MARKET RISK MEASURES: ACCURACY TESTING OF VAR MODELS IN THE MALAYSIAN MARKET

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Abstract

The objective of this paper is to determine the most accurate Value-at-Risk (VaR) model as market risk measure for the non-financial sectors in Malaysia. Using Monte Carlo Simulation (MCS) plus selected volatility models for seven sectors, the expected maximum losses are determined at 95% level of confidence. To complement the risk measure, several accuracy tests namely Kupiec, Christoffersen and Lopez tests were applied in later stage. Final results proved that by allowing abnormalities (such as fat tails or asymmetries), the estimation for market risk in the Malaysian market will certainly improve the reliability of the risk forecast.

Key Words: *Value-at-Risk; volatility modelling; accuracy test*

Introduction

Since 1970s, world business transactions have experienced and contributed to diverse sources of financial uncertainty or risk (Dowd, 2005; Jorion, 2006). The uncertainty scenario undoubtedly has had an impact on the volatility level of the financial market, thus influencing the return ofan investment. Portrayed in various dimensions such as the stock market, exchange rate, interest rate and commodity market, a volatile environment exposes firms to greater levels of financial risk. Volatility that creates new dimension of business and systematicriskthenforcesfirmstoamendcongruentlytheiroperationalstructuretoaccommodate changes in the environment. Undoubtedly as reported by Dowd (1999), these conditions motivate firms to find new and better ways to manage risk especially when investors were exposed to multiple problems of market risk. Morgan (1996) has pointed out that even if the trade-off between risk and return is well recognized (higher returns can only be obtained at the expense ofhigher risk), the risk measurement component ofthe analysis has not received broad attention. As a result, Value-at-Risk or VaR has been introduced to market users as an integral risk management tool and a standard to monitor and control a firm's market risk exposures. In a basic form, VaR answers the question "How much can an investor lose with x% probability over a given time horizon?" (Morgan, 1996). 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, 1998).

Despite the widespread use of VaR to evaluate risk of portfolio, the traditional VaR approaches consisting of Risk Metrics Variance-Covariance (VCV), Historical Simulation (HS) and non-volatility based Monte Carlo Simulation (MCS) have several shortcomings, most noticeably when VaR modelling fail to consider main sources of bias; heavy-tails and volatility clustering. Heavy-tailed circumstances cited by Baliand Gokcan (2003) and Cotter (2004) suggest that extreme outcomes will happen more frequently than would be predicted by the normal distribution (sometimes referred to as the Gaussian distribution). Although investors understand that a portfolio comprising of log-normal assets cannot itself be log-normal, they ignore this complication because assuming otherwise would simplify VaR estimation. Still, maintaining a normality assumption and failure to account for any financial time series imperfection will undoubtedly lead to underestimating or overestimating VaR (Choong, 2004; Giannopoulos, 2003; Luciano & Marena, 2002; Mohamed, 2005; Zangari, 1996). Danielson and de Vries (1997) also added that when higher moments such as skewness and kurtosis are ignored or misestimated, an inaccurate VaR estimator can be produced, thus influencing the decision of market users particularly the investors.

Thus, the main objective of this paper is to determine the most accurate VaR model as the measurement of market risk for the non-financial sectors in Malaysia. And for these reasons, the extent to which the VaR behaviours are affected by heavy-tails and volatility clustering will be determined. The following section provides the review of related literature. The description of the data and methodologies using the full valuation approach or MCS are explained in section 3. Section 4 presents the results and its interpretations. Finally for conclusions, section 5 summarizes the findings and highlights related limitations that can be considered to be improvised for future research.

Review of Literature

The earliest conceptual framework of VaR was recorded since five decades ago by Baumol (1963) when evaluating the *Expected Gain-Confidence Limit Criterion.* Since then, various forms of VaR have been developed by researcher including the VCV, HS and MCS to measure market risk in an attempt to minimize risk.

Nonetheless, the calculation of VaR is subjected to various sources of model errors. These model errors are related to biasness of data including heavy-tails and volatility clustering and methods employed during the parameter estimation (Beder, 1995). Obviously as noted by Johansson et al, (1999), these factors may cause the computation of VaR to be less accurate and sometimes potentially misleading. In fact, using an inaccurate VaR model will increase the unfairness of decision makers' behaviour and may expose firms to a higher risk than desired.

