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An Estimation of Value at Risk using GARCH Models for the Conventional and Islamic Stock Market in Malaysia

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ABSTRACT

This study attempts to estimate the value-at-risk (VaR) to forecast volatility for both conventional and Islamic stock markets in Malaysia. In particular, the purpose of the article is to investigate whether GARCH models are accurate in the evaluation of VaR in emerging stock markets such as Malaysia. The daily return of the conventional (KLCI) and Islamic (FBMS) stock market are analysed for the period 2000 – 2015. The volatility model of GARCH (1,1), TGARCH (1,1) and CGARCH (1,1) with a normal and student-t distribution are used to model the conditional variance of the stock market returns. The VaR violations of unconditional coverage and the backtesting procedure of Kupiec test are used to check the reliability and accuracy of the volatility model used for both normal and student-t distribution. Based on the Akaike Information Criterion (AIC), the best model for modelling the conventional and Islamic stock market returns is TGARCH (1,1). The backtesting results showed that for all GARCH models used, the normal distribution gives better forecast VaR compared to the student's t distribution.

Keywords: Value at Risk, Heavy Tails, GARCH Model, Volatility forecasting, Backtesting

INTRODUCTION

The modern portfolio theory (MPT) describes the strong relationship between risk and volatility where volatility generates risk associated with the level of dispersion around the mean. In stock market situation, the greater the standard deviation means the greater the stock market dispersion of returns and the greater the risk of the stock market. In other words, the investment is riskier given that the chance to generate excess returns is higher. Therefore, investors who desire for a higher

return must also prepare for any financial uncertainty. Many previous studies have found models and theories with sophisticated tools that are applicable in measuring and forecasting the stock market risk. One of the common used risk measure is called value at risk (VaR). VaR is used to calculate the maximum financial loss over a specific time frame for a given confidence level by focusing on the estimation of the tails distribution. The primary reason for the underestimation or overestimation of VaR is because numerous application in the financial field assume that stock market returns are normally distributed while in the real world it is leptokurtosis which exhibit skewness and excess kurtosis. This paper aims to explain the most accurate model to forecast volatility and analyzed the existence of empirical facts in conventional and Islamic market in Malaysia. This paper is organized into seven sections. Section one provides a literature review follows with the methodology used in Section three. Section four discusses the backtesting procedure to check the accuracy of the model used. Next, section five and six provides the descriptive statistics and empirical findings. Finally, section seven concludes the paper.

According to (Goudarzi, 2011), it is essential to continuous study and find out the most accurate measurement of volatility in assets pricing, risk and portfolio management. The application that commonly used in estimating the volatility of stock market returns is the ARCH (GARCH) models. This is due to the capability of these models to capture the characteristics of return series and identify the random movement of stock market prices. Previous studies show no final decision on which one is the best model to forecast volatility. There were studies present a good forecast result based on the simple GARCH (p,q) models but some present that the extensions of GARCH models such as TARARCH, EGARCH, APARCH and others provide a better forecast result. In research study done by (Angelidisa, Benosa, & Degiannakis, 2004) on S&P 500 Index proves that the combination of a leptokurtic distribution and a simple asymmetric volatility model AR (1) EGARCH (0, 1), is a good combination in estimating the VaR. Study done by (Smolović, Lipovina-Božović, & Vujošević, 2017) joined the ARMA model with different specifications of conditional heteroscedasticity models and found that GARCH (1,1), APARCH (1,1) and TGARCH (1,1) are accurate to forecast VaR in emerging stock market. Finding from (Li, Lian, & Zhang, 2016) presents that EGARCH (1,1) is the best forecasted model for Europe Brent crude oil while APARCH (1,1) and GJR-GARCH (1,1) outperformed other GARCH models for West Texas Intermediate (WTI) Cushing crude oil. The forecasting VaR procedure can also be used for the purpose of finding whether Islamic or Conventional stock market are less volatile to the financial uncertainty (Abdrashev, 2016). Study done by (Bhatt & Sultan, 2012) shows that the Shariah stock market has lower risk premium than the conventional market. In term of the risk premium, (Albaity & Ahmad, 2011) show that Islamic markets has leverage effects but no risk premium. Another study in Islamic market has been done by (Nasr, Lux, Ajmid, & Guptae, 2016) on the Dow Jones Islamic Market World Index (DJIM) and the result presents that Markov-switching multifractal (MSM) model outperform the GARCH, FIGARCH and FITVGARCH models in the prediction of VaR.

