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The Analysis of Risk Models for Malaysia's Non-financial Sectors

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Abstract

The research highlights three Value-at-Risk (VaR) representations that are integrated with GARCH-based models to estimate the Malaysian stock exchange market risk. The methodology covers the quantifications of expected maximum losses at 95% level of confidence for six non-financial sectors namely the construction, consumer product, industrial product, plantation, property and trade and services from the year of 1993 until 2006. Further analyses are conducted using Kupiec, Christoffersen and Lopez backtests. The results in particular based on Lopez's Quadratic Loss Function test proved that when the basic VaR is integrated with GARCH model under the assumption of t-distribution, the model is found to be at the most accurate level. Thus consideration on non-normal behaviour of the market is important to determine financial risk quantifications.

Keywords: Value-at-Risk, volatility modelling, backtesting
JEL classification: C53, G10

1 Introduction

In today's competitive business environment, financial markets have to face varieties of risks namely market, credit, liquidity, operational and legal risk. Even though the volatile environment exposes firms to greater financial risk levels, the conditions always provide the platform for firms to find new and better ways to manage risk. From time to time, combinations between fundamental and analytical methodologies create new and better risk measures thus helping financial decision maker to finalize more accurate investment results in order to minimize losses. Some of the major risk measurement tools can be categorized according to the type of financial instruments (Wiener, 1997). Bonds, for instance, can be associated with duration, convexity and term structure models while stocks utilize volatility, correlation and beta. The largest financial market in the world that is the foreign exchange uses spreads, exchange rate volatilities and target zones to measure risk. Credit instruments may comprehend rating and default models. Many academicians and practitioners agree that the evolution of

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risk measures since the mid-1970s has experienced a tremendous change due to the introduction of many new derivative instruments and engineered securities (refer to among others Alexander, 1998; Butler, 1999; Dowd, 1999, 2005; Jorion, 1997; Rahl & Esseghaier, 2000, Sharpe, 2000).

Undoubtedly, one of the risk measures that are getting more attention is the Value-at-Risk (VaR). Practically, it summarizes the worst expected loss that an institution can suffer over a target horizon under normal market conditions at a given confidence level (Dowd, 2005; Jorion, 1997). Together with the encouragement by the Basle Committee, VaR has been widely applied especially on banks. VaR popularity is influenced with the urgent need for a single risk measure in order to establish the capital adequacy limits for banks and other financial institutions

Nonetheless, many researchers give evidence that some of the studies on VaR require more in-depth investigation. As far as the literature is concerned, studies on VaR are micro-focused on VaR comparative assessment using the variance-covariance method (VCV), historical simulation (HS), Monte Carlo simulation (MCS) and extreme value theory (EVT) methods. For MCS in particularly, most research are done to enhance the computation speed or to handle methodological issues for example the variance reduction elements, effect of total risk factors and MCS in multivariate settings (Fuglsbejerg, 2000; Glasserman, Heidelberger & Shahabuddin, 2000a, 2000b; Papageorgiou & Paskov, 1999; Singh, 1997). Still studies on integrating MCS with volatility models as an additional parameter to maximise its accuracy capabilities have yet to be extensively and thoroughly examined.

Within these consequences, the objective of this paper is to test three VaR models on major non-financial sectors in the Malaysian market and finally to suggest the most accurate one that can be applied in the market. The full valuation approach namely the MCS is employed for this reasons. The following sections are structured as follows: Section 2 highlights the review of literature. Section 3 describes the data and the methodology used to determine the VaR values. Section 4 explains the findings and Section 5 concludes.

2 Review of Literature

Several research papers have reported ample evidence that market data can be more accurately explained when it is quantified by heavy-tailed distributions. Thus for this purpose, a technique via Monte Carlo simulation can be applied to capture fat-tail issues in verifying VaR. Historically, Monte Carlo which is named after a famous roulette wheel, is used to estimate VaR from a distribution of future portfolio values which is simulated using pseudo-random number or, in other general term, the random walk approach (Dowd, 1998).

