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ESTIMATING VALUE AT RISK FOR SUKUK MARKET USING GENERALIZED AUTO REGRESSIVE CONDITIONAL HETEROSKEDASTICITY MODELS

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ABSTRACT
In this paper, we compare the forecasting ability of different GARCH models to estimate value at risk in sukuk market. A wide extensive list of both symmetric and asymmetric GARCH models (including GARCH, EGARCH, GJR-GARCH, IGARCH and Asymmetric power GARCH) were considered in modeling the volatility in the sukuk market. All VaR estimations are carried out by "rugarch" package in "R" software. The performance of these models is compared by both in-sample and out-of-sample analysis. 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 in most cases the student-t distribution is more preferable than normal or generalized error distribution (GED).

Keywords: Sukuk, Value at risk, Risk management, GARCH, Asymmetry.

Contribution/ Originality
This study is one of very few studies which have investigated the behavior of sukuk data in secondary market and describes characteristics of its statistical distribution function. Another contribution is comparing the estimation ability of various GARCH models in order to find superior model to estimate VAR in sukuk market.

1. INTRODUCTION
Forecasting and estimating financial loss is the main task of financial managers and policy makers to survive in the competitive global market. The importance of financial risk management has increased in last decade mainly due to increased volatility in financial market all over the world. Several financial crises during last 15 years indicate the inefficiency in risk management methods and motivate both risk managers and policy makers to find a better measure for market

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risk estimation in financial industry. In spite of extensive research on behavior of stock prices in the conventional financial markets, less attention has been paid to the sukuk markets. Sukuk are long term financial instruments which have the features of conventional bonds and simultaneously is compliance with Shariah principle (Islamic principle).

Similar to bonds, in case of sukuk also there is a maturity date, predictable level of regular return and income stream over the holding time and a final balloon payment at maturity (Cakir and Raei, 2007). The main idea about sukuk is prohibition of riba in Islam that close the door for any kind of pure debt securities, interest-based contract, derivative instruments such as credit derivatives and also detachable options. The market price of sukuk is depended on the creditworthiness of the issuer alongside the market value of underlying assets (Godlewski *et al.*, 2011).