Volatility Factor

Volatiliy being a model input alongside the underlying price can assist to describe the market behaviour in a certain country. Various studies in this context fit the notion that when individual volatilities are high, the correlations between the markets risk factors will definitely rises. For example, according to Giot and Laurent (2005) and Hull and White (1998), incorporating volatility to a selected VaR method helps to improve the VaR ·estimates substantially because it enhances accuracy and efficiency. In practice, state Dunis and Chen (2005), market participants who have more reliable or superior ability to predict volatility will have an edge over their competitors in that they are able to control the financial risk and profiting from it at the same time.

Another study done by Bolgun (2004) points out that since the introduction of VaR, a new role for volatility models such as the ARCH has emerged. The study by Bolgun shows that volatility preferences 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 suggests that in emerging markets, GARCH can be quantified as a suitable model.

Pederzoli (2006), who used two types of volatility models for UK stock data returns ARCH-type and stochastic volatility (SV) - draws similar conclusions to Bolgun (2004). In this case, Pederzoli (2006) has provided further evidence that accounting for asymmetric effects is another important factor that leads to more reliable and stable VaR estimates (refer also to Christoffersen, Hahn & Inoue, 2001; Chiu, Lee & Hung, 2005; Brooks & Persaud, 2003).

Accuracy Tests of VaR Models

An accuracy test is observed 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). Inability to undergo this process will definitely jeopardize the quality of the information provided thus misstating a firm's true risk exposures. Due to the rising attention given by regulators and market users to implement VaR in financial institutions, the quest to evaluate the accuracy of underlying models becomes a necessity (Hendricks & Hirtle, 1997; Jorion, 2002). A focal point according to both authors is that inaccurate VaR models will reduce the main benefits of models-based capital requirements.

The performance measure can generally be done by computing the failure rate depicted in the left and right tails before performing the Kupiec likelihood ratio (LR) test (Giot & Laurent, 2005). A property of Kupiec test is that it can be more effective as the sample size increases. In advance Giot (2005) performed the Kupiec likelihood ratio and extended it by applying the Christoffersen independence and conditional coverage test. The idea is to test the model's performance and stability in a challenging trading environment. Using the weighted average of implied volatility on U.S. data covering both bull and bear markets from the year 1994 to 2003, Giot (2005) made several conclusions. First, the number of VaR violations was not significantly different from the target value in most cases, so the null hypotheses of the independence and conditional coverage were usually not rejected. Second, despite the differences and challenging market conditions, the VaR models did not break down or deteriorate throughout the timeframe. Finally the study proved that data volatilities are adequate inputs to market participants especially for managers who manage index funds (see also studies by Ane, 2005; Cifter & Ozun, 2007).

In addition, 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; namely, the HS. Using six foreign exchange data from 1990 to 1998, they suggested that the GARCH-based model have better accuracy. More importantly, the study also highlighted the importance of considering fat-tails and asymmetric properties when deciding the best VaR model.

Another alternative to evaluate VaR estimate accuracy is based on Lopez (1999) where several strategies are introduced by integrating three hypothesis-testing methods; namely, the binomial distribution, the interval forecast method and regulatory loss function. The statistical evidence in the study shows that the loss function method is superior to the other two in differentiating VaR from the actual and alternative models.

Data and Methodology

The data sample covers the time series indices of seven non-financial sectors traded in the first board of the Bursa Malaysia over the period 1993 until 2006. The need to study this sectorial behaviour as indicated by Darrat and Mukerjee (1995) is due to the fact that differences towards financial leverage activities and operations provide a sign that the risk level is different based on the industry classification. The non-financial industries are represented by sectors of construction (CON), consumer product (COP), industrial products (INP), plantation (PLN), properties (PRP), trading and services (TAS), and mining (TIN). Two other sectors, namely technology and hotels, have been omitted from this study because the former started its index listing only in year 2000, while the latter is not represented by a specific index on Bursa Malaysia.

The data set is then divided into two parts. The first part, from 1993 until 2006, 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 the years 2007 until 2010, is used for backtesting each estimated VaR models (Mohamed, 2005; Pederzoli, 2006).

VaR Theoretical Formula

VaR determines the probability level of loss for a portfolio and varies according to the use of VaR by management and asset liquidity. From Dowd (2005), 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:

(Eq. 1) $\Pr [r_{t+h} < VaR^t(h)] = \alpha$

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:

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

Theoretically, VaR can be presented as:

(Eq. 3) $$VaR_t = W_t \alpha \sigma \sqrt{\Delta t}$$

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.