METHODOLOGY

The data used are the daily return for FTSE Bursa Malaysia KLCI Index (KLCI), FTSE Bursa Malaysia EMAS Shariah Index (FBMS) from year 2000 – 2015. The continuously compounded rate of return is given by:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \quad (1)$$

Given that P_t is the closing price of the security at time t , the stock market returns contain predictable and unpredictable returns as presented in equation (2).

$$R_t = E(R_t | \psi_{t-1}) + \varepsilon_t \quad (2)$$

where ψ_{t-1} is all information available at time $t-1$ and ε_t is the unpredictable return written as $\varepsilon_t = z_t \sigma_t$, σ_t is the time varying volatility and z_t is iid with mean zero and standard deviation one, $z_t \sim N(0,1)$. In estimating the log return series, the ARCH (q) model which was introduced by (Engle, Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation, 1982) was used to represent the conditional mean equation thus the conditional variance is expressed as a linear function of the previous q squared innovations written as:

$$\sigma_t^2 = \omega + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 \quad (3)$$

To make sure that the conditional variance is positive, the parameters must satisfy $\omega > 0$, $\alpha_i \geq 0$ and $i = 1, 2, 3, \dots, q$. The higher order GARCH (p,q) model proposed by (Bollershev, 1986) is generalized from ARCH (p) model by adding the moving average term as below:

$$\sigma_t^2 = \omega + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-i}^2 \quad (4)$$

where $\omega > 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$, $i = 1, 2, 3, \dots, q$ and $j = 1, 2, 3, \dots, p$.

One of the extension model of GARCH (p,q) that consider the asymmetric effects observed in the data is the Threshold ARCH or TARARCH model which has been introduced by (Glosten, Jagannathan, & Runkle, 1993) and (Zakoian, 1994). The simple model of TARARCH (1,1) is defined as:

$$\sigma_t^2 = \omega + \beta \sigma_{t-1}^2 + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1}^2 \quad (5)$$

$$\text{where } I_t = \begin{cases} 1 & \text{if } \varepsilon_{t-1} < 0 \\ 0 & \text{otherwise} \end{cases}$$

The TARARCH model explains that a response of volatility is influenced by the news information either bad or good news. The bad news $\varepsilon_{t-1} < 0$ are followed by higher volatility while the good news $\varepsilon_{t-1} > 0$ are followed by the lower volatility. In addition, the GARCH (p,q) model are also arguably does not consider the trend and seasonality in stock prices. To capture the volatility dynamics of time varying persistence, the component GARCH model (CGARCH) has been introduced by (Engle & Lee, 1999) and (Ding & Granger, 1996) to capture the trend and seasonality in longer time period. The simplified CGARCH (1,1) equation is provided as below:

$$\sigma_t^2 = \sigma_{LR,t}^2 + \sigma_{SR,t}^2 \quad (6)$$

where

$$\begin{aligned}\sigma_{LR,t}^2 &= \omega + \gamma_{LR1}\sigma_{LR,t-1}^2 + \gamma_{LR2}(z_{t-1}^2 - \sigma_{t-2}^2) \\ \sigma_{SR,t}^2 &= \gamma_{SR1}\sigma_{SR,t-1}^2 + \gamma_{SR2}(z_{t-1}^2 - \sigma_{t-1}^2)\end{aligned}$$

Previous study done by (Engle, Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation, 1982) assumed that the distribution was normal. Subsequently, (Bollershev, 1986) has introduced the standardized t-distribution with degrees of freedom, $(\nu - 2)$ which given as:

$$D(z_t; \nu) = \frac{\Gamma((\nu+1)/2)}{\Gamma(\nu/2)\sqrt{\pi(\nu-2)}} \left(1 + \frac{z_t^2}{\nu-2}\right)^{-\frac{\nu+1}{2}} \quad (7)$$

where $\Gamma(\nu) = \int_0^\infty e^{-x} x^{\nu-1} dx$ is the gamma function and ν is the parameter that represents the thickness of the tail distribution. If $\nu > 4$, the conditional kurtosis is equal to $3(\nu-2)/(\nu-4)$ which above the usual normal value of 3. For the standardized normal distribution series ε_t , the estimation of VaR at 95% and 99% confidence level and for one-step ahead forecast horizon is computed as:

