Institutions and Economies
Vol. 7, No. 2, July 2015, pp. 1-29

The Effects of Risk Modelling: Assessing Value-at-Risk Accuracy

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Abstract: *This study examines Value-at-Risk (VaR) models that are integrated with several volatility representations to estimate the market risk for seven non-financial sectors traded on the first board of the Malaysian stock exchange. In a sample that spanned 19 years from1993 until 2012 for construction, consumer product, industrial product, plantation, property, trade and services and mining sectors, the expected maximum losses are quantified at 95% confidence level. For accuracy determination, assessments using Kupiec test and Christoffersen test have provided evidence that almost every model are found to be accurate for all sets of occurrence. However, using the Lopez test which takes into consideration the magnitude of the impact of exceptions, the most accurate model is the VaR which is integrated with GARCHt. This study found that fat tails and asymmetries are important issues that need to be considered when estimating VaR in managing financial risks.*

Keywords: Backtesting, Value-at-Risk, Volatility Modelling.
JEL Classification: C53, G10

Article Received: 22 March 2014; Article Accepted: 23 May 2014

1. Introduction

The uncertain scenario of the world business transactions undoubtedly has had an impact on the financial markets which may influence the returns on an investment. Reflected in many dimensions such as the stock market, exchange rate, interest rate and commodity market in a volatile environment, firms are indeed exposed to different levels of financial risks. Due to these circumstances, new dimension in business is created taking into account systematic risks which force firms to amend their operational structure. This is also in order to accommodate environmental changes. These conditions may also motivate firms to search for better methodologies to manage risk

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(Dowd, 1999). Although risks cannot be totally eliminated, Fong & Vasicek (1997) stressed that its effect, particularly on investment losses, can be minimised when one understands and manages risks based on an effective risk measurement methodology. Before Fong & Vasicek (1997) and Dowd (1999) came out with these statements, RiskMetrics introduced Value-at-Risk (VaR) in 1994 as a tool for market users. The diverse estimation techniques of VaR in representing adequate differentiation analysis are the focal point of attempts to assist financial risk management practices. Thus, many techniques of VaR have been developed by researchers to minimise risks. These include the variance-covariance method (VCV), historical simulation (HS) and Monte Carlo simulation (MCS).

Despite the fact that empirical testing has unveiled important issues pertaining to VaR methodologies and measurement, these works are still non-conclusive. It is important to note that the literature on VaR models over the last decade has mainly focused on developed countries such as the United States (US), European and Japanese markets (Hendricks, 1996; Ho, Chen, & Eng, 1996; Hull & White, 1998; Kritzman & Risch, 2002; Lee & Saltoglu, 2002; Linsmeier & Pearson, 2000; Luciano & Marena, 2002; Venkataraman, 1997). However, there is a dearth of studies on VaR models using emerging or developing as case studies like Malaysia. Why study emerging economies? Sinha and Chamu (2000) explained that these markets tend to show more volatile conditions and routinely produce risks with fat tails and asymmetry that are not consistent with well-behaved distribution. Seymour and Polakow (2003) added that studies observing developed market data may offer little basis for selection of a VaR estimation method in an anomalously volatile emerging market. As a matter of fact, only few studies have determined risk forecasts using VaR for the Malaysian market (Choong, 2004; Ahmad, Ahmad & Salamudin, 2007; Ahmad, Ahmad & Salamudin, 2013; Dargiri, Shamsabadi, Thim, Rasiah & Sayedy, 2013) and the existing ones are mostly carried out by comparing Malaysian performances with other Asian countries (for example, Zangari, 1996; Su & Knowles, 2006). For the benefit of both academic and policy makers, evaluating risk forecast based on the VaR method for the Malaysian case must be further examined.

The main aim of this paper is to compare the accuracy of the VaR estimates based on four different types of VaR plus volatility models. The study employs the full valuation approach namely, the MCS on a selection of non-financial sectors traded in the Malaysia stock market. The following section provides an overview of literature review. Section 3 briefly outlines the description of data used in the study and the methodology to assess VaR values. The final results are presented and interpreted in Section 4. The summary of findings and comments on its limitations and implications are addressed in the final part of this paper, Section 5.

2. Review of Literature

2.1 Volatility Models and VaR

The VaR estimations are greatly influenced by the input provided by volatility values in the market risk factors. This is because alongside the underlying price, it helps to describe the behaviour of the market. According to Ane (2005), the process of VaR modelling in its true sense is equivalent to the process of applying the volatility model to a selected VaR method. Various studies in this context fit the notion that when individual volatilities are high, the correlations between the market risk factors are increased. Market participants who have a more reliable or superior ability to predict volatility will have an edge over their competitors in that they are able to control financial risks and profiting from them at the same time (Dunis & Chen, 2005). According to Giot and Laurent (2005) and Hull and White (1998), adding volatility to the VaR theoretical formula helps to improve the VaR estimates substantially because it enhances accuracy and efficiency.

Jorion (2002) who investigated publicly disclosed VaR figures of banks reported that VaR-based volatility portrays a positive relationship with future market risk. Evidence based on the trading revenues of eight US commercial banks serves as a strong indicator of risk and return tradeoffs. Bolgun (2004) pointed out that since the introduction of VaR, a new role for volatility models such as the ARCH has emerged. Bolgun showed that volatility can be used together with VaR measures to indirectly help determine capital adequacy for financial institutions. Covering several trading portfolios of Turkish banks, the research clearly indicated that for emerging markets, GARCH can be quantified as a suitable model. In fact, Bolgun suggested that better volatility models such as TARCH and EGARCH are needed to handle more market variations in the time series (refer also to Christoffersen, Hahn & Inoue, 2001; Chiu, Lee & Hung, 2005; Pederzoli, 2006).

2.2 Accuracy Measures and VaR

An accuracy test is conducted by evaluating the extent to which the proportion of losses that exceed the VaR estimate is consistent with the model's chosen confidence level (Engel & Gizycki, 1999). According to Hendricks and Hirtle (1997) and Jorion (2002), due to increased scrutiny by regulators and market users on the implementation of VaR in financial institutions, the quest to evaluate accuracy of underlying models becomes a necessity. Not undergoing this process will definitely jeopardise quality of information provided thus, misstating a firm's true risk exposures. According to the authors, inaccurate VaR models will reduce the main benefits of models-based capital requirements. In addition, one should note that accuracy is also dependent on the composition of a particular portfolio (Angelidis, Benos & Degiannakis, 2003; Johannson, Seiler, & Tjarnberg, 1999; Papadamou & Stephanides, 2004). Clearly, as stressed by Engel and Gizycki (1999), accuracy measures are important for the users of VaR models.

Lopez (1999) introduced several strategies to address the issue of accuracy. The methods for evaluating it integrate three hypothesis-testing methods: [1] binomial distribution [2] interval forecast method; and [3] regulatory loss function. The statistical evidence in the study showed that the loss function method is much more superior compared with the other two in differentiating VaR from the actual and alternative models. Lopez declared that all three methods should be useful from the regulatory point of view as these methods provide complementary information and increase the accuracies of VaR estimates.