In basic terms, MCS will generate a series of underlying asset prices and then observe how the instrument behaves. To do this, it requires a distribution for changes in each market factor which include correlations between each factor. Typically, either one or both normal and lognormal distributions are utilized with correlations obtained from the historical financial data. MCS is strictly dependent on a statistical distribution assumption of market factors and its parameters (Linsmeier & Pearson, 1996). As mentioned by Davis and Fouda (1999):

> *With the Monte Carlo simulation method, the user specifies a distribution for the changes in the market factors. Although the normal and lognormal distributions are commonly used for this purpose, the user is free to use any distribution that is believed to adequately represent the possible changes in market factors. The distribution is used to simulate changes in market factors. These are then used to calculate thousands of potential future portfolio values. These portfolio values are sorted in descending order and VaR is determined in the same manner as in the historical simulation method. (p. 186)*

Among the method to quantify VaR, MCS is found to be the most powerful and yet the most intensive method because it can adapt to situations which other method is not able to. It accommodates nonlinearity conditions, fat-tails, extreme scenarios, volatility risk and model risk (refer among others Jorion, 2006; Lambardiaris, Papadopoulou, Skiadopoulos & Zoulis, 2003). Dowd (1998) and Jorion (2006) stressed that MCS is an ideal financial risk management tool for multidimensional scenarios where the outcomes depend on multiple risk variable.

Another research with significant impact on VaR literatures using MCS was conducted by Beder (1995). Based on three U.S. investment portfolios, Beder (1995) utilized both MCS and HS at two different holding periods specifically 1-day and two-weeks. The first portfolio which consisted of U.S. Treasury strips showed that the HS for the database of 100 and 250 days was highly appreciated compared to MCS. For the second portfolio based on the outright and option positions on S&P 500 equity index contract records for 1-day returns, both the HS and MCS showed low probability of high return/large loss expectation while for the two-week returns the distribution changes displayed upside down normal distribution (binomial behaviour). The result for portfolio three that is the combination of portfolio 1 and 2 displayed more consistency than single-asset class. In short, Beder provide evidence that different VaR calculations can produce drastically different results. It depends also on the correlation assumptions, the type of data and length of time horizons. Thus different capital requirements and allocation decisions can be achieved using a similar model that produces various VaR within the same investment's portfolio. Nonetheless, this study provided contradicting views compared to Hendricks (1996) who failed to justify any suitable model. This can be due to the fact that Beder (1995) intended to quantify only the magnitude of errors rather than evaluating models' performance, Vlaar (2000) on the other hand combined and tested the methodology of variance-covariance and MCS to address the dynamics of Dutch interest rates and its effect on the VaR models' accuracy. Besides that, three other methods namely HS, pure MCS and pure variance-covariance were also applied to the same data. Under the ten-day holding period, the research on 25 simulated and hypothetical portfolios of Dutch government bonds demonstrated that the combined variance-covariance and MCS gave the best outcomes. However, these results are only held for term-structure model with a normal distribution and GARCH specification. Unlikely performances are shown by t-distribution or co-integration specification due to less weight of extreme distribution. These results supported earlier views like those by de Raaji and Raunig (1998) that statistical distribution plays an important part in determining VaR numbers.

Earlier, Johansson, Seiler and Tjarnberg (1999) who focused exclusively on VaR for equities on a daily basis over a 1-day horizon for 261 trading days, proposed that the application of MCS with full valuation could be considered to obtain a more reliable risk estimate than analytical models. Their study applied a higher number of models as compared to Vlaar (2000). In precise, twenty VaR models which consist of four analytical models, four HS models, six MCS models and six analytical beta techniques (commonly known as beta VaR, is similar to the technique used in RiskMetrics) were put together to test the effectiveness of the downside risk measures.

It is important to note that VaR behaviour using MCS can be strictly influenced by imposing different types of marginal distributions other than normal distribution. A different behaviour towards interpreting a range of skewness and kurtosis coefficient effect is one of the expected outcomes attainable from it. Besides that the results are also constrained by the chosen level of probability. Some examples of other non-normal marginal distributions include a mixture of the normal distribution with and without skewness and also a generalised lambda distribution (Delianedis, Laknado & Tikhonov, 2000).

3 Data and Methodology

3.1 Data

Six non-financial sectors time series data traded in the first board of the Bursa Malaysia over the period 1993 until 2006 is chosen for the analysis. The data which consists of daily return of the indices is then divided into two parts in that data consist from year 1993 until 2004, is used to estimate the volatility parameters while from year 2005 until 2006, is used for backtesting the estimated VaR models (Mohamed, 2005; Pederzoli, 2006). The selected sectors are construction, consumer product, industrial products, plantation, properties, trading and services. The remaining two sectors namely technology and mining are not included because the former only started its index listing in the year of 2000, while the latter is represented by only one company. On the other hand, the financial sector which comprises of banking institutions, securities firms and unit trust companies are omitted because these institutions portray different regulatory background as compared with the non-financial ones (Ibrahim & Mazlan, 2006). These data were obtained from Datastream.