Volatility Modelling

For this research the volatility modelling process depends on either of two cases; normal (Gaussian) distribution, or non-normal distribution; that is, the t-distribution. Under the normal distribution, the study will implement two groups of conditional volatility models; the RiskMetrics Exponentially Weighted Moving Average (EWMA) and the Generalized Autoregressive Conditional Heteroscedasticity (GARCH). On the other hand, under t-distribution the study applies the GARCH (t-distribution) and the Exponential GARCH (EGARCH) model.

RiskMetrics EWMA

The RiskMetrics EWMA implies a first-order autoregressive structure that reflects the concept of volatility clustering. A distinguishing feature of EWMA is that it places more weight on more recent observations and less weight on older returns (Alexander, 1998; Brooks, 2002). One main assumption of this model is that the asset return mean is equal to zero besides treating 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:

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

Applying RiskMetrics and Engel and Gizycki (1999) methodologies, the empirical analysis considers $\lambda = 0.94$

+T

GARCH normal-distribution

To capture inadequate tail probability as portrayed in RiskMetrics EWMA, this research extends the quantification of VaR analysis by applying GARCH model introduced by Bollerslev (1986). For the normal GARCH model, the assumption is that ε_t is conditionally normally distributed with conditional variance $\hat{\sigma}_t^2$. The conditional variance of a generic GARCH model depends on both lagged values of squared returns and lagged volatility estimates. Bollerslev (1986) generalized Engle's ARCH *(p)* model by adding the *q* autoregressive terms to the moving averages of squared unexpected returns:

(Eq. 5) $\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_p \varepsilon_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \ldots + \beta_q \sigma_{t-q}^2$

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

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

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

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; Mat Nor, Yakob & Isa, 1999).

GARCH t-distribution

From equation (6), the GARCH-t is then expressed according to equation (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 (Alexander, 1998).

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

EGARCH

EGARCH is generated by taking the exponential function of conditional volatility (Nelson, 1991). Through this volatility log formulation, the impact of the lagged squared residuals is exponential

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

where

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

VaR Accuracy Test

To determine the best VaR model that can be implemented in a certain market, several tests of accuracy need to be addressed. This is in line with the suggestions by the Basle Committee in that backtesting are to be carried out to gauge the quality and accuracy of the VaR measurement. Three backtesting assessments are used for these reasons; Kupiec test, Christoffersen test and Lopez test.

Proportion of Failure Likelihood Ratio Test (Kupiec, 1995)

An elementary test to check VaR model validity is The Proportion of Failure Likelihood Ratio Test by Kupiec (1995). The test is based on the probability under the binomial distribution of

observing x exceptions in the sample size *T*.

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

An accurate VaR model should provide VaR estimates with unconditional coverage , 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:

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

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).

Conditional Testing (Christoffesen, 1998)

Christoffersen (1998) conditional testing is conducted because the former Kupiec (1995) test fails to capture time varying volatility. By extending the LR_{uc} to specify that exceptions must be independently distributed, the first test defines the indicator of exceptions as follows:

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

Second, defining 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 πi. Next, to test the hypothesis that the failure rate is independently distributed, the likelihood test for independence is calculated as:

(Eq. 13) $LR_{ind} = -2\ln\left(\frac{(1-\pi)^{(T_{00}+T_{10})}\pi^{(T_{01}+T_{11})}}{(1-\pi_0)^{T_{00}}\pi_0^{T_{01}}(1-\pi_1)^{T_{10}}\pi_1^{T_{11}}}\right) \sim \chi_1^2$

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

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

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

Quadratic Loss Function (Lopez, 1999)

Introduced by Lopez (1999), this test provides better and more powerful measure of model accuracy than former approaches. This model known as the Quadratic Loss Function (QLF) takes into account the magnitude of the exceptions. QLF is 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.

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

Results

Descriptive Statistical Analysis

As illustrated in Table 1, the sample mean for the observations is close to zero where the means are negative for all the sectors with the exceptions of COP, PLN and TIN. This shows that CON, INP, PRP and TAS have commonly more negative returns while the average values for sectors COP, PLN and TIN are positive-definite. The mining 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. Together with mean and standard deviation, the normality tests results as shown by the sample skewness, kurtosis and the consequent rejections of the normality hypothesis by the Jarque-Bera analysis confirm the empirical findings that daily returns are far from being normal (Gaussian).