Engel and Gizycki (1999) presented five accuracy measures: [1] binary loss functions, [2] quadratic loss functions, [3] scaling factors to obtain sufficient risk coverage, [4] average magnitude of losses; and [5] maximum magnitude of losses. Mixed results are recorded when these tests are applied to Australian banks data both at the 95% and 99% confidence level. For the 95% percentile, the exponential VCV, exponential HS, constant-correlation GARCH and OGARCH models showed higher accuracy levels while for the 99% percentile, models based on extreme value theory (EVT), simple MCS and normal-mixture MCS, simple and antithetic HS demonstrated better accuracy. Their research concluded that differences in a model's performance widens as confidence level increases.

Handling and interpreting this performance measurement may also be viewed based on the applications of Kupiec test. Giot and Laurent (2005) adopted two measures: first, by computing the failure rate depicted in the left and right tails and second, by running the Kupiec likelihood ratio (LR) test. A property of Kupiec test is that it can be more effective as the sample size increases. In order to test the model's performance and stability in a challenging trading environment, Giot (2005) performed the Kupiec likelihood ratio and extended it by applying the Christoffersen independence and conditional coverage test. Using the weighted average of implied volatility on US data covering both bull and bear markets from 1994 to 2003, Giot made several conclusions. First, the number of VaR violations was not significantly different from the target value in most cases and hence, the null hypotheses of the independence and conditional coverage are not rejected. Second, despite the differences and challenging market conditions, the VaR models did not break down or deteriorate throughout the timeframe. The study demonstrated that data volatilities are adequate inputs to market participants especially for managers who manage index funds. The degree of performance increases because the implied volatility pertaining to index tracking can be directly fed into the market risk model (see studies by Ane, 2005; Lin & Shen, 2006; Papadamou & Stephanides, 2004).

Bredin and Hyde (2004) tested the accuracies of six VaR forecasting models by adopting the interval forecast of Christoffersen (1998) and the binary and quadratic loss function applications of Lopez (1999). The models comprised EQMA and EWMA variance-covariance approach, three alternative multivariate GARCH methodologies and a non-parametric estimation model that is HS. Based on the portfolios of six foreign exchange data from 1990 to 1998 on four different horizons, the researchers indicated that the OGARCH is the most accurate model. In fact, they also highlighted the importance of considering fat tails and asymmetric properties when deciding the best VaR model (Pochon & Teiletche, 2007; Su & Knowles, 2006; Yao, Li & Ng, 2006).

Referring to earlier research carried out by Engel and Gizycki (1999), Lee and Saltoglu (2002) further investigated the relative predictive performance of various VaR model using three accuracy tests on the Japanese stock market. First, the Christoffersen test to calculate the coverage probability; second, the White's forecast evaluation criteria and; third, the reality check for predictive ability based on gathered loss function. Besides proving that VaR-GARCH models are better than the EWMA models, they concluded that market users can never avoid fundamental difficulties in the process of understanding financial risk to prevent potential financial crises.

3. Data and Methodology

3.1 Data

Data sample covers the time series indices of seven non-financial sectors traded in the First Board of the Malaysian stock exchange or Bursa Malaysia over the period 1993 until 2012. The data set is then divided into two parts. The first part, from 1993 until 2010, is used to estimate the volatility parameters. This sample size is chosen because it covers different economic conditions and includes complete data information, appreciation, depreciation and unchanged values. The second part which covers between 2011 and 2012 is used for backtesting each estimated VaR models (Pederzoli, 2006). The non-financial industries are represented by construction, consumer product, industrial products, plantation, properties, trading and services and mining sectors. Data were obtained from Datastream. Two non-financial sectors, namely technology and hotels, have been omitted from this study because the former started its index listing only in 2000 while the latter is not represented by a specific index on Bursa Malaysia. Financial-based firms which include banks, securities firms and unit trust companies have been omitted from the current data sample due to its heavy and different regulatory background (Ibrahim & Mazlan, 2006). Data are analysed using Eviews 5, WinRats 6.2 (Regression Analysis Time Series) and @RISK softwares.

3.2 VaR Theoretical Formula

According to Dowd (2005), VaR quantifies the probability level of loss for a portfolio and varies according to the use of VaR by management and asset liquidity. It measures the market risk for a portfolio of financial assets with a given degree of confidence level α and holding period *h.* Consider the return series r_{t+h} of a financial asset which denotes the portfolio wealth at time *t* and the portfolio return at time *t* + *h*. The probability of a return less than value-at-risk, denoted as $VaR_t(h)$, can be defined as the conditional quantile as follows:

$$\Pr\,[r_{t+h} < VaR_t(h)] = \alpha \tag{1}$$

VaR is a specific quantile of a portfolio's potential loss distribution over a given holding period. Assuming r_t follows a general distribution, f_t, VaR under a certain chosen *h* and α gives:

$$\int_{-\infty}^{VaR(,h\,)\alpha} f_{t+h}(x)\,dx = 1-\alpha \tag{2}$$

Theoretically, VaR can be formulated as:

$$VaR_t = W_t \alpha\sigma\sqrt{\Delta t} \tag{3}$$

where W_t is the portfolio value at time *t*, σ is the standard deviation of the portfolio return and $\sqrt{\Delta t}$ is the holding period horizon (*h*) as a fraction of a year.

3.3 Volatility Modelling

Volatility, σ, is an important input to VaR estimation as a risk measure (Glasserman, Heidelberger & Shahabuddin, 2000; Jorion, 2006). JP Morgan (1996) cites the main reason for preferring to work with standard deviations (volatility) is due to fact volatility of financial return is predictable. Inclusion of this parameter may also test how the risk estimator reacts to changes in market volatility (de Raaji & Raunig, 1998). Thus, if this variable is predictable then it makes sense to construct financial forecasts to predict future values of return distribution. For this study, four volatility models are applied with the theoretical formula of VaR based on two cases of statistical distribution assumptions; Normal distribution [Model 1: RiskMetrics Exponentially Weighted Moving Average (EWMA) and Model 2: Generalized Autoregressive Conditional Heteroscedasticity ($GARCH_n$)] and t-distribution [Model 3: $GARCH_t$ and Model 4: $EGARCH_t$].

RiskMetrics EWMA: A distinguishing feature of EWMA is that it places more weight on recent observations and less on older returns (Brooks, 2002). One main assumption of this model is that the asset return mean is equal to zero. The EWMA treats the forecast of volatility to be a weighted average of the previous period's forecast volatility and its current squared return. The expected volatility at time *t* is illustrated as:

$$\hat{\sigma}_t^2 = (1-\lambda)\sum_{i=0}^{\infty}\lambda^{i-1}x_{t-i} \qquad (4)$$

Referring to RiskMetrics and Engel and Gizycki (1999) methodologies, the decay factor is assumed to be $\lambda = 0.94$.

$GARCH_n$: For the normal GARCH model, the assumption is that ε_t is conditionally normally distributed with conditional variance σ_t^2. The GARCH model assumes that the variance of returns follows a predictable process. The conditional variance of a generic GARCH model depends on both lagged values of squared returns and lagged volatility estimates. Bollerslev (1986) generalised Engle's ARCH *(p)* model by adding the *q* autoregressive terms to the moving averages of squared unexpected returns:

$$\sigma_t^2 = \omega + \alpha_1\varepsilon_{t-1}^2 + \ldots + \alpha_p\varepsilon_{t-p}^2 + \beta_1\sigma_{t-1}^2 + \ldots + \beta_q\sigma_{t-q}^2$$

where $\omega > 0$; $\alpha_1, \ldots, \alpha_p$; $\beta_1, \ldots, \beta_q \geq 0$ (5)

The simplest model chosen is GARCH (1,1) if $p = q = 1$, thus the estimator is:

$$\sigma_t^2 = \omega + \alpha\ \varepsilon_{t-1}^2 + \beta\ \sigma_{t-1}^2 \qquad (6)$$

where $\omega > 0$ and $\alpha, \beta \geq 0$. GARCH (1,1) model is selected because it is relatively easier to estimate and is more parsimonious (Bollerslev, 1986; Mat Nor, Yakob & Isa, 1999).