3.2 VaR Theoretical Formula

From Dowd (2005), Value-at-risk, VaRt(h), can be defined as the conditional quantile as follows:

$$\Pr\left[\rho_{\tau+\eta} < \mathrm{VaR}_t\,(h)\right] = \alpha \tag{3.1}$$

where return series r_{t+h} of a financial asset denotes the portfolio wealth at time t, the portfolio return at time $t + h$, degree of confidence level α and holding period h. 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:

$$\int_{-\infty}^{\mathrm{VaR}\,(h,\alpha)} f_{t+h}(x)dx = 1 - \alpha \tag{3.2}$$

Infinitely, VaR can be presented as the followings:

$$VaR_t = \mathrm{W}_t\,\alpha\sigma\sqrt{\Delta t} \tag{3.3}$$

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

The Monte Carlo methodology consists of a number of specific steps (Jorion, 2006):

1. Select a model for the stochastic variable(s) of interest.
2. Estimate its parameters; volatilities, correlations, and etc. based on historical or market data.
3. Construct fictitious or simulated paths for the stochastic variables where 'random' numbers are produced.
4. Each set of 'random' numbers then produces a set of hypothetical terminal price(s) for the portfolio.
5. Repeat these simulations (steps 3 and 4) as many times as necessary to be confident that the simulated distribution of portfolio values is sufficiently close to the 'true' distribution of actual portfolio values.
6. VaR values are then inferred from this proxy distribution.

3.4 Volatility Modelling under a Normal Distribution

Under the normal (Gaussian) distribution, the study will implement the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) while under t-distribution, the study applies the GARCH (t-distribution) and the Exponential GARCH (EGARCH) model,

Volatility Modelling under a Normal Distribution

From Bollerslev (1986) generalized Engle's ARCH *(p)* model by adding the *q* autoregressive terms to the moving averages of squared unexpected returns:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_p \varepsilon_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \ldots + \beta_q \sigma_{t-q}^2 \qquad (3.4)$$

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

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

$$\sigma_t^2 = \omega + \alpha\, \varepsilon_{t-1}^2 + \beta\, \sigma_{t-1}^2 \qquad (3.5)$$

where $\omega > 0$ and $\alpha, \beta \geq 0$. Commonly, most researchers apply GARCH (1,1) model due to the fact that it is relatively easier to estimate and more parsimony (Bollerslev, 1986).

Volatility Modelling under Non-Normal Distribution

a. GARCH t-distibution

From equation (3.4), the GARCH-t is then expressed 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 $t-1$.

b. EGARCH

EGARCH is generated by taking the exponential function of conditional volatility. Through this volatility log formulation, the impact of the lagged squared residuals is exponential

$$\text{In}\, \sigma_t^2 = \alpha + g(z_{t-1}) + \beta\, \text{In}\, \sigma_{t-1}^2 \qquad (3.5)$$

where

$$g(z_t) = \omega z_t + \lambda \left(|z_t| - \sqrt{\frac{2}{\pi}} \right) \qquad (3.6)$$

3.5 Test of Accuracy

Proportion of Failure Likelihood Ratio Test (Kupiec, 1995)

Based on the probability under the binomial distribution of observing x exceptions in the sample size *T*.

$$f(x) = \binom{T}{x} p^x \, (1-p)^{T-x} \tag{3.7}$$

an accurate VaR model should provide 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 (5% for 95% confidence levels). Therefore, under the null hypothesis $H_0 = \hat{p} = p$, the appropriate likelihood ratio is given by:

$$LR_{uc} = -2\text{h}\left((1-p)^{T-x} p^x\right) + 2\text{h}\left((1-\hat{p})^{T-x} \hat{p}^x\right)) \tag{3.8}$$

Conditional Testing (Christoffersen, 1998)

Firstly, by extending the LR_{uc} to specify that exceptions must be independently distributed, the test needs to define the indicator of exceptions as follows:

$$I_t = \begin{cases} 1, f & \Delta P_{i,t} < VaR_{t|t-1} \\ 0, f & \Delta P_{i,t} \geq VaR_{t|t-1} \end{cases} \tag{3.9}$$

Secondly, 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* tthe previous day as π_i. In order to test the hypothesis that the failure rate is independently distributed, the likelihood test for independence is calculated as:

$$LR_{ind} = -21\text{n}\left(\frac{(1-\pi)^{(T_{00}+T_{10})}\pi^{(T_{01}+T_{11})}}{(1-\pi_0)^{T_{00}}\pi_0^{\ T_{01}}(1-\pi_1)^{T_{10}}\pi_1^{\ T_{11}}}\right) \sim \mathcal{X}_1^2$$

where (3.10)

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

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

$$LR_{cc} = -2\ln\left(\frac{(1-P)^{T_1} P^{T_0}}{(1-\pi_0)^{T_{00}} \pi_0^{\ T_{01}} (1-\pi_1)^{T_{10}} \pi_1^{\ T_{11}}}\right) \sim \chi_2^{\ 2} \tag{3.11}$$