$$VaR_{5\%} = \hat{r}_t(1) - 1.65\hat{\sigma}_t(1) \quad (8)$$

$$VaR_{1\%} = \hat{r}_t(1) - 2.33\hat{\sigma}_t(1) \quad (9)$$

For the standardized student-t distribution series ε_t , the estimation of VaR at 95% and 99% confidence level and for one-step ahead forecast horizon is computed as:

$$VaR_{5\%/1\%} = \hat{r}_t(1) - t_\nu^* \hat{\sigma}_t(1) \quad (10)$$

where $t_\nu^* = \frac{t_\nu(1-\alpha)}{\sqrt{\frac{\nu}{\nu-2}}}$ and $t_\nu(1-\alpha)$ is the correlated critical value of $(1-\alpha)$ quantile, ν degrees of

freedom from t-distribution. The backtesting procedure was done after VaR estimation to test the reliability and accuracy of the model used. The procedure is important to identify the amount of losses predicted by VaR model is accurate by comparing the forecasted VaR with the actual realized returns generated from the historical stock prices observation. According to (Danielsson, 2011) the VaR limit is said to have been violated given that a financial loss on a particular day exceeds the forecasted VaR as formulated below:

$$\eta_t = \begin{cases} 1 & \text{if } r_t \leq -VaR_t \\ 0 & \text{if } r_t > -VaR_t \end{cases} \quad (11)$$

The violation ratio (VR) is calculated by dividing the observed number of VaR violations and the expected number of VaR violations. The expected number of violations is calculated as $p \times w_t$ where p is the

respective probability used and w_t is the number of observation used to forecast risk. The VaR model is said to be under forecasts risk if the violation ratio is greater than one while on the other hand if it is smaller than one the VaR model is said to be over forecasts risk. To confirm whether any other value is statistically significant other than expected VR=1, the following guideline explained by (Danielsson, 2011) to explain the accuracy of the selected VaR model. The first one is if the value of the VR $\in [0.8, 1.2]$ the forecast is good. If VR<0.5 or VR>1.5 the model is imprecise and if VR<0.3 or VR>2 the model is not good. Another process of backtesting involved unconditional coverage tests for the correct number of exceedances is the Proportion of Failure test (POF-test) which also known as Kupiec test. Let $N = \sum_{t=1}^T I_t$ be the number of days over a time period T when the portfolio loss was greater than the VaR estimate given by :

$$I_t = \begin{cases} 1 & \text{if } r_{t,t+1} \geq -VaR_t \\ 0 & \text{if } r_{t,t+1} < VaR_t \end{cases} \quad (12)$$

The unconditional coverage for 95% confidence regions introduced by (Kupiec, 1995) are presented in Table (i). The failure rate recorded follows a binomial distribution given that the number of exceptions in the sample is N and the failure rate is N/T. The no rejection region in Table (i) are defined by the appropriate log-likelihood ratio statistics:

$$LR_{POF} = -2 \ln \left[(1-p)^{(T-x)} p^x \right] + 2 \ln \left[\left(1 - \frac{x}{T} \right)^{(T-x)} \left(\frac{x}{T} \right)^x \right] \quad (13)$$

The Kupiec test is asymptotically distributed Chi-square with degree of freedom equal to one.

Table (i)
Unconditional Coverage for 95% Nonrejection Region

p	c	Nonrejection Region		
		T=252	T=510	T=1000
0.01	99%	N<7	1<N<11	4<N<17
0.03	97.50%	2<N<12	6<N<21	15<N<36
0.05	95%	6<N<20	16<N<36	37<N<65
0.08	92.50%	11<N<28	27<N<51	59<N<92
0.1	90%	16<N<36	38<N<65	81<N<120

RESULTS

DATA & DESCRIPTIVE STATISTICS

The data consist of approximately 3935 daily returns of FTSE Bursa Malaysia KLCI Index (KLCI) and FTSE Bursa Malaysia EMAS Shariah Index (FBMS) during trading day's period of 2000 – 2015.