$GARCH_t$: According to Alexander (1998), a leptokurtic (fatter tails than normal) of unconditional returns distribution is due to changing conditional variance that allows more outliers or unusually large observations. From equation (3.5), the GARCH-t is then expressed according to equation (3.7) for which $\mu = v_t\sqrt{h_t}$ where $v_t \sim t(0,1,\upsilon)$ is a student t-distribution with a mean equal to zero, variance unity, υ degrees of freedom and h_t, a scaling factor that depends on the squared error term at time *t*-1. For univariate series, the t-distribution is:

$$f(t \mid \nu) = \Gamma\left(\frac{\nu+1}{2}\right) / \sqrt{\pi(\nu-2)} / \Gamma(\nu/2)\left(1+\frac{t^2}{\nu-2}\right)^{-(\nu+1)/2} \tag{7}$$

EGARCH$_t$: Nelson (1991) introduced this model specifically to reduce the volatility asymmetric effect in addition to eliminating the non-negativity constraints of the GARCH model. This constraint may restrain the dynamics of the obtained conditional variances (Alexander, 1998). The EGARCH is generated by taking the exponential functions of conditional volatility. Through this volatility log formulation, the impact of lagged squared residuals is exponential

$$\ln \sigma_t^2 = \alpha + g(z_{t-1}) + \beta \ln \sigma_{t-1}^2 \tag{8}$$

where

$$g(z_t) = \omega z_t + \lambda\left(|z_t| - \sqrt{\frac{2}{\pi}}\right) \tag{9}$$

3.4 Test of accuracy

To estimate accuracy of the VaR measurement, the Basle Committee stipulates that backtesting must be carried out. Three selected accuracy assessments are applied namely, the Kupiec test, Christoffersen test and Lopez test. The Kupiec test is used to verify whether models provide proper coverage according to the chosen confidence level, the Christoffersen test to examine independence and Lopez test to benchmark models with better performance.

The Proportion of Failure Likelihood Ratio Test (Kupiec, 1995)**:** The test is based on the probability under the binomial distribution of observing *x* exceptions in the sample size *T*.

$$f(x) = \binom{T}{x} p^x (1-p)^{T-x} \tag{10}$$

An accurate VaR model provides VaR estimates with unconditional coverage $(\hat{p})$, given by the failure rate $\left(\frac{x}{T}\right)$, equal to the desired coverage (p), given by the chosen confidence level (1% for 99% and 5% for 95% confidence levels). Under the null hypothesis $H_0 = p = p$, the appropriate likelihood ratio is given by:

$$LR_{uc} = -2\ln\left((1-p)^{T-x} p^x\right) + 2\ln\left((1-\hat{p})^{T-x} \hat{p}^x\right) \tag{11}$$

which is asymptotically distributed Chi-square with one degree of freedom.

Thus, the null hypothesis will be rejected if LR_{uc} exceeds the expected number of exceedances, x (Dowd, 2005).

The Conditional Testing (Christoffesen, 1998)**:** Christoffersen (1998) conditional testing is important as it tackles the limitation of Kupiec (1995) since the latter fails to capture time varying volatility. *This can be made by extending the* LR_{uc} *to specify that exceptions must be independently distributed whereby the first part of the Conditional Testing defines* the indicator of exceptions as follows:

$$I_t = \begin{cases} 1, if & \Delta P_{i,t} < VaR_{t|t-1} \\ 0, if & \Delta P_{i,t} \geq VaR_{t|t-1} \end{cases} \tag{12}$$

Next is to define the number of days in which state i is followed by state j as T_{ij}, and the probability of observing an exception conditional on state i the previous day as π_i. Subsequently, to test the hypothesis that the failure rate is independently distributed, the likelihood test for independence is calculated as:

$$LR_{ind} = -2\ln\left(\frac{(1-\pi)^{(T_{00}+T_{10})}\pi^{(T_{01}+T_{11})}}{(1-\pi_0)^{T_{00}}\pi_0^{T_{01}}(1-\pi_1)^{T_{10}}\pi_1^{T_{11}}}\right) \sim \chi_1^2$$

where

$$\pi = \frac{T_{01}+T_{11}}{T}, \pi_0 = \frac{T_{01}}{T_{00}+T_{01}}, and \pi_1 = \frac{T_{11}}{T_{10}+T_{11}} \tag{13}$$

The likelihood test for conditional coverage is $LR_{cc} = LR_{uc} + LR_{ind}$ which is quantified as:

$$LR_{cc} = -2\ln\left(\frac{(1-P)^{T_1}P^{T_0}}{(1-\pi_0)^{T_{00}}\pi_0^{T_{01}}(1-\pi_1)^{T_{10}}\pi_1^{T_{11}}}\right) \sim \chi_2^2 \tag{14}$$

Quadratic Loss Function (Lopez, 1999)**:** The third accuracy test was introduced by Lopez (1999) who believed it provided better and more powerful accuracy than the other approaches. This model is known as Quadratic Loss Function (QLF) which takes into account the magnitude of exceptions. The QLF is based on the concept of failure rate; if actual loss is greater than the VaR value, then it is considered a failure. Each failure rate is assigned a constant 1, otherwise it is stated as zero.

$$L_{i,t+1} = \begin{cases} 1+\left(\Delta r_{i,t+1} - VaR_{i,t}\right)^2, & if \Delta r_{i,t+1} < VaR_{i,t} \\ 0, & if \Delta r_{i,t=1} \geq VaR_{i,t} \end{cases} \tag{15}$$

4. Results

4.1 Descriptive Statistical Analysis

The descriptive statistics presented in Table 1 illustrate the basic statistical characteristics of the return series (i.e. in log-differenced form). The sample mean for data is almost zero where the means are negative for all the sectors with the exceptions of COP, PLN and TIN. This implies that COP, PLN and TIN have more positive returns while the average values for sectors CON, INP, PRP and TAS are negative-definite. Compared with the other six sectors, TIN with the highest standard deviation value portrays the largest average deviation from the mean.

The normality test results as projected by the sample skewness, kurtosis and the rejections of the normality hypothesis based on Jarque-Bera analysis provide strong evidence of non-normality. In addition, skewness ranging from a low of 0.4700 (INP) to a high of 0.9465 (CON) suggests that the series distributions are skewed. The high kurtosis values compared with the normal distribution which is 3 imply that the distributions of series are leptokurtic or fat tailed. The rejection of the null hypothesis in all series using Ljung-Box Q tests shows that the squared returns have a serial correlation. Similar table also highlights the presence of ARCH effect in the data as shown by the large values of chi-square and small values of probability statistics. This supports the hypothesis in that the series is heteroscedastic at the 1% significance level.