Quadratic Loss Function (Lopez, 1999)

Quadratic Loss Function (QLF) is indicated based on the concept of failure rate; if actual loss is greater than the VaR value then it is considered as failure. Every failure is assigned a constant 1, otherwise is zero.

$$L_{i,t+1} = \begin{cases} 1 + \left(\Delta r_{i,\, t+1} - VaR_{i,t}\right)^2, & if \Delta r_{i,\, t+1} < VaR_{i,t} \\ 0, & if \Delta P_{i,t=1} \geq VaR_{i,t} \end{cases} \tag{3.12}$$

4 Results

4.1 Descriptive Statistical Analysis

Table 1 presents the basic statistical characteristics of the return series. The sample mean for is close to zero. Except for COP and PLN, the calculated means are negative for all the sectors. This indicates CON, INP, PRP and TAS have more negative returns compared to COP and PLN which are positive-definite. The construction sector with the highest standard deviation value indicates that it has the largest average deviation from the mean compared to other returns series. For similar parameter, the consumer product has the lowest number. In addition, the normality tests outputs as indicated by the sample skewness, kurtosis and the consequent rejections of the normality hypothesis based on Jarque-Bera analysis confirm the empirical findings that daily returns for the data are far from being normal (Gaussian).

A low –0.5700 (INP) to a high of 0.9145 (CON) for skewness values suggest that the series distributions are skewed. Besides that the distributions of series are leptokurtic or fat-tailed as shown by the high kurtosis as compared to the normal distribution which is 3. Strong evidence of non-normality is also given by the large JB statistics. The Ljung-Box Q tests reject the null hypothesis in all series with serial correlation of the squared returns. Referring to Table 4.1, ARCH effect is present in the data together with the large values of chi-square statistics and small values of probability statistics which indicates the hypothesis that the series is not heteroscedastic is rejected at the 1% significance level.

With these evidences of non-normal return distribution, it is then appropriate to apply volatility models in this study. The estimated values for three models namely the GARCH(1,1)N, GARCH(1,1)t and EGARCH(1,1)t will be compared in Subsection 4.2. Denote that subscript 'N' is referred to model under normal distribution while subscript 't' is referred to model under t-distribution. Then the models are cointegrated with the VaR framework to construct risk models for each of the six non-financial sector.

4.2 GARCH-based Model Estimates

The GARCH-based models are estimated by maximum likelihood method and the results are presented in Table 2. Subsequently, Table 3 shows the findings of several diagnostic tests for each model.

a. GARCH $(1,1)_N$

Overall results of parameter ω, α and β are found to satisfy the condition; $\omega > 0$ and $\alpha, \beta \geqslant 0$ (Panel A, Table 2). The intercept term 'ω' is extremely small while the coefficient on the lagged conditional variance, β is approximately 0.9. The sum of the estimated coefficient for each sector of the variance equations (3.16) α and β, which is the persistence coefficient, is very close to unity. It signifies highly persistent shocks to the conditional variance. The coefficients on all three terms in the conditional variance equation are highly statistically significant except for COP. Referring to Table 4.3, the residual based diagnostic tests indicate that the squared standardized returns present no significant autocorrelation. This is found consistent with the LB which finally verifies GARCH(1,1)N is expected to capture the non-linear dependence. Conclusively, the estimated models are also well-specified as there is no residual ARCH evidence in the standardized returns.

b. GARCH $(1,1)_N$,

Referring to Panel B, Table 2, the parameters for GARCH(1,1)t verify the restriction that $\omega > 0$ and $\alpha, \beta \geqslant 0$. For all series, the coefficients for the three terms in the conditional variance equation are found to be highly statistically significant. Besides providing intercept ω values that are very small, β shows a high value between 0.8 and 0.9. The sum of coefficient α and β for the sectors indicate values close to one, which portrays a high persistence level of volatility. From Table 3, the Ljung-Box statistics test indicates at lag 20, no evidence of non-linear dependence is seen in the standardized squared residuals. This proves the model is well-specified in that Engle's first-order LM test for ARCH residuals show no evidence of time-varying volatility for the tested series.

c. EGARCH $(1,1)_t$,

The conditional variance equation coefficients including asymmetry coefficient δ, are significantly different from zero. This confirms the existence of asymmetric impacts of returns on conditional variance. For the diagnostic tests, the model has approximately zero mean and unit variance. Furthermore no autocorrelation is indicated as shown by the squared standardized residuals meaning all nonlinear dependencies are captured in all the returns. In all, the estimated model is well-specified since the ARCH effects are also not present for the sample.