The values of skewness ranging from a low of -0.5701 (INP) to a high of 0.9146 (CON) suggest that the series distributions are skewed. The high kurtosis compared to the normal distribution which is 3, imply that the distributions of series are leptokurtic or fat-tailed. The large values of the JB statistics provide strong evidence of non-normality. The Ljung-Box Q tests reject the null hypothesis in all series, which shows that the squared returns have serial correlation. Table 1 also reports the presence of ARCH effect in the data. Based on the large values of chi-square statistics and small values of probability statistics, it indicates that the hypothesis that the series is not heteroscedastic is rejected at the 1% significance level.

Due to the above evidence 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 appropriate to consider the application of volatility models in further analysis. In this study four models are estimated: EWMA, GARCH$(1,1)_n$, GARCH$(1,1)_t$ and EGARCH$(1,1)_t$.

Volatility Model Summary

Implementing RiskMetrics EWMA Model

Table 2 displays the results of estimated future volatility or σ_t^2 for RiskMetrics EWMA model. At $\lambda = 0.94$, the highest value is documented by the mining sector (0.0199) while the lowest estimation is given by the plantation sector (0.0020). Similarly, the table also reports the diagnostic test for the model. It can be seen that the results confirm that these models have approximately zero mean and unit variance. The sector series are also positively skewed, except for industrial product and plantation. Besides that, excess kurtosis can still be observed in all series where the values are slightly higher than 3, with the most extreme case being consumer products with 11.3492.

Implementing GARCH-based Model

The GARCH-based models are estimated by maximum likelihood method and the results are presented in Table 3. Subsequently, Table 4 shows the findings of several diagnostic tests for each model.

For GARCH$(1,1)_N$ the overall results of parameter ω, α and β are found to satisfy the condition; ω>0 and α , β ≥ 0 (Panel A, Table 3). Precisely, the intercept term 'ω' is very small while the coefficient on the lagged conditional variance, β is approximately 0.9. In each sector, the sum of the estimated coefficient of the variance equations (Eq. 6) α and β, which is the persistence coefficient, is very close to unity. This indicates shocks to the conditional variance will be highly persistent.

Similar to GARCH$(1,1)_N$, the parameters for GARCH$(1,1)_t$ are also found to satisfy the restriction that ω>0 and α, β ≥ 0. The coefficients on all three terms in the conditional variance equation are found to be highly statistically significant for all series. In this case, values of intercept ware also very small, while the shows a high value between 0.8 and 0.9. The sum of coefficient a and for all the non-financial sectors also illustrates values that are very close to one, which portrays a high persistence level of volatility.

Viewing the diagnostic test results in Table 4, the Ljung-Box statistics test shows no evidence of non-linear dependence in standardized squared residuals at lag 20 for both models. In fact the ARCH tests also confirm that there are no residual ARCH effects in the standardized return. This implies that the models are well-specified.

Looking at EGARCH(l ,1) , all the conditional variance equation coefficients, inclusive of the results of asymmetry coefficient 8, are significantly different from zero. This supports the existence of a symmetric impacts of returns on conditional variance. The results of the diagnostic tests confirm that this model has approximately zero mean and unit variance. Besides that the squared standardized residuals indicate no autocorrelation, thus all nonlinear dependencies are captured in all the returns. There is also no evidence of ARCH effects for any sample. In conclusion, these diagnostics show that the estimated model is also well-specified.

Testing for Accuracy

The accuracy test in this study comprises of Failure Likelihood Ratio Test (Kupiec Test), Conditional Testing (Christoffesen Test) and Quadratic Loss Function (Lopez Test). All the outputs from these three evaluations are set out in Table 5. Figures 2, 3 and 4, display visual adaptations from the following tables in accordance with the three tests.