The above evidence shows that the indices return series are not normally distributed with variances that are changing through time or volatility clustering (see also Figure 1). It is thus appropriate to consider the application of volatility models in further analysis. Four models namely, EWMA, GARCH $(1,1)_n$, GARCH$(1,1)_t$ and EGARCH$(1,1)_t$ are estimated and compared in the next subsections.

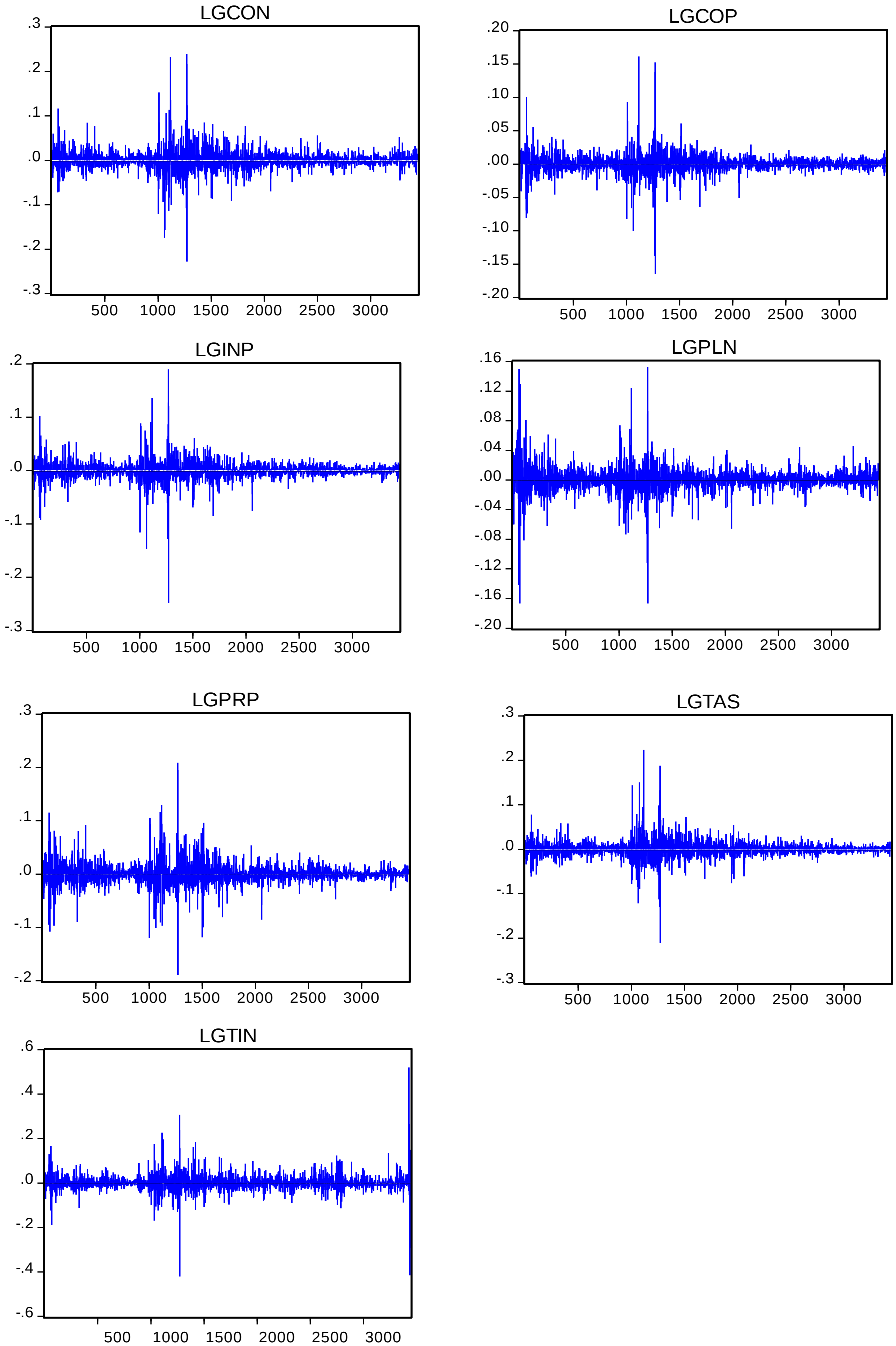
Table 1: Basic Statistics of the Full Sample

	CON	COP	INP	PLN	PRP	TAS	TIN
Mean	-0.0001	0.0001	-0.0002	0.0002	-0.0004	-3.99E-05	5.95E-05
Std Dev	0.0312	0.0249	0.0179	0.0151	0.0212	0.0187	0.0532
Skewness	0.9465	0.2411	-0.4700	-0.2766	0.6539	0.7994	0.7092
Kurtosis	27.8457	39.4113	40.7671	25.8423	20.1267	31.7329	44.3672
JB	91372.35 (0.0000)***	199828.20 (0.0000) ***	215402.20 (0.0000) ***	81513.64 (0.0000)***	46731.86 (0.0000)***	128776.00 (0.0000)***	253804.10 (0.0000) ***
LB(20)r^2	2100.10 (0.0000) ***	1316.00 (0.0000) ***	1571.00 (0.0000) ***	2097.65 (0.0000) ***	1577.7 (0.0000) ***	1401.00 (0.0000) ***	820.47 (0.0000) ***
ARCHLM(1)	1296.31	593.58	1433.05	973.98	1412.95	564.01	599.33

Notes:

1. JB test statistics are based on Jarque-Bera (1987) and are asymptotically chi-square-distributed at 2 degrees of freedom.
2. LB(20) is the Ljung-Box test for serial correlation with 20 lags, applied to squared returns (r2).
3. ARCH-LM(1) is the test for ARCH effects for 1 lag.
4. Values in parentheses denote the p-value. *** denotes significance at 1% level.
5. Industries (Symbol used): Construction (CON), Consumer Product (COP), Industrial Product (INP), Plantation (PLN), Property (PRP), Trade & Service (TAS), Mining (TIN)

Figure 1: Non-Financial Sectors Return



4.2 RiskMetrics EWMA Model

Table 2 displays the estimation results of future volatility or σ_t^2 for RiskMetrics EWMA model. Given λ = 0.94, the highest value is documented by the mining sector (TIN) while the lowest estimation by the plantation sector (PLN). Referring to the diagnostic evidences, it can be concluded that these models have approximately zero mean and unit variance. The series are found to be positively skewed excluding INP and PLN. In addition, excess kurtosis can be observed in all series in that the values are slightly higher than 3, with the most extreme case being COP

Table 2: Estimation and Diagnostic Tests Results of RiskMetrics EWMA

	λ= 0.94	Mean of Conditional Volatility $E(\mu_1/\sigma_1)$	Variance of Conditional Volatility $E(\mu_1/\sigma_1)^2$	Volatility Skewness	Volatility Kurtosis
CON	0.0059	-0.0431 (0.9870)**	0.9442	0.2576	6.6282
COP	0.0034	-0.0176 (0.9976)	0.9673	0.2993	10.9872
INP	0.0022	-0.0613 (1.0000)***	1.0004	-0.1095	3.9675
PLN	0.0021	-0.0257 (0.9999)	0.9891	-0.0651	3.5598
PRP	0.0023	-0.0157 (0.9987)	0.9914	0.1324	6.0231
TAS	0.0029	-0.0334 (0.9964)**	0.9230	0.2870	3.6540
TIN	0.0201	-0.0176 (0.9857)	0.9874	0.8132	5.5439

Notes:
1. Standard errors are in parentheses.
2. *, ** and *** denote significance at 10%, 5% and 1% levels.
3. λ represents the decay factor.