Table 1 Basic statistics of the full sample

	CON	**COP**	**INP**	**PLN**	**PRP**	**TAS**
Mean	–0.0001	0.0001	–0.0002	0.0002	-0.0004	–3.99E-05
Std Dev	0.0207	0.0126	0.0154	0.0152	0.0187	0.0169
Skewness	0.9145	0.2221	–0.5700	–0.2813	0.6349	0.8322
Kurtosis	28.1857	40.3411	41.7549	26.8443	21.0114	32.9321
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)* ***
LB(20)r^2	2163.20 *(0.0000)* ***	1356.00 *(0.0000)* ***	1721.00 *(0.0000)* ***	2123.6 *(0.0000)* ***	1732.7 *(0.0000)* ***	1370.10 *(0.0000)* ***
ARCH-LM(1)	1296.31 *(0.0000)* ***	593.58 *(0.0000)* ***	1433.05 *(0.0000)* ***	973.98 *(0.0000)* ***	1412.95 *(0.0000)* ***	564.01 *(0.0000)* ***

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 (r^2).*
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 (Symbols used): Construction (CON), Consumer Product (COP), Industrial Product (INP), Plantation (PLN), Property (PRP), Trade & Service (TAS)*

Table 2 Estimation results of GARCH-based model

Panel A: GARCH(1,1)$_N$				
	ω	α_1	β_1	$\alpha+\beta$
CON	4.64E-06 (1.79E-06)***	0.0877 (0.0142)***	0.9014 (0.0146)***	0.9891
COP	6.19E-07 (1.17E-06)	0.0721 (0.0223)***	0.9199 (0.0332)***	0.9843
INP	2.31E-06 (7.68E-07)***	0.1161 (0.0191)***	0.8639 (0.0153)***	0.9854
PLN	2.81E-06 (9.04E-07)***	0.1391 (0.0197)***	0.8451 (0.0195)***	0.9842
PRP	3.95E-06 (1.10E-06)***	0.1390 (0.0258)***	0.8394 (0.0204)***	0.9784
TAS	1.64E-06 (7.50E-07)**	0.0889 (0.0146)***	0.9100 (0.0149)***	0.9989
Panel B: GARCH(1,1)$_t$				
	Ω	α_1	β_1	$\alpha+\beta$
CON	8.55E-06 (1.90E-06)***	0.1497 (0.0245)***	0.8331 (0.0148)***	0.9828
COP	1.28E-06 (3.24E-07)***	0.1015 (0.0131)***	0.8761 (0.0099)***	0.9776
INP	2.77E-06 (6.78E-07)***	0.1201 (0.0177)***	0.8573 (0.0126)***	0.9774
PLN	3.67E-06 (8.51E-07)***	0.1571 (0.0261)***	0.8256 (0.0151)***	0.9827
PRP	4.02E-06 (5.95E-07)***	0.1576 (0.0115)***	0.8251 (0.0101)***	0.9827
TAS	3.33E-06 (8.15E-07)***	0.1218 (0.0152)***	0.8779 (0.0119)***	0.9997
Panel C: EGARCH(1,1)$_t$				
	Ω	α_1	β_1	δ
CON	−0.4131 (0.0527)***	0.2799 (0.0289)***	0.9710 (0.0056)***	−0.0794 (0.0157)***
COP	−0.2485 (0.0352)***	0.1876 (0.0192)***	0.9783 (0.0034)***	−0.0376 (0.0104)***
INP	−0.3296 (0.0450)***	0.2322 (0.0239)***	0.9799 (0.0043)***	−0.1025 (0.0337)***
PLN	−0.4001 (0.0500)***	0.3035 (0.0287)***	0.9694 (0.0049)***	−0.0450 (0.0148)***
PRP	−0.4395 (0.0492)***	0.3391 (0.0291)***	0.9714 (0.0054)***	−0.0332 (0.0148)**
TAS	−0.2599 (0.0298)***	0.1892 (0.0210)***	0.9845 (0.0035)***	−0.0419 (0.0115)***

Notes:
1. *GARCH(1,1)$_N$ is the GARCH model under normal distribution; GARCH(1,1)$_t$ is the GARCH model under t-distribution and EGARCH(1,1)$_t$ is the EGARCH model under t-distribution.*
2. *Standard errors are in parentheses.*
3. **, ** and *** denote significance at 10%, 5% and 1% levels.*
4. *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 3 GARCH-based models diagnostic tests