The global sukuk issuance has increased sharply from 2001 to 2012 (see Figure.1

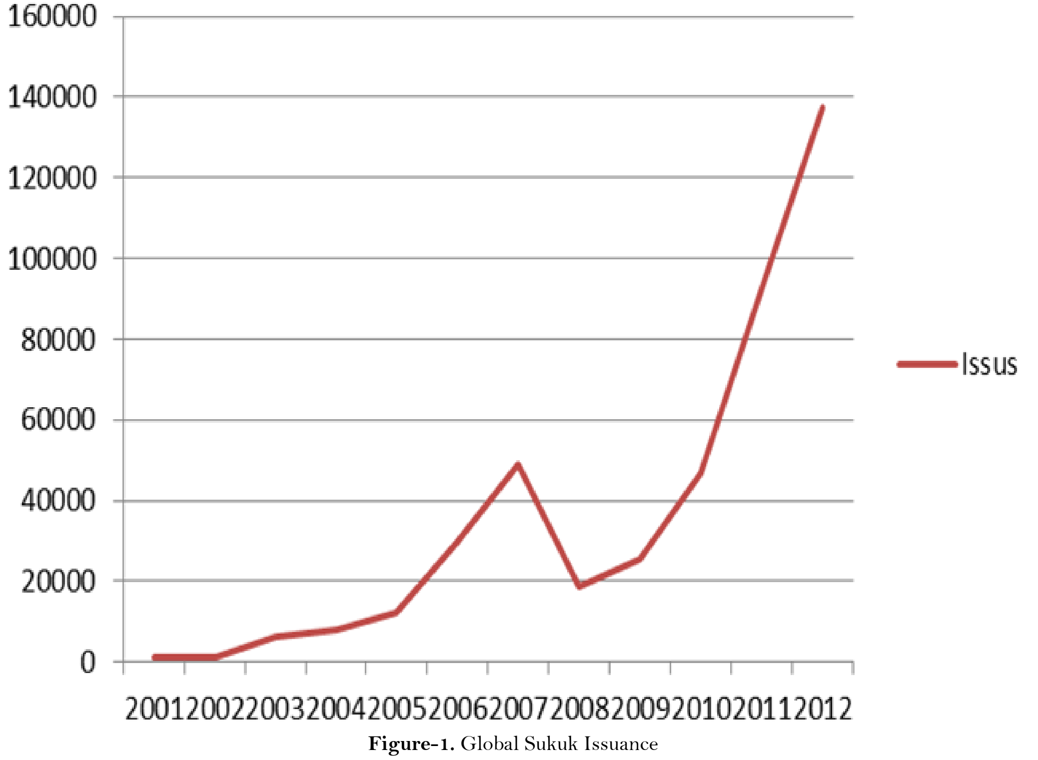

Figure-1. Global Sukuk Issuance

As figure 1 show, a unique growth in sukuk issuances is witnessed over past decade. Recent figure indicate that the issuance of sukuk rose from $1.172 million in 2001 to $137.3111million in 2012 (Poor's, 2012). However the growth of sukuk issuance decreased in 2007 due to global market turmoil, but the global sukuk issued increased 55% in second quarter of 2012 in compare to same period in 2011 and reached to $ 25 billion (Saripudin *et al*., 2012).

Sukuk is now better established in several Muslim and non-Muslim countries and there are increasing number of sukuk issuance in non- Muslim countries such as United State, Europe, and Asia in order to tap Islamic funds (Damak and Volland, 2008).

The main idea behind introducing Sukuk was high demand for an Islamic kind of long-term financial instruments which can play a similar role as conventional fixed-income debt securities (such as Treasury bonds and bills) (Iqbal and Tsubota, 2006).

One of the most suitable and remarkable mathematical approach to quantify financial risk is value at risk (VaR). VaR is defined as the maximum amount of loss which we are expecting for a portfolio over a given holding period at a certain confidence level (Jorion, 2007). However, in spite of simple concept, using VaR became more complicated during the last decade due to lake of unique accepted method for calculation it.

Early approaches of VaR estimation such as Variance-Covariance and Historical Simulation are almost abandoned due to considering inappropriate assumptions, such as normal distribution for asset return in parametric approaches and constant variance in case of non-parametric approaches (Romero and Muela, 2009).

The dynamic and volatile condition in financial market requires more flexible methods to capture shocks in financial markets. There are significant evidences that in financial markets large shocks (in both positive and negative side) happen more frequently than normal distributions which indicate of existence fat tail in financial return distribution (Assaf, 2009). So a method which consider higher percentiles of a distribution is more appropriate

Generalized Autoregressive Conditional Heteroskedasticity (GARCH) introduce by Bollerslev (1986) for modeling time-varying volatility data in financial markets.

Although GARCH is proven itself as one of the best methods for modeling financial time series, there are two shortcomings about it. The first one is about residual distributions. In original GARCH method normal distribution was employed for residuals (mainly because it was easy in practical use) while later researches demonstrate existence of heavy tail in financial time series. Several fat tail distributions such as student-t and generalized error distribution was applied in order to overcome this shortcoming while still there is not a unique accepted distribution in the literature (Liu and Hung, 2010).

Another criticized about GARCH is related to existence of asymmetric volatility or leverage effect in financial time series. It is highly documented that the impact of negative shocks or bad news is larger than good news or positive shocks in financial markets. This characteristic cannot be captured by symmetric GARCH models. This restriction is overcame by establishing asymmetric GARCH models such as EGARCH, Nelson (1991) and GJRGARCH, Glosten *et al.* (1993)

There is an increasing amount of literature in applying GARCH model in financial market. Various studies took place in order to improve GARCH method forecasting by introducing different fat-tail distribution instead of normal one. Bollerslev (1986) suggested replacing student-t distribution instead of normal one while Theodossiou (1998) found that the SGT (skewed generalized student-t) distribution can properly deal with both leptokurtosis and skewness in financial time series.

Hartz *et al.* (2006) used various financial asset returns over a long out-of-sample forecasting period and demonstrated that the forecasting ability of normal-GARCH model will be improved by applying bias correction. They showed that this method is more easy and fast to apply, and not sensitive to the window length in comparison with other more sophisticated methods. At the other side Bhattacharyya *et al.* (2008) recommended that using Pearson's Type IV distribution improve the estimating process of VaR. They applied their methods on Stock Indices of 14 countries and conducted that the combination of the Pearson's Type IV distribution and the GARCH (1, 1) approach with improve predictive abilities.

By using Malaysian Stock Exchange data Chin (2008) suggest that simple Pareto distribution can be applied instead of normal distribution to take account the heavy tail of return series. They also found that the Pareto distribution can deal conveniently by asymmetric properties in both the lower and upper tails, While Fan *et al.* (2008) used crude oil price data and showed that using generalised error distribution (GED) will improve forecasting ability of VaR.

Politis (2004) investigated that heavy- tail distribution improves forecasting ability of GARCH model. Same result obtained by Hung *et al.* (2008), who analysed the effect of considering heavy-tail distribution on one day ahead VaR estimation in several energy daily spot prices. They conclude that the forecasting of GARCH-HT model have better accuracy at both high and low confidence level.