Failure Likelihood Ratio Test (Kupiec Test)

The basic frequency test as suggested by Kupiec (1995) is conducted in order to compare the observed tail losses with the predicted tail losses by the model. In short, it is quivalent to test $H_0 = jJ' = p$ where the unconditional coverage, ft:equals the desired coverage level, p. All VaR models for CON, COP, PRP and TAS pass LR , test at 95% confidence level (Table 5 and Figure 2). Within this manner, Figure 2 illustrated that all VaR models for these sectors do not exceed the critical value of 3.84. Thus, the null hypothesis is not rejected and it also illustrates that these models generate reasonable unconditional coverage probabilities. For the case ofI NP, it is found that only MCS_1+$EGARCH_1$ fails to pass the LuR, 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. For both sectors, all the models are inaccurate. The cause of this situation can be attributed to the fact that the models under investigation led to an excessive number of exceedances (Zucchini & Newmann, 2001). Kupiec test is implemented using knowledge of only n (number of sample), p (p=l-a, where a is the confidence level) and x (number of exceedances or violations or exceptions) thus it accepts models no matter how the exceptions are distributed.

Conditional Testing(Christoffesen Test)

From Table 5, Column 4 at 95%, all models for CON, COP and PRP sector pass the LR_{cc} test. However as in Kupiec test, similar conclusion cannot be made for every single model for the PLN and TIN sector s in that all models for both sectors exceed the critical value, 5.99 (Figure 3). The coverage estimates obtained by INP and TAS are only supported by three models. The results for these two sectors indicate that MCS_1+$EGARCH_t$ for INP fail to pass the LR_a test, while MCS_1+RMN have an unfavourable risk forecast for TAS. Failure to generate a reasonable conditional coverage for all these models can be attributed to a high value of either one or both components of LR,, as well as exceeding the determined critical value.

Quadratic Loss Function (Lopez Test)

In general, Table 5, Column 5 and Figure 4 verify that MCS_1+RMN to be the least accurate model compared to other alternatives while from a greater part of the observation, it is also learnt that the model with the highest accuracy value is the MCS $_{1}$+GARCH$_{t}$. This is especially true for five sectors at the 95% confidence level, excluding COP and TIN. According to Lopez QLF test with the exception to the mining sector, the next model that has the second lowest point of accuracy is also the model under a similar normal distribution; MCS $_{1}$+GARCHN instead of the other two simulated VaR models under the t-distribution.

Overall, the backtesting assessments using Kupiec and Christoffersen test provide evidence that almost every model was found to be accurate for all sets of occurrence. Nonetheless, using Lopez test, which takes into consideration the magnitude of the impact of exceptions, the most accurate model was MCS,+GARCH,. As a result, it is best to conclude that the most accurate model to be applied in the Malaysian market particularly for the non-financial sectors where it passes all the stated accuracy tests is the MC,+GARCH,.

Conclusions

In the matter of accuracy, from the Kupiec test, almost all models were found to be accurate at the 95 % confidence level whether the evaluation was quantified in a normal or t-distribution circumstances (Table 5, Column 2). This shows 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; Giot & Laurent, 2005).

Similar conclusions can also be made from the Christoffersen test in that almost all models assessed under normal and t-distribution, were estimated to be accurate (Table 5, Column 4). Others are considered rejected or inaccurate. As explained earlier, a model may be rejected for two reasons: it fails to produce correct unconditional coverage or if the failures are not independent, or both (Table 5, Column 2 and 3). Again, models that fail LRu,' produce coverage probabilities statistically different from the theoretical coverage probabilities. For models that fail LR,nd' this is because they fail to capture the volatility dynamics of the return process (Bredin & Hyde, 2004; Christoffersen, 1998; Christoffersen *et al.,* 2001). This is especially true for models constructed under the t-distribution.

For Lopez test when the magnitude of the exceptions impact on different VaR models is taken into consideration it is best to assume that the most superior risk forecast model is MC,+GARCH,. This indicates that should the VaR methods only rely on the first two moments ofloss distribution, the accuracy of estimating the maximum loss is diminished. Models quantified for leptokurtic distribution (in this case student-t) illustrate a greater tendency to handle tail dynamics of the conditional distribution which in return produces more accurate VaR forecast than in Gaussian distribution (refer among others Bolgun, 2004; Danielsson & de Vries, 1997; Lee & Saltoglu, 2002; Mohamed, 2005).

By comparing each model, the reason for rejecting these two normally distributed models (RiskMetrics and GARCHN) 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 unsuitable modelling approaches and perform quite poorly in the above-mentioned manner (Danielsson & De Vries, 1997; Giot & Laurent, 2005; Lopez, 1999).