Table (ii)
 Descriptive Statistics of the daily log returns for the period 2000-2015

Statistics	KLCI	FBMS
Mean	-0.000144	-0.000138
Median	-0.0004	-0.00038
Maximum	0.10493	0.11986
Minimum	-0.04403	-0.048
Std. Dev.	0.008509	0.008977
Skewness	0.980215	1.19813
Kurtosis	14.28124	17.24644
Jarque-Bera	21496.51	34218.6
Probability	0	0
Observations	3935	3935

Both conventional and Islamic time series shows signs of volatility clustering as shown in Figure (i). The tendency of large changes in prices shows that there is persistence in the magnitude of the price changes. Based on the unconditional variance of standard deviation from Table (ii), FBMS has the highest volatility followed by KLCI. For normality test, the series must have skewness equal to zero, kurtosis coefficient equal to three and has probability of Jacque-Bera greater than 0.05 to meet the requirement of normal distribution. Table (ii) presented that KLCI and FBMS have positive skewness which showed that the returns are inclined to the right side of the distribution. The kurtosis value represents that the return distributions of KLCI and FBMS the thickness in the tail of KLCI and FBMS feature leptokurtic distribution due to coefficients larger than three. Finally, the Jacque-Bera p-value show KLCI and FBMS Index violated the normal distribution criteria.

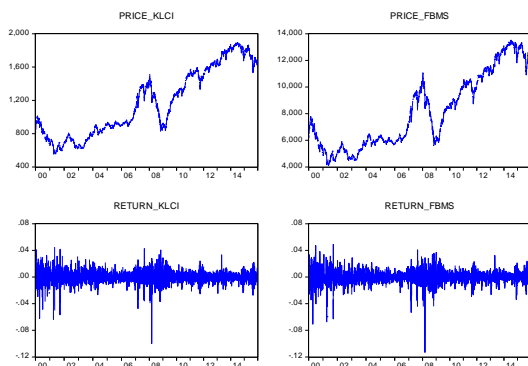


Fig. (i) Continuous Compounded Daily Returns of KLCI and FBMS Index from 2000-2015

EMPIRICAL RESULTS

From Figure (i), the existence of volatility clustering emerged due to the frequent changes of stock returns show unpredictability of volatility. Table (iii) shows the value of Akaike information criterion (AIC) and Schwarz information criterion (SIC) for KLCI both conventional and Islamic market for normal and student's t distribution. Based on the information criteria of the Akaike Information Criteria (AIC) and Schwarz Information Criteria (SIC) presented in Table (iii), TAR(1,1) is the best

estimated model for modelling the logarithmic return series of both KLCI and FBMS Index since it has the lowest values of AIC and SIC.

Table (iii)
Criteria for Model Selection

Index	Distribution	Model selection	
		AIC	SIC
KLCI	GARCH (1,1)-n	-7.0453	-7.0373
	GARCH (1,1)-t	-7.1143	-7.1048
	TARCH (1,1)-n	-7.0541	-7.0446
	TARCH (1,1)-t	-7.1182	-7.1071
	CGARCH (1,1)-n	-7.0672	-7.0545
	CGARCH (1,1)-t	-7.1141	-7.0997
FBMS	GARCH (1,1)-n	-6.9709	-6.9629
	GARCH (1,1)-t	-7.0548	-7.0452
	TARCH (1,1)-n	-6.9808	-6.9713
	TARCH (1,1)-t	-7.0595	-7.0484
	CGARCH (1,1)-n	-6.9867	-6.9739
	CGARCH (1,1)-t	-7.0534	-7.0391

Table (iv)
Parameter Estimates of the GARCH Family Model for KLCI Index (2000-2015)

Parameter	KLCI					
	GARCH (1,1)		TARCH(1,1)		CGARCH (1,1)	
	normal	stud t	normal	stud t	normal	stud t
C	4.00E-04	3.70E-04	2.46E-04	2.89E-04	3.75E-04	3.66E-04
AR(1)	0.1669	0.1344	0.1706	0.1371	0.1653	0.1424
ω	1.02E-06	1.13E-06	1.17E-06	1.19E-06	4.19E-05	1.12E-04
α	0.1190	0.1208	0.0727	0.0825	0.0983	0.0022
β	0.8727	0.8687	0.8725	0.8682	0.7275	-0.9927
γ	-	-	0.0893	0.0745	0.0181	0.1226
ρ	-	-	-	-	0.9965	0.9904
ν	-	5.6620	-	5.8001	-	5.7184
resQ-(12)	9.9926	17.5290	11.0080	18.1160	9.9810	17.4540
	0.5310	0.0930	0.4430	0.0790	0.5321	0.0950
res squ	12.8840	12.0170	12.4290	12.1980	12.1120	11.8360
Q-(12)	0.3780	0.4440	0.4120	0.4300	0.4370	0.4590
ARCH (12)	1.0013	0.9384	0.9891	0.9780	0.9680	0.9209
	0.4447	0.5069	0.4564	0.4673	0.4772	0.5247