Angelidis *et al.* (2004) assess a wide range of different ARCH and GARCH models in order to forecast daily VaR of portfolios consist of five stock indices. They showed that more flexible models such as EGARCH are more superior in forecasting volatility. Wilhelmsson (2006) in his article assess the estimation performance of the GARCH model by applying nine different error distributions. The result showed that the forecasting ability of GARCH model improve substantially by considering leptokurtic error distribution while applying skewness and time variation in the higher moments of the distribution does not lead to forecast improvement. Same result obtained by Chuang *et al.* (2007) who showed that the exponential power and mixture of two normal distributions are less recommended since they don't always outperform a simple distribution.

At the other hand there are considerable amount of literature which examine different volatility specifications in GARCH modeling in order to find best predictive ability. Several studies are in favor of EGARCH model, for instance, Chong *et al.* (1999) in their research studied the efficiency of different specification of GARCH models by using the rate of returns from various daily stock market indices of the Kuala Lumpur Stock Exchange (KLSE). The result indicated that the exponential GARCH model showed the best performance in out of sample forecasting while the integrated GARCH showed the poorest performance. Loudon *et al.* (2000) in their paper examined the effectiveness of several parametric ARCH models in describing daily stock returns. The results strongly showed that recognizing asymmetric behavior of volatility are very important in every models. Overall, they conclude that the performance of EGARCH model is superior in predicting stock market volatility.

Same result obtained by Awartani and Corradi (2005) which examine out of sample predictive ability of several GARCH models. Their results demonstrated that in case of one step ahead forecasting, GARCH model is beaten by asymmetric GARCH models. The result is same in case of longer forecast horizons. Evans and McMillan (2007) obtained supportive results which show that the asymmetric GARCH models achieve more accurate volatility forecasting.

Although in most cases these researches demonstrated that the rule of asymmetries is crucial in volatility predictions, the results are not always in favor of asymmetric models. Using stock market data from emerging countries. Gokcan (2000) showed the EGARCH model is outperformed by GARCH model, the result is same even in case of skewed return distributions. McMillan *et al.* (2000) provide supportive evidence that EGARCH cannot outperforms simple GARCH (1,1) in estimating stock index volatility.

Considering the importance of sukuk, the main contribution in this research is providing an overview for sukuk data time series and describes characteristics of its statistical distribution function. According to our knowledge very few researches took place in aspect of analysing the behaviour of sukuk as a liquidity tool in secondary market. Another contribution of this research is comparing the performance of different GARCH methods to estimate value at risk of sukuk in different countries in order to find which method is more appropriate to risk estimation in sukuk market.

2. GARCH MODELS

Let $r_t = \ln(p_t/p_{t-1})$. 100 denote continuously compounded rate of return from time t-1 to t. In this equation p_t is the price level of underlying assets at time t. Different GARCH methods based on this information is described as below. It is important to mention that all this methods can be compute based on different error distribution to provide more flexible tool for modeling the empirical distribution of financial data. If we consider returns to be belonged to location-scale parametric class, we can write

$$r_t = \mu_t + \varepsilon_t = \mu_t + \sigma_t z_t \tag{1}$$

In this equation μ and σ^2 denote the mean and conditional variance of returns, respectively. Based on this information we will have GARCH family models as bellow

2.1. GARCH (1,1)

The symmetric GARCH model can be formulated as below

$$\sigma_t^2 = \omega + \alpha\, \varepsilon_{t-1}^2 + \beta\, \sigma_{t-1}^2 \qquad (2)$$

In this equation μ and σ^2 denote the mean and variance of returns, respectively. ε_t is the innovation process, that different distribution function can be assumed for it. Moreover, ω, α and β are parameters that must be nonnegative with the restriction of $\alpha + \beta < 1$. This restriction is required to make sure about a positive conditional variance and stationary.

2.2. EGARCH (1,1)

It is an asymmetric model which can carry on with asymmetric volatility as follows

$$\log \sigma_t^2 = \omega + \alpha\, [\gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - \sqrt{2/\pi} + \beta \log (\sigma_{t-1}^2) \qquad (3)$$

In this equation γ is a coefficient that captures the asymmetric impact of news. As it is clear, in case of $\gamma < 0$, the impact of negative shocks will be bigger than equal magnitude of positive shocks. Another advantage of this model is that, by using log form, the parameters can be negative without conditional variance become negative.