And interestingly, though the EGARCH model theoretically is able to handle any asymmetry properties in a distribution, in this present study EGARCH is not as accurate and consistent as MC,+GARCH$_{1}$. This is perhaps due to the fact that assuming EGARCH will work with a t-distribution may not maximize its potential in VaR estimation. As an alternative, applying other form of statistical distribution like the Generalized Error Distribution (GED) may give better solution to increase the EGARCH-based model's accuracy (Pederzoli, 2006; Yao *et al.,* 2006).

Hence for future research, attention should be given to the limitation issues highlighted as follows. Firstly, in this study the statistical distributions assumed are limited to normal and student-t distributions. If used under more extreme conditions more robust results could be attained if distribution classes like Frechet, Weibull and Gumbel distribution were included. To handle these situations will however involve more distinctive VaR estimation of EVT parameters that is by using the Hill estimator. Secondly, this study only focuses on three types of volatility models namely; the Risk Metrics EWMA, GARCH(l,l) and EGARCH(l,l). The underlying reasons are either 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 conditions like the leverage effect and jump-dynamics that need to be addressed. Next, when calculating and evaluating the VaR models in this study, the data of the Malaysian market is taken as a whole. The study would be more vigorous if each economic phase is examined individually and compared between one phase and another. Further argued by Lee and Saltoglu (2002), using separate time periods such as before recession, in-recession and post recession, allow diverse interpretation ofVaR application to be made.

As a summary, in this study adequate MCS plus volatility models are proven to deliver more accurate VaR forecasts. For the evaluation of market risk measures of the Malaysian non-financial sectors, it can be concluded that allowing for abnormalities (such as fat tails or asymmetries) will certainly improve the reliability ofrisk forecast.

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Table 1: Basic Statistics of the Full Sample

	CON	COP	!NP	PLN	PRP	TAS	TIN
Mean	-0.0001	0.0001	-0.0002	0.0002	-0.0004	-3.99E-05	5.95E-05
Std Dev	0.0208	0.0127	0.0155	0.0153	0.0188	0.0170	0.0335
Skewness	0.9146	0.2222	-0.5701	-0.2814	0.6350	0.8321	0.7093
Kurtosis	28.1858	40.3412	41.7550	26.8444	21.0115	32.9322	45.0623
JB	91372.35	199828.20	215402.20	81513.64	46731.86	128776.00	253804.10
	*(0.0000)******	*(0.0000)* ***	*(0.0000)* *"	*(0.0000)* *"	*(0.0000)* ***	*(0.0000)* ***	*(0.0000)* "*
LB(20)r'	2163.20	1356.00	1721.00	2123,6	1732.7	1370.10	813.37
	(0.0000) ***	*(0.0000)* ***	*(0.0000)* **'	*(0.0000)*	*(0,0000)* ***	*(0.0000)* "*	*(0.0000)* ***
ARCH-LM(l)	1297.30	594.57	1434.04	***974.99	1413.96	565.02	598.34
	(0.0000) ***	*(0.0000)* ***	*(0.0000)* ***	*(0.0000)* '**	*(0.0000)* **'	*(0.0000)* ***	*(0.0000)* ***

Notes:
JB test statistics are based on Jarque-Bera {1987) and are asymptotically chi-square-distributed at 2 degrees of freedom.
LB(20) is the Ljung-Box test for serial correlation with 20 lags, applied to squared returns (r).
ARCH-LM(l) is the test for ARCH effects for I lag.
Values in parentheses denote the p-value, *** denotes significance at 1 % level.

Table 2: Estimation and Diagnostic Tests Results of Risk Metrics EWMA

	A,=0.94	Mean of Conditional Volatility E(μ/a-J	Variance of Conditional Volatility E(μ/ a-)	Volatility Skewness	Volatility Kurtosis
CON	0.0056	-0.0430 (0.9875)**	0.9743	0.2671	5.6283
COP	0.0032	-0.0171 (0.9991)	0.9974	0.3088	11.3493
!NP	0.0022	-0.0626 (1.0005)*'*	1.0094	-0.1140	3.9916
PLN	0.0020	-0.0251 (0.9995)	0.9999	-0.0649	3.5749
PRP	0.0024	-0.0161 (0.9952)	0.9915	0.1466	6.0462
TAS	0.0027	-0.0375 (0.9929)'*	0.9851	0.2503	3.7159
TIN	0.0199	-0.0190 (0.9962)	0.9915	0.8555	5.6140