		$E(\mu_1/\sigma_1)$	$E(\mu_1/\sigma_1)^2$	$LB^2(20)$	ARCH(1)
CON	$GARCH(1,1)_N$	−0.0423	0.9983	21.8000 (0.3410)	1.4622 (0.2150)
	$GARCH(1,1)_t$	−0.0053	0.9562	21.4750 (0.3680)	0.0473 (0.8161)
	$EGARCH(1,1)_t$	0.0283	0.9639	16.0430 (0.7130)	0.0801 (0.7688)
COP	$GARCH(1,1)_N$	−0.0268	1.0005	21.1120 (0.3900)	5.7870 (0.1712)
	$GARCH(1,1)_t$	−0.0159	0.9887	13.5510 (0.8420)	1.2146 (0.2602)
	$EGARCH(1,1)_t$	0.0001	0.9981	9.8627 (0.9500)	1.8258 (0.1776)
INP	$GARCH(1,1)_N$	−0.0481	0.9982	10.5050 (0.9560)	2.9312 (0.8544)
	$GARCH(1,1)_t$	−0.0179	0.9700	10.1030 (0.9650)	3.7216 (0.5249)
	$EGARCH(1,1)_t$	0.0131	0.9703	13.6430 (0.8430)	1.3087 (0.2558)
PLN	$GARCH(1,1)_N$	−0.0226	1.0002	25.3860 (0.1850)	5.6295 (0.1776)
	$GARCH(1,1)_t$	−0.0145	0.9434	23.8530 (0.2480)	2.6075 (0.1055)
	$EGARCH(1,1)_t$	0.0010	0.9398	24.0100 (0.2410)	6.3301 (0.1176)
PRP	$GARCH(1,1)_N$	−0.0154	1.0002	18.4770 (0.5550)	4.3774 (0.3325)
	$GARCH(1,1)_t$	−0.0112	1.0549	15.6060 (0.7400)	2.2917 (0.1202)
	$EGARCH(1,1)_t$	0.0388	0.9610	21.8970 (0.3450)	7.3616 (0.6328)
TAS	$GARCH(1,1)_N$	−0.0319	1.0004	15.1460 (0.7690)	1.6123 (0.2030)
	$GARCH(1,1)_t$	−0.0113	0.9698	12.8240 (0.8840)	0.4655 (0.4819)
	$EGARCH(1,1)_t$	0.0184	0.9794	13.0820 (0.8730)	2.0487 (0.1425)

Notes:
1. *Standard errors are in parentheses.*
2. *$LB^2(20)$ 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.*

4.3 Testing for Accuracy

To determine whether the suggested VaR model is accurate, tests are conducted based on Kupiec, Christoffersen and Lopez test. The results are shown in subsequent Table4 while visual illustrations are presented via Figures 1, 2 and 3.

Table 4 Accuracy test performance summary

	LRuc	LRind	LRcc	AQLF
CON				
MC_1+ $GARCH_N$	0.1719	2.8652	3.0372	0.1746
MC_1+ $GARCH_t$	0.0108	1.4207	1.4315	0.0777
MC_1+ $EGARCH_t$	0.0016	1.8156	1.8172	0.1019
COP				
MC_1+$GARCH_N$	0.5470	4.1999	4.7469	0.2473
MC_1+$GARCH_t$	0.1456	3.0627	3.2083	0.1677
MC_1+$EGARCH_t$	0.1211	2.9572	3.0783	0.1607
INP				
MC_1+$GARCH_N$	1.1812	0.8578	2.0390	0.0431
MC_1+$GARCH_t$	0.8278	0.3686	1.1964	0.0223
MC_1+$EGARCH_t$	6.8934	5.8698	12.7632	0.3788
PLN				
MC_1+$GARCH_N$	7.9534	6.3792	14.2326	0.4411
MC_1+$GARCH_t$	6.5989	5.4559	12.0548	0.3615
MC_1+$EGARCH_t$	6.7167	5.5378	12.2545	0.3684
PRP				
MC_1+$GARCH_N$	0.7690	0.2577	1.0267	0.0188
MC_1+$GARCH_t$	0.7101	0.1714	0.8815	0.0153
MC_1+$EGARCH_t$	0.7100	0.1714	0.8814	0.0154
TAS				
MC_1+$GARCH_N$	2.5357	2.3535	4.8892	0.1227
MC_1+$GARCH_t$	1.5345	1.2929	2.8274	0.0638
MC_1+$EGARCH_t$	1.8879	1.6897	3.5776	0.0846