2.3. GJR-GARCH (1,1)

This model provides an alternative asymmetric model as follow:

$$\sigma_t^2 = \omega + \alpha\, \varepsilon_{t-1}^2 + \delta I_{t-1} \varepsilon_{t-1}^2 + \beta\, \sigma_{t-1}^2 \qquad (4)$$

In this equation I_{t-1} is the indicator function, that take value of one if $\varepsilon_{t-1} < 0$ and otherwise it will be zero. The asymmetric effect in this model in captured by δ, as the equation shows, the impact of positive news is α while the impact of negative news is $\alpha + \delta$, so the impact of negative news will be greater if $\delta > 0$.

2.4. IGARCH (1,1)

Integrated GARCH is the particular form of GARCH model. This model is based on assumption that the sum of persistent parameters will be one so there is unit root in GARCH process. This assumption will be imposed during all process of estimation and forecasting.
The condition for this model is as below:

$$\sum_{i=1}^{p} \beta_i + \sum_{i=1}^{q} \alpha_i = 1 \qquad (5)$$

2.5. Asymmetric Power GARCH Model

This model is suggested by Ding *et al.* (1993) after observing that the sample autocorrelation of absolute returns is higher than squared returns. In general ASP-GARCH model allows broader class of power transportation in compare to considering absolute value or squaring the data as in classical heteroskedasticity models. This model can be formulated as:

$$\sigma_t^\delta = \omega + \sum_{j=1}^{q} \alpha_j \left(|\varepsilon_{t-j}| - \gamma_j \varepsilon_{t-j} \right)^\delta + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^\delta \qquad (6)$$

In this equation δ is the Box-Cox transformation of σ_t and γ_j is the coefficient of leverage term.

3. VALUE AT RISK ESTIMATION AND EVALUATING METHODS

Value at risk is a mathematical approach that shows the maximum amount of loss which is expected for a portfolio over a given holding period at a certain confidence level. From statistical view VaR imply estimation quantile of return distribution.

If $r_1, r_2, r_3 \dots\dots.. r_n$ represent financial return with an i.i.d distribution and $\alpha \epsilon\ (0,1)$ be the probability distribution of financial returns

$$VaR(\alpha) = F^{-1}(\alpha) \quad (7)$$

F is the cumulative distribution function of returns and F^{-1} indicates its inverse function.

In order to select a best model both in-sample and out-of-sample tests are performed in this research. However more focus will be on out of sample performance since it is already documented that a good in sample performance does not guarantee a good out of sample performance. At the other side a model might be insufficient based on in-sample performance while it may show better forecast performance by using out-of-sample framework (Hansen and Lunde, 2005).

3.1. Information Criterions

The classical in-sample model selection criteria such as Akaike Information Criterion (Akaike, 1974), Bayesian information Criterion (Schwarz, 1978) and Hannan–Quinn information criterion (Hannan and Quinn, 1979) which, have been applied widely in ARCH and GARCH literature, will be used in this research in order to select the best in-sample performance. However it is already mentioned that a good in-sample performance doesn't necessary mean a good out-of-sample performance.

All criteria are based on likelihood functions and all are closely related to each other and can be used alternatively. The best model is the one which minimize the criterion. The mathematical formula is coming in follow:

$$AIC = 2k - 2\log\ (L) \quad (8)$$

Where k is the number of parameters in statistical model and L is the likelihood evaluated at the MLE.

$$BIC = K\log\ (n) - 2\log\ (L) \quad (9)$$

Where n is length of time series .And the last criteria Hannan-Quinn information criteria is:

$$HQC = n\log\frac{RSS}{n} + 2k\log lon\ (n) \quad (10)$$

Where k is number of parameters, n is number of observations and RSS is residual sum of the squares that results from liner regression or other statistical model.

3.2. Out-of-Sample Evaluation and Backtesting Methods

The estimation qualities need to be evaluated by appropriate methods. Backtesting is a statistical method to compare the actual profit and losses to corresponding estimation. An observation which actual return is exceeds the estimated VaR is called exception[1]. The model is inappropriate in case of having more or less exception than expected.

Generally the performance of VaR estimators are evaluating by two basic tests: conditional and unconditional coverage tests.

3.2.1. Unconditional Coverage

In unconditional coverage the frequency of exception is compared by selected confidence level during an specification time. In this research we use Kupiec (1995) test to evaluate unconditional coverage of different GARCH estimations. The indicator variable can be defined as:

$$I_r = \begin{cases} 1, if\ r_t < VaR_t \\ 0, otherwise \end{cases} \quad (11)$$

According to Kupiec, considering constant probability for exceptions, then the distribution of exceptions $(x = \sum I_t)$ will be binomial distribution B(N, α)2. So, a Null Hypothesis for testing unconditional coverage is equation of $(\hat{\alpha} = \sum \frac{I_t}{N})$ to α per cent $(\hat{\alpha} = \alpha)$. The likelihood test statistic that is using for unconditional coverage is:

$$LR_{uc} = 2[\log(\hat{\alpha}^x)\,(1-\hat{\alpha})^{N-x} - \log(\alpha^x)(1-\alpha)^{N-x}] \quad (12)$$

K follows an asymptotic χ^2 distribution with 1 degree of freedom. The smaller amount of χ^2 is more acceptable (In case of $x/_N = \alpha$, k will be zero), If K > 10.83 the Null Hypothesis will be rejected.

