tempered stable models for Islamic finance asset management". *International Journal of Islamic and Middle Eastern Finance and Management*,7(1). 2014.

[33] Saiti B, Bacha O.I, Masih M.: "The diversification benefits from Islamic investment during the financial turmoil: the case for the US based equity investors", *Borsa Istanbul review*, 14(4), 196–211. 2014.

[34] Hansen P.R, Lunde A. "A forecast comparison of volatility models: does anything beat a GARCH(1,1)?" *Journal of Applied Econometrics*, 20(7), 873–889. 2005.

[35] Van den Goorbergh, R.W.J. and Vlaar, P.J.G.: 'Value-at-Risk Analysis of Stock Returns: Historical Simulation, Variance Techniques or Tail Index Estimation?" Research Memorandum WO&E, 579, De Nederlandsche Bank.1999.

[36] Giot, P.: "Intraday Value-at-Risk," *CORE DP 2045, Maastricht University METEOR* RM/00/030. 2000.

[37] Pagan, A. R., Schwert, G. W.: "Alternative Models for Conditional Stock Volatility", *Journal of Econometrics*, 45(1-2), 267-290. 1990.

[38] Giot P, Laurent S.: "Value at risk for long and short trading positions" *Journal of applied Econometrics*, 18, 641-664. 2003.

[39] Al-Zoubi, H. & Maghyereh, A.: The relative risk performance of Islamic finance: a new guide to less risky investments. *International Journal of Theoretical & Applied Finance*, 10(2), 235-249. 2007.

[40] Miletic M, Miletic S.: "Performance of Value at Risk models in the midst of the global financial crisis in selected CEE emerging capital markets, *Economic Research -Ekonomska Istraživanja*, 28(1), 132-166. 2015.

[41] Chapra, U.: "Discussion Forum on the Financial Crisis: Comments from Islamic perspective" *IIUM Journal of Economics and Management*, Vol. 16, No. 2. 2008.

[42] Hassan M et Dridi J.: "The effects of the global crisis on Islamic and conventional banks: A comparative study" *IMF WP/10/ 201*. 2010.

[43] Mwamba JWM, Hammoudeh S, Gupta R: "Financial tail risks and the shapes of the extreme value distribution: A comparison between conventional and sharia compliant stock indexes" *Working paper series*. 2014.