Table (v)
 Parameter Estimates of the GARCH Family Model for FBMS Index (2000-2015)

Parameter	FBMS					
	GARCH (1,1)		TARCH(1,1)		CGARCH (1,1)	
	normal	stud t	normal	stud t	normal	stud t
C	4.36E-04	3.85E-04	2.65E-04	3.05E-04	4.59E-04	3.74E-04
AR(1)	0.163	0.131	0.162	0.134	0.151	0.130
ω	9.95E-07	1.09E-06	1.07E-06	1.17E-06	4.79E-05	1.25E-04
α	0.127	0.112	0.076	0.074	0.058	0.012
β	0.869	0.879	0.871	0.876	0.785	-0.519
γ	-	-	0.094	0.080	0.023	0.114
ρ	-	-	-	-	0.997	0.991
v	-	5.066	-	5.184	-	5.079
resQ-(12)	18.349	26.039	19.449	25.662	20.429	26.494
	0.074	0.006	0.054	0.007	0.040	0.005
res squ	7.931	7.276	7.316	6.423	3.597	7.258
Q-(12)	0.791	0.839	0.836	0.893	0.990	0.840
ARCH (12)	0.628	0.563	0.603	0.517	0.295	0.563
	0.820	0.873	0.603	0.905	0.990	0.873

Table (vi)
 Backtesting results using Violation Ratio for KLCI and FBMS

Index	Model	Violation ratios	
		95%	99%
KLCI	GARCH (1,1) - n	0.8943	1.626
	GARCH (1,1) - t	0.4065	0
	TARCH (1,1) - n	0.813	1.626
	TARCH (1,1) - t	0.4065	0
	CGARCH (1,1) - n	1.3008	1.2195
	CGARCH (1,1) - t	0.4065	0
FBMS	GARCH (1,1) - n	1.1382	0.813
	GARCH (1,1) - t	0.4878	0
	TARCH (1,1) - n	0.8943	0.4065
	TARCH (1,1) - t	0.3252	0
	CGARCH (1,1) - n	0.9756	1.2195
	CGARCH (1,1) - t	0.4878	0

Table (vii)
 Backtesting results using Kupiec Test for KLCI and FBMS

Index	Model	Binomial Test			
		95%		99%	
		N	Test Stats	N	Test Stats
KLCI	GARCH (1,1) - n	11	-0.38	4	0.987
	GARCH (1,1) - t	5	-2.136	0	-1.576
	TARCH (1,1) - n	10	-0.673	4	0.987
	TARCH (1,1) - t	5	-2.136	0	-1.576
	CGARCH (1,1) - n	16	1.082	3	0.346
	CGARCH (1,1) - t	5	-2.136	0	-1.576
FBMS	GARCH (1,1) - n	14	0.497	2	-0.295
	GARCH (1,1) - t	6	-1.843	0	-1.576
	TARCH (1,1) - n	11	-0.38	1	-0.936
	TARCH (1,1) - t	4	-2.428	0	-1.576
	CGARCH (1,1) - n	12	-0.088	3	0.346
	CGARCH (1,1) - t	6	-1.843	0	-1.576

Table (viii)
Backtesting results using Kupiec Test for KLCI and FBMS

Index	Model	Unconditional Coverage			
		95%		99%	
		N	Test Stats	N	Test Stats
KLCI	GARCH (1,1) - n	11	0.1497	4	0.8188
	GARCH (1,1) - t	5	5.8241	0	NA
	TARCH (1,1) - n	10	0.4823	4	0.8188
	TARCH (1,1) - t	5	5.8241	0	NA
	CGARCH (1,1) - n	16	1.0746	3	0.1119
	CGARCH (1,1) - t	5	5.8241	0	NA
FBMS	GARCH (1,1) - n	14	0.2372	2	0.0928
	GARCH (1,1) - t	6	4.1542	0	NA
	TARCH (1,1) - n	11	0.1497	1	1.1284
	TARCH (1,1) - t	4	7.9049	0	NA
	CGARCH (1,1) - n	12	0.0078	3	0.1119
	CGARCH (1,1) - t	6	4.1542	0	NA