3.2.2. Conditional Coverage

Although the Kupiec test is frequently using for backtesting the VaR models, but there are some shortcoming about it. For example, its focus is only on the frequency of exceptions while it is not care about the sequences of exceptions. Christoffersen (1998) try to overcome this problem by developing a conditional coverage test. This test examine whether the frequency of exceptions is equal to expected one and at the same time it investigate the serial independence of It.(It examine whether the probability of exception of day t_n is depend on outcome of day t_{n-1}) The exeption is independent if there would not be any significant difference between the ration of preceding exeption and non-exeptions.

[1] According to Jorion (2001). The nomber of exceptions should be equal one minus confidence level. For example, in case of 99% confidence level and 200 observation, the exception should be .100% □ 99% _ 200 = 2

[2] N is the number of observations

n_{ij} is defined as the number of observation, i,j = 0, 1 ,which 1 point to exception and 0 point to no exception.(when the happening of observation is followed by observation j), we also have π_{ij} which stand for the probability of occurring an exception conditional on the previous day and is equal to $\pi_{ij} = n_{ij}/\sum n_{ij}$ The relevant test statistic for independence of exceptions is:

$$LR_{ind} = 2\ln\left(\frac{(1-\pi_{01})^{n_{00}}\,\pi_{01}^{n_{01}}\,(1-\pi_{11})^{n_{10}}\,\pi_{11}^{n_{11}}}{(1-\alpha)^{N-F}\,\alpha^{F}}\right) \quad (13)$$

LR_{ind} is the statistic likelihood ratio for testing serial independence in exceptions and follows the χ^2 distribution with 2 degrees of freedom.. The likelihood ratio statistic for conditional coverage test can be obtained by combining LR_{ind} independence statistic with Kupiec's test, which investigate both correct failure rate and their independence. The likelihood for conditional coverage is :

$$LR_{cc} = LR_{uc} + LR_{ind} \quad (14)$$

4. DATA DESCRIPTION AND EMPIRICAL RESULT

4.1. Data and Descriptive Statistics

The data in this research is consisted of three sukuk issued by Malaysia (petrol), United Arab Emirate (RAK) and Islamic Development bank (IDB). In order to investigate the risk and return dynamics in these three markets daily sukuk closing price is downloaded from Bloomberg database. Descriptive statistics of daily returns are presented in Table.1. As it is clear from Table.1 all returns show positive mean which are considerably small in compare to standard deviation of variables in all markets. The highest average of the daily returns is in Malaysia, while the highest standard deviation is related to UAE (0.292) and IDB (0.192) respectively. According to the sample kurtosis estimates, the daily rates of returns are far from being normally distributed. The lowest kurtosis estimates are 7.04(Malaysia) while the highest is 113.77(UAE). Based on the sample kurtosis estimates, it may be argued that the return distributions in all markets are fat-tailed. The sample skewness shows that the daily return have a near symmetric distribution only in Malaysia. The sample skewness is negative in UAE (-2.36) which indicate that the asymmetric tail extends more towards negative values than positive ones while it is apposite in IDB.

Table-1. Summary Statistics

	mean	Std.dev	min	max	skewness	Kurtosis	J-B
Malaysia	0.0052	0.13	-0.63	0.66	0.037	7.04	667.25 ($2.2e^{-16}$)
IDB	0.001	0.192	-2	2.003	0.54	40.01	49820 ($2.2e^{-16}$)
UAE	0.0042	0.292	-4.12	4.030	-2.36	113.77	535285 ($2.2e^{-16}$)

4.2. Inferential Analysis

Table.2 show the inferential analysis for all data. The Jarque and Bera (1987) statistic shows that the null hypothesis of normality is rejected at any level of significance which is in line with the skewness and kurtosis of return. These results encourage application of more sophisticated distributions which embody heavy-tailed characteristics. The Ljung and Box (1978) statistic test is applied for analyzing serial correlation. According to the result the null hypothesis of no autocorrelation for up to 20th order is rejected by the highly significant test statistics (and also very small p-value of test) at any level of significance which indicates high level of dependency and the presence of conditional heteroskedasticity.