4.3 GARCH-based Model

Based on maximum likelihood method, the GARCH-based models estimation results are presented in the following Table 3. The diagnostic test findings are shown in Table 4.

The overall results of parameter ω,α and β for GARCH$(1,1)_N$ are found to satisfy the condition: $\omega>0$ and α, $\beta \geq 0$ (Panel A, Table 3). The intercept term 'ω' is very small while the coefficient on the lagged conditional variance, β, is approximately 0.9. For every sector, the sum of estimated coefficient of the variance equations α and β, which is the persistence coefficient, is very close to unity. This shows shocks to the conditional variance will be highly persistent. With the exception of the constant value for series COP, the coefficients on all three terms in the conditional variance equation are highly statistically significant. For this model, the residual based diagnostic tests (Table 4) provide evidence that the squared standardised returns present no significant autocorrelation, consistently with LB, Ljung-Box. The LB statistic confirms the ability of GARCH$(1,1)_N$ to capture the non-linear dependence: the squared standardised returns are in fact independent. Further test also confirms that there are no residual ARCH effects in the standardised return. This implies that the models are well-specified.

Thus, a non-normal distribution most commonly the t-distribution can be applied to model the excessive third and fourth moment of the sample due to the fact that the normality condition fails to capture any existence of fat-tailed property. Panel B of Table 3 shows the results for GARCH$(1,1)_t$ and Panel C exhibits an asymmetric GARCH model, the EGARCH$(1,1)_t$.

Explaining for GARCH$(1,1)_t$, the parameters for this model are also found to satisfy the restriction that $\omega>0$ and α, $\beta \geq 0$. The coefficients on all three terms in the conditional variance equation are found to be highly statistically significant for all series. The intercept values ω are also very small while the β shows a high value between 0.8 and 0.9. The sum of coefficient α and β for all the non-financial sectors too indicates values that are very close to one portraying a high persistence level of volatility. As shown in Table 4, the Ljung-Box statistics test shows no evidence of non-linear dependence in standardised squared residuals at lag 20. Furthermore, it can be concluded that since Engle's first-order LM test for ARCH residuals found no evidence of time-varying volatility for all series, the model is well-specified.

As for EGARCH$(1,1)_t$, the conditional variance equation coefficients, inclusive of the results of asymmetry coefficient δ, are significantly different from zero. This supports the existence of asymmetric impacts of returns on conditional variance. Further diagnostic tests confirm that this model has approximately zero mean and unit variance. Squared standardised residuals indicate no autocorrelation, thus, all nonlinear dependencies are captured in all the returns. Finally, there is also no evidence of ARCH effects for any of the samples and thus, the estimated model is concluded well-specified.

Table 3: Estimation Results of GARCH-based Model

Panel A: GARCH(1,1)$_N$				
	ω	α_1	β_1	$\alpha+\beta$
CON	4.62E-06 (1.79E-06)***	0.0900 (0.0142)***	0.9016 (0.0146)***	0.9916
COP	6.17E-07 (1.17E-06)	0.0691 (0.0223)***	0.9304 (0.0332)***	0.9304
INP	2.29E-06 (7.68E-07)***	0.1154 (0.0191)***	0.8644 (0.0153)***	0.9798
PLN	2.79E-06 (9.04E-07)***	0.1431 (9.04E-07)***	0.8541 (0.0195)***	0.9972
PRP	3.93E-06 (1.10E-06)***	0.1400 (0.0258)***	0.8494 (0.0204)***	0.9894
TAS	1.62E-06 (7.50E-07)**	0.0969 (0.0146)***	0.9030 (0.0149)***	0.9999
TIN	1.46E-05 (4.89E-06)***	0.1296 (0.0164)***	0.8669 (0.0169)***	0.9965
Panel B: GARCH(1,1)$_t$				
	ω	α_1	β_1	$\alpha+\beta$
CON	8.54E-06 (1.90E-06)***	0.1507 (0.0245)***	0.8441 (0.0148)***	0.9948
COP	1.27E-06 (3.24E-07)***	0.1005 (0.0131)***	0.8891 (0.0099)***	0.9896
INP	2.76E-06 (6.78E-07)***	0.1188 (0.0177)***	0.8673 (0.0126)***	0.9861
PLN	3.66E-06 (8.51E-07)***	0.1611 (0.0261)***	0.8316 (0.0151)***	0.9927
PRP	4.01E-06 (5.95E-07)***	0.1626 (0.0115)***	0.8291 (0.0101)***	0.9917
TAS	3.32E-06 (8.15E-07)***	0.1188 (0.0152)***	0.8789 (0.0119)***	0.9977
TIN	2.17E-05 (5.60E-06)***	0.1798 (0.0354)***	0.8071 (0.0158)***	0.9869

Table 3:(Continued)

Panel C: EGARCH(1,1)$_t$				
	ω	α_1	β_1	$\alpha+\beta$
CON	-0.4141 (0.0537)***	0.2839 (0.0289)***	0.9720 (0.0056)***	-0.0804 (0.0157)***
COP	-0.2495 (0.0362)***	0.1886 (0.0192)***	0.9873 (0.0034)***	-0.0396 (0.0104)***
INP	-0.3306 (0.0460)***	0.2362 (0.0239)***	0.9809 (0.0043)***	-0.1055 (0.0337)***
PLN	-0.400 (0.0513)***	0.3038 (0.0287)***	0.9774 (0.0049)***	-0.0460 (0.0148)***
PRP	-0.4465 (0.0532)***	0.3411 (0.0291)***	0.9744 (0.0054)***	-0.0352 (0.0148)**
TAS	-0.2639 (0.0368)***	0.1982 (0.0210)***	0.9855 (0.0035)***	-0.0599 (0.0115)***
TIN	-0.5197 (0.0659)***	0.3795 (0.0408)***	0.9596 (0.0078)***	-0.0609 (0.0212)***

Notes:

1. Standard errors are in parentheses.
2. *, ** and *** denote significance at 10%, 5% and 1% levels.
3. ω is the constant in the conditional variance equations. α refers to the lagged squared error. β coefficient refers to the lagged conditional variance and δ coefficient is the EGARCH asymmetric term.