Notes:
1. *LRuc (Kupiec Test) and LRind follow asymptotically $\chi(1)$ with critical value 3.84. LRcc (Christoffersen Test) is asymptotically $\chi 2$ distributed with critical value 5.99.*
2. *MC1 denotes Monte Carlo Cases*

a. *Failure Likelihood Ratio Test (Kupiec Test)*

Referring to Column 2, Table 4 all VaR models for CON, COP, PRP and TAS pass LRuc test at 95% confidence level. Figure 1 illustrates the outcomes. Thus, the null hypothesis $H_0 = \hat{p} = p$ where the unconditional coverage, $\hat{p}$ equals the desired coverage level, p is not rejected and it also illustrates that these models generate reasonable unconditional coverage probabilities. However for the other two sectors, observing INP, only MC_1+$EGARCH_t$ fails to pass the LR_{uc} test and for PLN, none of its model passes the Kupiec test. Thus the suggested models are not suitable to be implemented for the plantation sector. In comparing between normal and t-distribution models, the former provides better accuracy outcome.

b. Conditional Testing (Christoffesen Test)

Referring to Column 4, Table 4, again all VaR models for CON, COP, PRP and TAS sector pass the LR_{cc} test. Similar evidences are also shown for both INP and PLN sectors. One of the reasons for these is because the reasonable conditional coverage values for LR_{cc} are found to be on the high side in that it exceeds the critical value of 5.99 (Figure 2).

c. Quadratic Loss Function (Lopez Test)

Observing Column 5, Table 4, model with the lowest values is represented by the MC_1+$GARCH_t$. This clearly indicates that when VaR is integrated with GARCH-based model under t-distribution assumption, it provides the highest accuracy level. Similar conclusion cannot be made for sector COP. However, in all sectors except for, the most inaccurate model is MC_1+$GARCH_N$ which means that when VaR is integrated with GARCH-based model under normal distribution, it does not provide the avenues for making the best risk quantification decisions.