In order to examine constant and trend stationary of return series the KPSS (Kwiatkowski *et al.*, 1992) test is used. The null hypothesis in this test is existence of stationary. The test will be rejected if the test statistic be higher than critical value of the respective significant level (1% : 0.739, 5% : 0.463 , 10% : 0.347). The test result indicate trend stationary in all return series and constant stationary in Petrol and IDB return series.

Table-2. Diagnostic Statistics of Daily Returns

	Ljung-Box	LM- test (12)	Kpss test (const)	Kpss test (trend)
Malaysia	57.21 (1.9 e^{-5})	149.8157(2.2e^{-16})	0.44 (0.060)	0.0313 (0.1)
IDB	191.84 (2.2e^{-16})	266.2987(2.2e^{-16})	0.2766 (0.1)	0.1718 (0.0285)
UAE	142.45 (2.2e^{-16})	201.1192(2.2e^{-16})	0.6076 (0.22)	0.0421(0.1)

LM test is used to examine the autocorrelation of the squared returns. The Null hypothesis of this test is "No ARCH Effect" which examine against the ARCH Effects via Engle's Maximum Likelihood Test. As it is clear from Table.1 the test statistic is highly significant which indicate the existence of ARCH Effects for all countries. Based on this result we conclude the appropriateness of GARCH models to model volatility of related data and calculating VaR.

The results of above analysis show that all sukuk samples have the characteristics of financial time series such as volatility clustering, leptokurtosis, heteroskedasticity in residuals and autocorrelation in the residuals. Based on these results we can apply GARCH-type models to model and forecast conditional volatility.

4.3. In-Sample Evaluation

In this section various GARCH models will be evaluated based on their in-sample performance. Tables 2-4 show estimated parameters, information criteria and log- likelihood function for all models applied in this research.

In all asymmetric GARCH models (EGARCH, GJR- GARCH and AP-GARCH) the coefficient γ is considerably more than zero which indicates existence of asymmetric and leverage effect. γ in IDB data series is relatively higher than other ones which indicate higher leverage effect. In case of negative value of coefficient γ it means bad news increases the future volatility more than good news.

Based on information criteria and log-likelihood function a model with minimum value of AIC, BIC and HQC and maximum value of log-likelihood function is the most appropriate one. According to this information for petrol returns IGARCH model with student-t distribution is more appropriate (AIC= -2.3082, BIC= -2.2782, HQC= -2.2968) while in case of IDB, EGARCH model with ged distribution shows a better performance (AIC=-2.2281, BIC=-2.1818 and HQC=-2.2103).

Table-3. In-sample evaluation for Petrol sukuk returns series

models	ω	α	β	γ	AIC	BIC	HQC	Log-likelihood
GARCH-n	0.000001	0.06945	0.9295	-	-2.2522	-2.2222	-2.2408	1106.211
GARCH-t	0	0.06813	0.9308	-	-2.306	-2.271	-2.2927	1133.467
GARCH-ged	0	0.07003	0.9289	-	-2.3044	-2.2694	-2.2911	1132.688
EGARCH-n	-0.0087	-0.03342	0.997	0.1953	-2.2491	-2.2141	-2.2358	1105.7
EGARCH-t	-0.00823	-0.3895	0.999	0.213143	-2.306	-2.266	-2.2908	1134.5
EGARCH-ged	-0.0089	-0.0299	0.999	0.19002	-2.3019	-2.2619	-2.2866	1132.456
GJR-GARCH-n	0.000003	0.05996	0.9251	0.02783	-2.2525	-2.2175	-2.2392	1107.345
GJR-GARCH-t	0	0.06011	0.92755	0.02264	-2.305	-2.265	-2.2898	1134.01
GJR-GARCH-ged	0	0.0601	0.92722	0.023277	-2.3036	-2.2636	-2.2883	1133.29
IGARCH-n	0.000001	0.07126	0.9287	-	-2.2545	-2.2295	-2.245	1106.313
IGARCH-t	0	0.07087	0.9291	-	-2.3082	-2.2782	-2.2968	1133.57
IGARCH-ged	0	0.073102	0.9268	-	-2.3066	-2.2766	-2.2951	1132.754
Ap-GARCH-n	0.000003	0.07393	0.92503	0.096262	-2.2505	-2.2105	-2.2352	1107.346
Ap-GARCH-t	0.000003	0.09672	0.92302	0.1317	-2.3056	-2.2606	-2.2885	1135.282
Ap-GARCH-ged	0.00006	0.090126	0.9228	0.1196	-2.3024	-2.2574	-2.2853	1133.744