Table 4: Diagnostic Tests for Single Variable Models (GARCH-based Models)

		$E(\mu_1/\sigma_1)$	$E(\mu_1/\sigma_1)^2$	$LB^2(20)$	ARCH(1)
CON	$GARCH(1,1)_N$	-0.0433	0.9993	21.8100 (0.3510)	1.4812 (0.2150)
	$GARCH(1,1)_t$	-0.0051	0.9572	21.4850 (0.3690)	0.0573 (0.8161)
	$EGARCH(1,1)_t$	0.0293	0.9649	16.0450 (0.7140)	0.0721 (0.7658)
COP	$GARCH(1,1)_N$	-0.0278	1.0008	21.1140 (0.3900)	5.7810 (0.1512)
	$GARCH(1,1)_t$	-0.0160	0.9898	13.5600 (0.8520)	1.2246 (0.2602)
	$EGARCH(1,1)_t$	0.0001	0.9977	9.8717 (0.9700)	1.8158 (0.1666)
INP	$GARCH(1,1)_N$	-0.0491 -	0.9993	10.5050 (0.9580)	2.9502 (0.8544)
	$GARCH(1,1)_t$	0.0185	0.9701	10.1030 (0.9660)	3.7206 (0.5249)
	$EGARCH(1,1)_t$	0.0141	0.9700	13.6441 (0.8480)	1.3187 (0.2468)
PLN	$GARCH(1,1)_N$	-0.0236	1.0004	25.3860 (0.1870)	5.6215 (0.1669)
	$GARCH(1,1)_t$	-0.0165	0.9444	23.8543 (0.2490)	2.6186 (0.1165)
	$EGARCH(1,1)_t$	0.0011	0.9468	24.0100 (0.2420)	6.3391 (0.1086)
PRP	$GARCH(1,1)_N$	-0.0164	1.0003	18.4790 (0.5560)	4.4754 (0.3325)
	$GARCH(1,1)_t$	-0.0114	1.0579	15.6060 (0.7410)	2.2808 (0.1202)
	$EGARCH(1,1)_t$	0.0398	0.9710	21.8970 (0.3460)	7.3706 (0.6528)
TAS	$GARCH(1,1)_N$	-0.0328	1.0004	15.1460 (0.7680)	1.6033 (0.2140)
	$GARCH(1,1)_t$	-0.0114	0.9788	12.8240 (0.8850)	0.4635 (0.4809)
	$EGARCH(1,1)_t$	0.0194	0.9804	13.0820 (0.8740)	2.0367 (0.1425)

Table 4: (Continued)

		$E(\mu_1/\sigma_1)$	$E(\mu_1/\sigma_1)^2$	$LB^2(20)$	ARCH(1)
TIN	$GARCH(1,1)_N$	-0.0191	1.0005	20.0700 (0.4530)	3.4833 (0.6068)
	$GARCH(1,1)_t$	0.0372	0.9007	20.3120 (0.4390)	0.8879 (0.3331)
	$EGARCH(1,1)_t$	0.0491	0.9035	24.7840 (0.2100)	3.4219 (0.6301)

Notes:
1. Standard errors are in parentheses.
2. LB2(20) is the Ljung-Box statistics at lag 20, distributed as a chi-square with 20 degrees of freedom. The critical values for LB tests at lag 20 are 37.56, 31.41 and 28.41 at 1%, 5% and 10% levels of significance respectively.

4.4 Results of VaR Models

The VaR values based on the volatility models estimated in subsection 4.2 and 4.3 are calculated using the @RISK (4.5) software. Applying the Monte Carlo Simulation, quantifications of VaR are carried out using a simulation process of 10,000 iterations. Table 5 shows the VaR results of the seven sectors based on daily returns with 95% confidence level.

Table 5: VaR Results

Industry	**MC_1+RM_N (%)**	**$MC_1+GARCH_N$ (%)**	**$MC_1+GARCH_t$ (%)**	**$MC_1+EGARCH_t$ (%)**
CON	1.24	1.63	2.13	2.51
COP	0.92	1.13	1.38	2.00
INP	0.78	0.96	1.24	1.19
PLN	0.76	0.96	1.22	1.13
PRP	0.80	0.99	1.32	1.35
TAS	0.81	1.06	1.35	1.43
TIN	2.27	2.40	3.14	2.82

Notes:
1. MC1+RMN denote simulation integrated with RiskMetrics EWMA model under normal distribution.
2. MC1+GARCHN denote simulation integrated with GARCH model under normal distribution.
3. Subscript N for normal distribution.
4. MC1+GARCHt denote simulation integrated with GARCH model under t-distribution.

Referring to the calculated VaR values, all models ranked Mining sector as having the highest risk followed by the Construction sector. The Plantation sector was marked as having the lowest risk. The results also rated Consumer Product and Trade and Service in third and fourth places while Property and Industrial Product sectors were in fifth and sixth respectively.

Under the normal distribution, each volatility model that is integrated together with VAR namely, MC_1+RM_N and MC_1+$GARCH_N$, portrays a relatively equivalent performance. However, when looking at each individual VaR numbers for all the seven non-financial sectors, the values constructed by MC_1+$GARCH_N$ are higher than those of MC_1+RM_N. Nonetheless, under the t-distribution for VaR results between MC_1+$GARCH_t$, and MC_1+$EGARCH_t$, it is ascertained that the estimated maximum loss values of these GARCH-based volatility are quite different. In this manner, a conclusive statement whether MC_1+$GARCH_t$, provides higher VaR numbers in comparison with MC_1+$EGARCH_t$ or otherwise cannot be made though the spectrum of the riskiest industry to the lowest. At this point of analysis, whether the normal distribution is less successful in capturing the downside risk than the alternative distribution cannot be conclusively determined and therefore, further thorough accuracy tests have to be carried out.

4.5 Accuracy Tests of VaR Models

The accuracy test comprises Failure Likelihood Ratio Test (Kupiec Test), Conditional Testing (Christoffesen Test) and Quadratic Loss Function (Lopez Test). The outputs are stated in Table 6. Figures 2, 3 and 4 illustrate visual adaptations for the three mechanisms under 95% level of confidence.

Table 6: Accuracy Test - Forecasting Performance Summary for Different VaR Models at 95% Confidence Level

	LRuc	LRind	LRcc	AQLF
CON				
MC_1+RM_N	0.4328	3.5722	4.0150	0.2300
MC_1+$GARCH_N$	0.1619	2.8552	3.0272	0.1746
MC_1+$GARCH_t$	0.0112	1.4107	1.4215	0.0777
MC_1+$EGARCH_t$	0.0019	1.8056	1.8072	0.1019
COP				
MC_1+RM_N	0.6718	4.4684	5.1512	0.2681
MC_1+$GARCH_N$	0.5360	4.1899	4.7369	0.2473
MC_1+$GARCH_t$	0.1346	3.0527	3.2183	0.1677
MC_1+$EGARCH_t$	0.1211	2.9472	3.0683	0.1607

Table 6: (Continued)