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

Table 3: Estimation Results of GARCH-based Model

Pauel A: GARCH(l,l)N				
	w	***a,***	P,	***a+P***
CON	4.64E-06 (l.79E-06)*"	0.0900 (0.0142)'**	0.9017 (0.0146)'**	0.9917
COP	6.19E-07 (l.17E-06)	0.0691 (0.0223)***	0.9305 (0.0332)***	0.9996
lNP	2.31E-06 (7.68E-07)*"	0.1154 (0.0191)*"	0.8645 (0.0153)'**	0.9799
PLN	2.8IE-06 (9.04E-07)'**	0.1431 (0.0197)*'*	0.8542 (0.0195)"*	0.9973
PRP	3.95E-06 (l.l0E-06)*'*	0.1400 (0.0258)***	0.8495 (0.0204)'**	0.9895
TAS	1.64E-06 (7.S0E-07)'*	0.0969 (0.0146)*"	0.9031 (0.0149)*'*	0.9998
TIN	1.48E-05 (4.89E-06)*"	0.1296 (0.0164)*'*	0.8670 (0.0169)*'*	0.9966
Pauel B: GARCH(l,1),				
	w	***a,***	P,	***a+p***
CON	8.55E-06 (1.90E-06)***	0.1507 (0.0245)***	0.8442 (0.0148)*"	0.9949
COP	1.28E-06 (3.24E-07)""	0.1005 (0.0131)**'	0.8892 (0.0099)"*	0.9897
!NP	2.77E-06 (6.78E-07)"'	0.1188 (0.0177)'**	0.8674 (0.0126)'*'	0.9862
PLN	3.67E-06 (8.SIE-07)***	0.1611 (0.0261)*'*	0.8317 (0.0151)"'	0.9928
PRP	4.02E-06 (5.95E-07)"'	0.1626 (0.0115)*'*	0.8292 (0.0101)*'*	0.9918
TAS	3.33E-06 (8.15E-07)*"	0.1188 (0.0152)'*'	0.8790 (0.0119)*'*	0.9978
TIN	2.ISE-05 (5.60E-06)*'*	0.1798 (0.0354)*"	0.8072 (0.0158)**'	0.9870

Panel C: EGARCH(l,1),				
CON	-0.4141 (0.0537)'''	0.2839 (0.0289)'''	0.9721 (0.0056)'''	-0.0805 (0.0157)'''
COP	-0.2495 (0.0362)'''	0.1886 (0.0192)'''	0.9874 (0.0034)'''	-0.0397 (0.0104)'''
!NP	-0.3306 (0.0460)'''	0.2362 (0.0239)'''	0.9810 (0.0043)'''	-0.1056 (0.0337)'''
PLN	-0.400 (0.0513)'''	0.3038 (0.0287)'''	0.9775 (0.0049)'''	-0.0461 (0.0148)'''
PRP	-0.4465 (0.0532)'''	0.3411 (0.0291)'''	0.9745 (0.0054)'''	-0.0353 (0.0148)''
TAS	-0.2639 (0,0368)'''	0.1982 (0.0210)'''	0.9856 (0.0035)'''	-0.0600 (0.0115)'''
TIN	-0,5197 (0.0659)'''	0.3795 (0.0408)'''	0.9597 (0.0078)'''	-0.0610 (0.0212)'''

Notes:
1. Standard errors are in parentheses.
2. ", ** and *** denote significance at 10%, 5% and 1% levels.
w. istheconstantintheconditionalvarianceequations.ar'eferstothelaggedsquarederror./3coefficientreferstothelagged conditional variance and 8 coefficient is the EGARCH asymmetric term.