Table-4. In sample evaluation for - IDB sukuk return series

models	ω	α	β	γ	AIC	BIC	HQC	Log-Likelihood
GARCH-n	0.000023	0.05159	0.94741	-	-1.2338	-1.1991	-1.2205	507.5267
GARCH-t	0.000191	0.161096	0.837904	-	-1.8162	-1.7758	-1.8007	745.2975
GARCH-ged	0.0043	0.000513	0.9982	-	-2.1568	-2.1164	-2.1413	883.7516
EGARCH-n	0.02876	-0.0366	0.999	0.1628	-1.2472	-1.2076	-1.2317	513.9943
EGARCH-t	-0.0795	-0.1564	0.97299	0.67434	-1.8767	-1.8305	-1.859	770.8839
EGARCH-ged	0.09432	-0.11032	0.9778	0.59977	-2.2281	-2.1818	-2.2103	913.7055
GJR-GARCH-n	0.00017	0.12799	0.847888	0.046233	-1.8146	-1.7683	-1.7968	745.6333
GJR-GARCH-t	0.00017	0.12799	0.84788	0.046233	-1.8146	-1.7683	-1.7968	745.6333
GJR-GARCH-ged	0.00018	0.12781	0.84793	-	-1.8149	-1.7658	-1.8032	745.4932
IGARCH-n	0.000022	0.052786	0.94721	-	-1.2385	-1.2096	-1.2274	508.4543
IGARCH-t	0.000189	0.16123	0.8387	-	-1.819	-1.7843	-1.8057	745.4226
IGARCH-ged	0.000185	0.006616	0.993384	-	-2.0484	-2.0137	-2.0351	838.6821
Ap-GARCH-n	0.000019	0.05166	0.94553	0.103147	-1.2322	-1.1859	-1.2144	508.8879
Ap-GARCH-t	0.000398	0.120116	0.9255	0.2768	-1.8456	-1.7935	-1.8256	759.2205
Ap-GARCH-ged	0.04188	0	0.000003	0.54081	-2.0064	-1.9543	-1.9864	824.5943

About RAK data APGARCH model with student-t distribution is superior method (AIC= -1.4213, BIC= -1.3773 and HQC= -1.4046).

Overall these results investigate that asymmetric models show better performance in compare to symmetric models. Furthermore, after neglecting asymmetric, in most cases the GARCH model with student-t distribution is preferable to normal and ged distribution.

Table-5. In sample evaluation for RAK sukuk return series

models	ω	α	β	γ	AIC	BIC	HQC	Log-Likelihood
GARCH-t	0.000624	0.249323	0.749677	-	-1.3893	-1.355	-1.3763	705.1036
GARCH-ged	0.000748	0.2628	0.736199	-	-1.3796	-1.3454	-1.3666	700.2376
EGARCH-n	-0.33805	-0.26641	0.8486	1.2575	-0.90522	-0.871	-0.89222	461.8725
EGARCH-t	-0.11966	0.091295	0.96555	0.365532	-1.4064	-1.3673	-1.3915	714.7131
EGARCH-ged	-0.111	0.047537	0.971615	0.283916	-1.3875	-1.3484	-1.3726	705.2049
GJR-GARCH-n	0.000037	0.052637	0.969393	-0.04606	-0.78443	-0.75021	-0.77142	401.1743
GJR-GARCH-t	0.00064	0.280907	0.750899	-0.06561	-1.3885	-1.3494	-1.3736	705.7011
GJR-GARCH-ged	0.000745	0.244676	0.733777	0.041092	-1.3779	-1.3388	-1.363	700.3964
IGARCH-n	0.000015	0.0298	0.9702	-	-0.7327	-0.70826	-0.72341	373.1804
IGARCH-t	0.000621	0.250021	0.749979	-	-1.3914	-1.3621	-1.3803	705.1907
IGARCH-ged	0.000745	0.263251	0.73674	-	-1.3818	-1.3525	-1.3706	700.346
Ap-GARCH-n	0.00727	0.47903	0.61043	0.23174	-1.0457	-1.0066	-1.0308	533.469
Ap-GARCH-t	0.005177	0.3212	0.7953	-0.00689	-1.4213	-1.3773	-1.4046	723.2012
Ap-GARCH-ged	0.00414	0.29023	0.7922	0.07192	-1.3972	-1.3532	-1.3805	711.0808

4.4. Out-of-Sample Performance Evaluation

Tables 6-8 present the failure percentages and the Kupiec and Christoffersen's Test statics for estimated GARCH models. Table 6 reports the ratio of exeption (column F/N) and Kupiec and Christoffersen results for petrol sukuk. The superior and poor performances are displayed by green and red cells, respectively. Based on both Kupiec and christoferson evaluation the best performance is related to IGARCH with normal distribution (Kupiec= 20.439, christoferson=21.214) while the worst performance is related to GJR-GARCH model with normal distribution (Kupiec= 53.724 , christoferson=53.709).