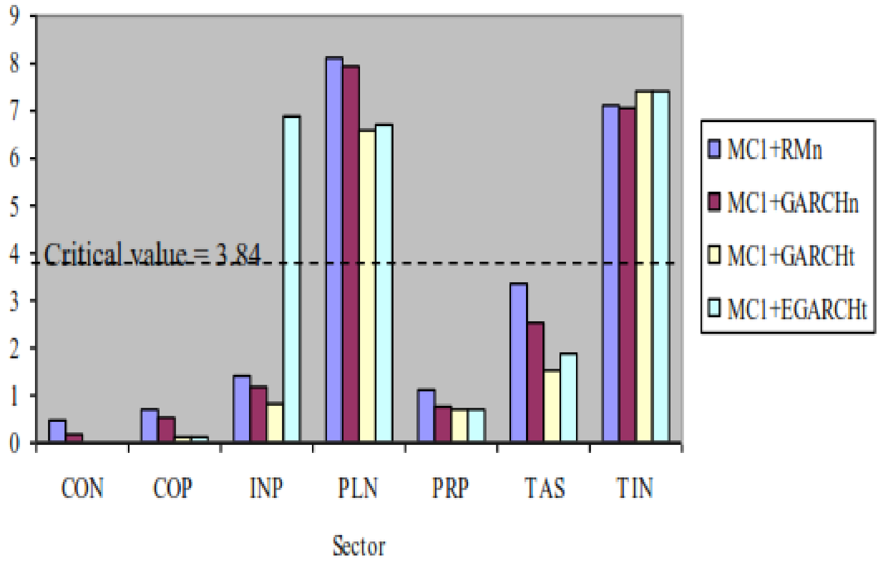
	LRuc	LRind	LRcc	AQLF
INP				
MC_1+RM_N	1.4168	1.1406	2.5574	0.0569
$MC_1+GARCH_N$	1.1712	0.8478	2.0290	0.0431
$MC_1+GARCH_t$	0.8178	0.3586	1.1864	0.0223
$MC_1+EGARCH_t$	6.8834	5.8598	12.7532	0.3788
PLN				
MC_1+RM_N	8.1201	6.4869	14.6170	0.4515
$MC_1+GARCH_N$	7.9434	6.3692	14.3226	0.4411
$MC_1+GARCH_t$	6.5889	5.4459	12.0448	0.3615
$MC_1+EGARCH_t$	6.7067	5.5278	12.2445	0.3684
PRP				
MC_1+RM_N	1.1123	0.7097	1.8410	0.0396
$MC_1+GARCH_N$	0.7590	0.2477	1.0257	0.0188
$MC_1+GARCH_t$	0.7001	0.1614	0.8805	0.0153
$MC_1+EGARCH_t$	0.7000	0.1714	0.8804	0.0154
TAS				
MC_1+RM_N	3.3501	3.1081	6.4762	0.1712
$MC_1+GARCH_N$	2.5257	2.3435	4.8792	0.1227
$MC_1+GARCH_t$	1.5245	1.2829	2.8174	0.0638
$MC_1+EGARCH_t$	1.8779	1.6797	3.5676	0.0846
TIN				
MC_1+RM_N	7.1189	6.0495	13.1684	0.3927
$MC_1+GARCH_N$	7.0601	6.0089	13.0678	0.3892
$MC_1+GARCH_t$	7.4134	6.2467	13.6701	0.4100
$MC_1+EGARCH_t$	7.4133	6.2470	13.6703	0.4100

Notes:
1. *LRuc* and *LRind* follow asymptotically $\chi(1)$ with critical value 3.84. *LRcc* is asymptotically $\chi2$ distributed with critical value 5.99.

a. Failure Likelihood Ratio Test (Kupiec Test)

As one of the most widely used tests to evaluate the accuracy of a VaR model, the basic frequency test as suggested by Kupiec (1995) is conducted to compare the observed tail losses with the predicted tail losses by the model. In short, it is equivalent to test $H_0 = \hat{p} = p$ where the unconditional coverage $\hat{p}$ equals the desired coverage level, p. According to Kupiec test, almost all four VaR models are found to be accurate at 95% level of confidence whether the evaluation is quantified in a normal or t-distribution circumstances (Table 6, Column 2). This implies that the models provide proper coverage to the true underlying risk according to the chosen confidence levels. Statistically, the reason for this accurate behaviour is because the observed frequency of tail losses (or frequency of losses that exceed VaR) is consistent with the frequency of tail losses predicted by the model (Dowd, 2005). Nonetheless, findings from this study are restricted to the type of sector whereby all VaR models for CON, COP, PRP and TAS pass LR_{uc} test at 95% confidence level (Table 6 and Figure 2). Thus, the null hypothesis is not rejected and it also illustrates that these models generate reasonable unconditional coverage probabilities. In the case of INP, it is found that only MC_1+$EGARCH_t$ fails to pass the LR_{uc} test while other models produce favourable coverage probabilities. In more extreme views, no models for sector PLN and TIN pass this test, thus, making it less accurate than others.

Figure 2: Likelihood Ratio Tes (Kupiec Test) LRuc – 95%



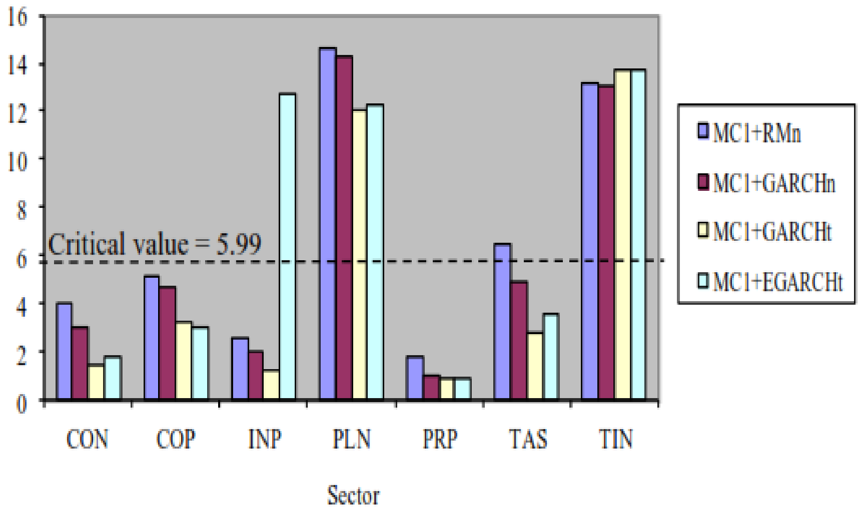
b. Conditional Testing (Christoffesen Test)

The Christoffersen test also offers almost similar conclusions like the Kupiec test in restricted type of sector and almost all models assessed under normal and t-distribution were estimated to be accurate. At 95%, the four VaR models for CON, COP and PRP sector pass the LR_{cc} test (Table 6, Column 4). However, a similar conclusion cannot be made for every single model for the

PLN and TIN sectors. The coverage estimates obtained by INP and TAS are only supported by three models. The results for these two sectors indicate that MC_1+$EGARCH_t$ for INP fail to pass the LR_{cc} test while MC_1+RM_N poses an unfavourable risk forecast for TAS.

According to Christoffersen test, a model may be rejected based on the following reasons namely, it fails to produce correct unconditional coverage, $LR_{uc,}$ or if the failures are not independent, LR_{ind}, OR both (Table 6, Column 2 and 3). Models that fail $LR_{uc,}$ produce coverage probabilities which are statistically different from the theoretical coverage probabilities. Models that fail $LR_{ind,}$ were unable to capture the volatility dynamics of the return process (Christoffersen, 1998; Christoffersen, Hahn & Inoue, 2001). Visible illustration for the Conditional Testing is as follows:

Figure 3: Conditional Test (Christoffersen Test) LRcc – 95%

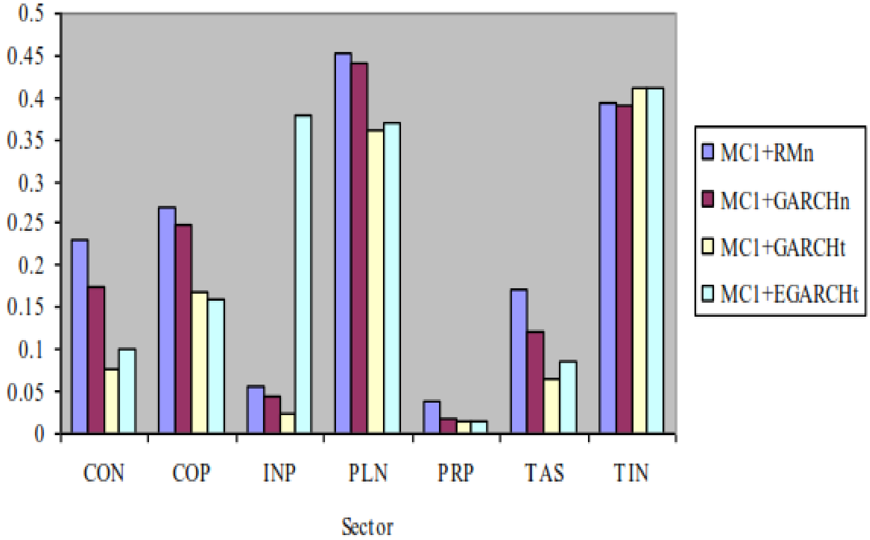


c. Quadratic Loss Function (Lopez Test)