DISCUSSION

To check the model accuracy, the backtesting procedures of violation ratio, Binomial test and Kupiec test has been done to compare the forecast VaR with the ex-post realized returns for all models. The procedure of violation ratio is occurred when financial losses exceed the previous day's VaR. By using a sample of T = 246 days observations, the violation ratios for both conventional and Islamic indices based on 95% and 99% confidence level are considered as shown in Table (vii). The expected number of violations for 95% is calculated by using the formula explained in [6] thus, for 95% confidence level, the expected number of violation is $0.05 \times 246 = 12.3$ while for 99%, $0.01 \times 246 = 2.46$. By using 95% confidence level, the KLCI Index results exhibit that all model is said to be over forecasts risk because the value is smaller than 1 except for the CGARCH (1,1) normal distribution model. However, for student's t distribution, all models are over forecasts risk. Different with Islamic Index (FBMS), all models over forecasts risk except for the GARCH (1,1) normal distribution model. For KLCI Index, the GARCH (1,1) and TARCH (1,1) with normal distribution displays the forecast model is good because the value of the VR $\in [0.8, 1.2]$. For FBMS Index, the TARCH (1,1) and CGARCH (1,1) normal distribution showed the forecast model is good. All model with student's t distribution for both KLCI and FBMS Index showed that the model is imprecise because $VR < 0.5$ or $VR > 1.5$. Based on the Binomial test, the result show that for 5%, the critical values used are ± 1.96 while for 1% the values are ± 2.57 . Based on 95% confidence level, the forecast VaR for all models with normal distribution are located under the non-rejection area thus the null hypothesis is accepted. However, for student's t distribution, the forecast VaR in under rejection area which reject the null hypothesis. The result for 99% confidence level shows that all test statistic values are located under the non-rejection area thus the null hypothesis is accepted. The results of the Kupiec test are presented in Table (viii). The forecasted value of VaR for 95% confidence level with normal distribution gives good results where VaR forecast values are below than $\chi^2 = 3.841$ thus accepting the null hypothesis of correct unconditional coverage. Furthermore, for student's t distribution, the null hypothesis of correct unconditional coverage is rejected. The number of exception, N for student's t distribution is far too small compared to the expected excesses 12.3. Additional, for 99% confidence level, the models with normal distribution yield satisfactory results with forecast VaR less than $\chi^2 = 6.635$ however for

student's t distribution, the result indicate NA (not applicable) due to insufficient number of convergences.

CONCLUSION

Based on the descriptive statistics result, both markets feature leptokurtic distribution with skewness skewed to the right and heavy tails. The TARCH (1,1) is the best fitted models based on the values of AIC and SIC. The backtesting result of violation ratio show that for 95% confidence level, the KLCI and FBMS Index show the result of over forecasts risk for both normal and student's t. The TARCH (1,1) model with normal distribution displays as the good forecast model for both conventional and Islamic Index based on the violation value $VR \in [0.8, 1.2]$. The backtesting result of Kupiec test also show that all models with normal distribution passed the Kupiec test at 95% and 99% confidence level. However, for student's t distribution, the result does not accept the null hypothesis of correct unconditional coverage. The Kupiec test results for student's t distribution of both markets indicate NA (not applicable) due to insufficient number of convergences. The good forecast result for TARCH (1,1) model based on the violation ratio, Binomial test and Kupiec test are consistent with the AIC and SIC criteria to be the most accurate model to forecast VaR. Based on the given result, 95% confidence level yielded a good forecast result but when the confidence level is increased to 99%, a small sample size may lead to lack of convergence in estimating the number of exceptions. The normal distribution provides a good forecast VaR than student's t distribution. To overcome the problem of difficulty of VaR models in estimating the heavy tailed of the return distribution, further study will be focuses on the heavy tails distribution by comparing GARCH models and the conditional Extreme Value Theory (EVT) specifications to improve the VaR forecasting performance.

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