Table-6. Out- of- sample performance evaluation for Petrol sukuk return series

model	F/N	Kupiec	Christoffersen
GARCH-n	0.29	31.217	32.998
GARCH-t	0.25	36.555	38.932
GARCH-ged	0.22	39.493	42.227
EGARCH-n	0.13	53.526	53.609
EGARCH-t	0.12	53.520	53.702
EGARCH-ged	0.13	53.526	52.436
GJR-GARCH-n	0.137	53.726	53.709
GJR-GARCH-t	0.16	49.618	49.731
GJR-GARCH-ged	0.14	53.526	53.609
IGARCH-n	0.4	20.439	21.214
IGARCH-t	0.2	42.634	45.773
IGARCH-ged	0.2	42.634	45.773
Ap-GARCH-n	0.21	42.634	45.773
Ap-GARCH-t	0.27	33.802	34.135
Ap-GARCH-ged	0.2	42.634	45.773

In case of IDB data in three models GARCH-t, GARCH-ged and GJR-GARCH-ged the exeption ration is more than one, amounting to 1.177, 1.4 and 1.07 respectively, which means the actual VaR is higher than expected one that indicate loss is lower estimated. Apart from these models the best forecasting ability is related to AP-GARCH-t (Kupiec =3.023, christoferson=

3.993) while the worst performance is related to GJR-GARCH-n (Kupiec =11.154, christoferson=18.167).

Table-7. Out- of- sample performance evaluation for IDB sukuk return series

model	F/N	Kupiec	christoffersen
GARCH-n	0.48	12.631	13.462
GARCH-t	1.77	18.162	49.34
GARCH-ged	1.4	4.736	18.688
EGARCH-n	0.53	9.792	16.187
EGARCH-t	0.61	6.334	11.134
EGARCH-ged	0.57	8.538	14.361
GJR-GARCH-n	0.49	11.154	18.167
GJR-GARCH-t	0.57	8.538	14.361
GJR-GARCH-ged	1.07	0.16	20.053
IGARCH-n	0.48	12.631	13.462
IGARCH-t	0.67	4.506	4.551
IGARCH-ged	0.59	7.387	8.664
Ap-GARCH-n	0.73	3.023	6.176
Ap-GARCH-t	0.73	3.023	3.993
Ap-GARCH-ged	0.814	1.391	9.305

The best forecasting ability for RAK return series is related to EGARCH with student-t distribution (Kupiec=11.307, christoferson= 13.223) and the poorest performance is related to IGARCH with normal distribution (Kupiec=60.328, christoferson=60.884) .

Table-8. Out- of- sample performance evaluation for RAK sukuk return series

Models	F/N	Kupiec	Christoffersen
GARCH-n	0.13	56.02	60.875
GARCH-t	0.55	11.327	13.901
GARCH-ged	0.3	28.427	29.785
EGARCH-n	0.3	20.318	13.785
EGARCH-t	0.42	11.307	13.223
EGARCH-ged	0.28	33.266	33.646
GJR-GARCH-n	0.31	30.774	31.215
GJR-GARCH-t	0.37	24.133	25.198
GJR-GARCH-ged	0.37	24.133	25.198
IGARCH-n	0.11	60.328	60.884
IGARCH-t	0.533	12.582	14.723
IGARCH-ged	0.266	35.915	38.03
Ap-GARCH-n	0.355	26.216	27.373
Ap-GARCH-t	0.39	22.196	22.986
Ap-GARCH-ged	0.76	14.17	17.506

5. CONCLUSION

In this paper the value at risk forecasting ability of various popular and widely used GARCH approaches are evaluated in both in sample and out of sample performance. In the first step, by using various statistical tests such as Jarque and Bera test, Ljung and Box test, KPSS test and LM test we find evidence that daily returns of sukuk can be characterised by the GARCH-type models.

In the next step, the forecasting performance of several GARCH models with different error distributions is compared in terms of in-sample and out of sample performance. Based on massive estimation and evaluation process following results are conducted:

1- Based on the results of inferential analysis the sukuk return series have the characteristics of conventional bonds returns such as volatility clustering, leptokurtosis, heteroskedasticity and autocorrelation in the residuals.

2- Overall we conclude that although the forecasting ability of asymmetric GARCH models is better but, there is not a superior unique approach to forecast Value at risk for all kind of data. Different methods show different performance based on characteristics of return series such as stationary and asymmetry. For instance although IGARCH-n model shows the best performance in petrol return, it shows the poorest performance in RAK sukuk return.

3- In case of in-sample performance the student-*t* distribution is more preferable than *normal* or *generalised error distribution* (*ged*), in out-of-sample also in most cases (not all) student-t shows slightly better estimates than other ones.

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