For the Lopez test where the magnitude of the exceptions impact on different VaR models is taken into consideration, the MC_1+RM_N provides the highest values in all sectors (except INP). Thus, this VaR model has been verified to be the least accurate model compared with other alternatives. Observation with the lowest loss function values is MC_1+$GARCH_t$, which quantified for the most accurate model. This is especially true for five sectors at the 95% confidence level, excluding COP and TIN. The next model that has the second lowest point of accuracy is also the model under normal distribution:

MC_1+$GARCH_N$. This result supports the entire sector but with the exception of INP and TIN. Both yield either one or two simulated VaR models under the t-distribution.

Figure 4: Quadratic Loss Function (Lopez Test) – 95%



A summary of the backtesting results is presented in Table 7 which summarises the most appropriate model/models representing the non-financial sectors.

Table 7: Summary of Backtesting Results

Industry	Kupiec Test LRuc	Christoffersen Test LRcc	Lopez Test QLF
CON	I, II, III, IV	I, II, III, IV	III
COP	I, II, III, IV	I, II, III, IV	IV
INP	I, II, III	I, II, III	III
PLN	-	-	III
PRP	I, II, III, IV	I, II, III, IV	III
TAS	I, II, III, IV	II, III, IV	III
TIN	-	-	II

Notes:
1. The models are successively MC_1+RM_N *(I)*, $MC_1+GARCH_N$ *(II)*, $MC_1+GARCH_t$ *(III)*, $MC_1+EGARCH_t$ *(IV)*

5. Conclusions

This study shows that since volatility is predictable, financial forecasts to predict future values of return distribution and finally VaR are possible but must be complied with the best accuracy attributes (de Raaji & Raunig, 1998; Hull & White, 1998). The inclusion of several volatility models reveals interesting results regarding the calculated VaR in various settings.

VaR behaviour patterns of non-financial sectors in Malaysia: In comparing the sectors, two of the most traditional sectors namely, Mining and Plantation, gives the highest and the lowest VaR respectively. The Mining sector provides the most extreme VaR which means that this sector has the highest absolute downside risk. This could be due to high peakedness in the estimation sample of the mining sector. Another reason is because this sector has been experiencing lesser and unsteady demand in the domestic and global market which indirectly led to many tin mines discontinuing its operation. This causes sudden decrease in its activities especially in 2004 and 2005. The Plantation sector, for most VaR circumstances, illustrates the mildest position. This can be influenced by minor or extreme events that have effect on the plantation sector which in turn indirectly affect profit or loss (S.M. Zain, 2005). The agricultural sector has received strong and continuous support from the government with various policies, for example, biotechnology policy and subsidies throughout the observation period even in difficult times. The findings for both mining and plantation sectors are consistent with the findings of Su (1999) who studied various industries in the Taiwan equity market and found that in most circumstances, traditional sectors may generate either the highest or the lowest values of VaR. In summary, the increasing/decreasing contribution of risks in observed sectors are mostly caused by the rising/declining exposures and volatilities (Choong, 2004).

VaR behaviour patterns between Normal distribution and t-distribution: The overall picture highlights the dominance of t-distribution-based method over normal-distribution-based method (Angelidis et al., 2003). Explicitly, VaR models under t-distribution are found to be more accurate when predicting VaR. It is important that risk management practices are based on VaR which focuses on higher moments of the observed distribution. This is absolutely critical from an econometric view since volatilities can be estimated more efficiently than means. The condition indicates that should the VaR methods only rely on the first two moments of loss distribution, the accuracy of estimating the maximum loss is diminished. Models quantified for leptokurtic distribution (in this case t-distribution) illustrate a greater tendency to handle tail dynamics of the conditional distribution which in return generate more accurate VaR forecast than in normal distribution. This is due to the fact that when VaR quantifications involve models that are more flexible in handling fat tail effects such as $GARCH_t$, the volatility asymmetric effect is reduced. Evidence from these findings contribute to the growing but still limited empirical research such as by Bredin and Hyde (2004), Hull and White (1998), Lee and Saltoglu (2002), Lin and Shen (2006) and Su and Knowles (2006). Thus, it can be concluded that allowing for abnormalities (such as fat tails or asymmetries) in the evaluation of the Malaysian non-financial sectors will certainly improve the reliability of risk forecast. The VaR models under t-distribution provide better and more adequate risk forecast which were recognised earlier by Lee and Saltoglu (2002) and Lin and Shen (2006).

VaR behaviour patterns between different forms of volatility modelling: By examining model-to-model basis based on the three accuracy tests, the most accurate model is the VaR embedded with $GARCH_t$ [MC_1+$GARCH_t$]. In other words, MC_1+$GARCH_t$ provides the best capability to produce superior risk forecasts compared with other models, particularly more conventional VaR models such as RiskMetrics and $GARCH_N$. The reason for rejecting these two normally distributed models is not uncommon since the return distribution portrays non-normal traits, thus making the models less tolerable to accommodate tails and underestimate true VaR. This means that the two normally distributed models are less accurate and may perform rather poorly in the above-mentioned manner (see Giot & Laurent, 2005; Lopez, 1999).

Although the EGARCH model theoretically is able to handle any asymmetrical properties in a distribution, in the present study, MC_1+$EGARCH_t$ is not as accurate or as consistent as MC_1+$GARCH_t$. Perhaps it is due to the fact that assuming EGARCH will work with a t-distribution may not maximise its potential in VaR estimation. As an alternative solution by applying other forms of statistical distribution like the Generalized Error Distribution (GED), it may increase the EGARCH-based model's accuracy.

Future research within this context can address the following limitations. In this study, the statistical distributions are assumed to be either normal distribution or t-distributions. For extreme conditions, more robust distribution classes such as Frechet, Weibull and Gumbel distribution can be considered. Another fact is that only three types of volatility models are embedded within the VaR theoretical formula: RiskMetrics EWMA, GARCH(1,1) and EGARCH(1,1). Though the main reasons are to capture inadequate tail probability or to reduce the volatility asymmetric effect besides eliminating the non-negativity constraints of a less 'efficient' model, there are also conditions such as leverage effect and jump-dynamics that could be considered. Thus, different forms of GARCH-family models can be set as inputs of VaR.

In summary, accurate VaR forecasts for an economy can be highly dependent on the types of volatility modelling. This criterion is crucial for institutions as a prerequisite for the Basel Commitment. In conclusion, forecasts are also very much reliant on other VaR parameter settings, the statistical distribution properties, type of sectors and level of confidence.

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