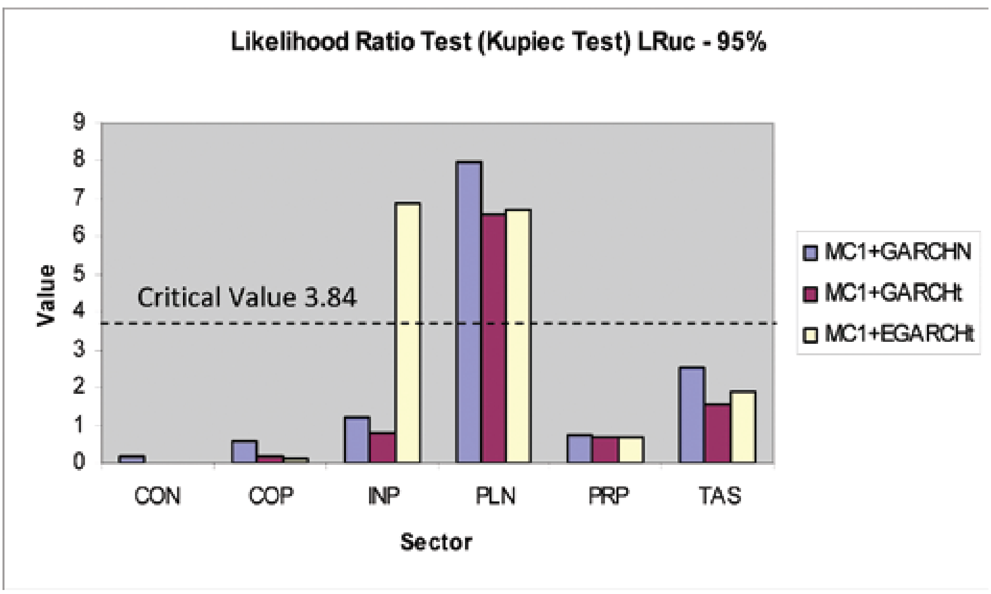

Figure 1 Kupiec test

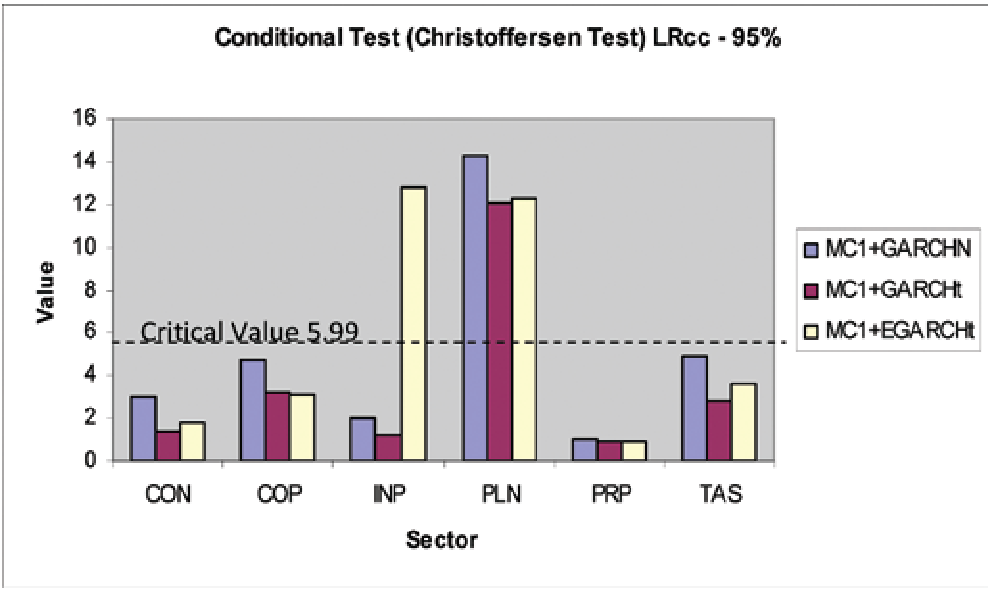

Figure 2 Christoffersen test

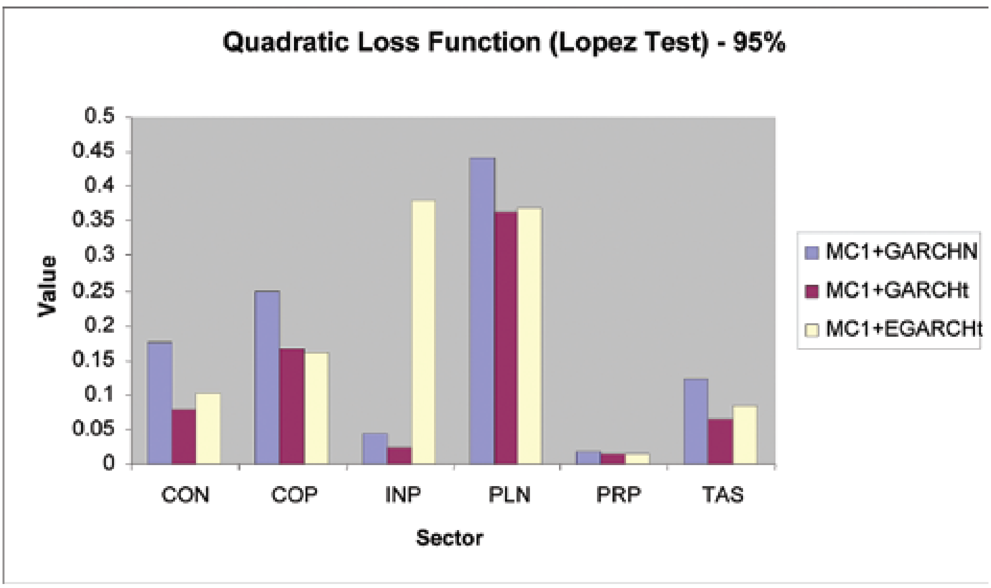

Figure 3 Lopez test

5. Conclusions

Overall when analysing the performance of VaR risk models for the Malaysian non-financial sectors, it is important when one should take into consideration the statistical properties of distribution. Assuming a normal distribution trait is easy but it may also has limited capabilities to tolerate fat tails or asymmetries.

As a general conclusion drawn from the accuracy tests, the most accurate model that can be associated with the Malaysian stock market is the VAR MC1+GARCHt. This is due to the fact that it quantifies for leptokurtic distribution or t-distribution thus illustrates a greater tendency to handle tail dynamics of the conditional distribution. It is important to note that accuracy of a model will gradually reduce if it relies only on the first two moments of loss distribution. Similar justifications can be referred to earlier studies by de Raaji and Raunig (1998), Lee and Saltoglu (2002), Lin and Shen (2006), Mohamed (2005) and Vlaar (2000). And even though EGARCH theoretically may handle asymmetry properties, this research found that VaR model is less accurate within the framework. This can be the result of assuming EGARCH will work with a t-distribution may not maximize its potential in VaR estimation. Thus to handle more extreme cases, for future research EGARCH should be associated with other forms of statistical distribution for example the Generalized Error Distribution (GED), Frechet, Weibull or even Gumbel distribution. Apart from that, other model from the GARCH-family may also be an interesting methodology to deal with VaR. In fact, the overall findings and concluding notes are also limited to the six sectors. Dealing with the remaining two non-financial sectors namely technology and mining plus the financial sector may quantified for different perspectives of discussions.

In summary, consideration on non-normal behaviour of the market is important to determine financial risk quantifications. In fact to establish the best model, VaR should be supported with backtesting techniques besides high dependencies on the settings of its data and methodology.

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