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

		E(μ/O'i)	E(μ/0'1)'	LB2(20)	ARCH(!)
CON	GARCH(l,l)N	-0.0438	0.9993	21.2100 (0.3410)	1.4722 (0,2250)
	GARCH(l,l),	-0.0056	0.9572	21.4950 (0.3790)	0.0483 (0.8261)
	EGARCH(l,l),	0.0298	0.9649	16.0550 (0.7240)	0.0811 (0.7758)
COP	GARCH(l,l)N	-0.0283	1.0008	21.1250 (0.4900)	5.7970 (0.1612)
	GARCH(l,l),	-0.0165	0.9898	13.5710 (0.8620)	1.2156 (0.2702)
	EGARCH(l,l),	0.0001	0.9977	9.8827 (0.9800)	1.8268 (0.1766)
!NP	GARCH(l,l)N	-0.0496	0.9993	10.5160 (0.9590)	2.9412 (0.8644)
	GARCH(l,l),	-0.0190	0.9701	10.1140 (0.9670)	3.7316 (0.5349)
	EGARCH(l,l),	0.0145	0.9700	13.6540 (0.8490)	1.3097 (0.2568)
PLN	GARCH(l,l)N	-0.0241	1.0004	25.3970 (0.1970)	5.6325 (0.1769)
	GARCH(l,l),	-0.0170	0.9444	23.8640 (0,2590)	2.6076 (0.1065).
	EGARCH(l,l),	0.0015	0.9468	24.0210 (0.2520)	6.3401 (0,1186)
PRP	GARCH(l,l)N	-0.0169	1.0003	18.4880 (0.5660)	4.4864 (0.3425)
	GARCH(l,l),	-0.0119	1.0579	15.6080 (0.7510)	2.2918 (0.1302)
	EGARCH(l,1),	0.0395	0.9710	21.8970 (0.3560)	7.3816 (0.6628)

TAS	GARCH(l,l)N	-0.0329	1.0004	15.1570 (0.7780)	1.6143 (0.2040)
	GARCH(l,1),	-0.0115	0.9788	12.8350 (0.8950)	0.4745 (0.4909)
	EGARCH(l,l),	0.0195	0.9804	13.0930 (0.8840)	2.0477 (0.1525)
TIN	GARCH(l,l)N	-0.0190	1.0005	20.0810 (0.4630)	3.4943 (0.6168)
.,	GARCH(l,l),	0.0370	0.9007	20.3120 (0.4490)	0.8989 (0.3431)
	EGARCH(l,l),	0.0490	0.9035	24.7860 (0.2200)	3.4329 (0.6401)

Notes:
1. ***Standard errors are in parentheses.***
2, LB[1] (20) is the Ljung-Box statistics at lag 20, distributed as a chi-square with 20 degrees of freedom.

Table 5: Accuracy Test - Forecasting Performance Summary for Different VaR Models at 95% Confidence Level

	LRuc	LRind	LRcc	AQLF
CON				
MCI+RMN	0.4429	3.5822	4.0250	0.2301
MC,+GARCHN	0.1720	2.8652	3.0372	0.1747
MC,+GARCH,	0.0109	1.4207	1.4315	0.0778
MC,+EGARCH,	0,0017	1.8156	1.8172	0.1020
COP				
MC,+RMN	0.6829	4.4784	5.1612	0.2682
MC,+GARCHN	0.5471	4.1999	4.7469	0.2474
MC,+GARCH,	0.1457	3.0627	3.2083	0.1678
MC,+EGARCH,	0.1212	2.9572	3.0783	0.1608
INP				
MC,+RM,,	1.4169	1.1506	2.5674	0.0570
MC,+GARCHN	1.1813	0.8578	2.0390	0.0432
MC,+GARCH,	0.8279	0.3686	1.1964	0.0224
MC,+EGARCH,	6.8935	5.8698	12.7632	0.3789
PLN				
MC,+RMN	8.1302	6.4969	14.6270	0.4516
MC,+GARCHN	7.9535	6.3792	14.3326	0.4412
MC,+GARCH,	6.5990	5.4559	12.0548	0.3616
MC,+EGARCH,	6.7168	5.5378	12.2545	0.3685
PRP				
MC,+RMN	1.1224	0.7197	1.8420	0.0397
MC,+GARCHN	0.7691	0.2577	1.0267	0.0189
MC,+GARCH,	0.7102	0.1714	0.8815	0.0154
MC,+EGARCH,	0.7101	0.1714	0.8814	0.0155
TAS				
MC,+RMN	3.3602	3.1181	6.4782	0.1713
MC,+GARCHN	2.5358	2.3535	4.8892	0.1228
MC,+GARCH,	1.5346	1.2929	2.8274	0.0639
MC,+EGARCH,	1.8880	1.6897	3.5776	0.0847

TIN				
MC,+RMN	7.1290	6.0495	13.1784	0.3928
MC,+GARCHN	7.0702	6.0077	13.0778	0.3893
MC,+GARCH,	7.4235	6.2567	13.6801	0.4101
MC,+EGARCH,	7.4234	6.2570	13.6803	0.4101

Notes:

LRuc and LRind follow asymptotically X(1) *with critical value 3.84. LRcc is asymptotically* X2 *distributed with critical value 5.99.*

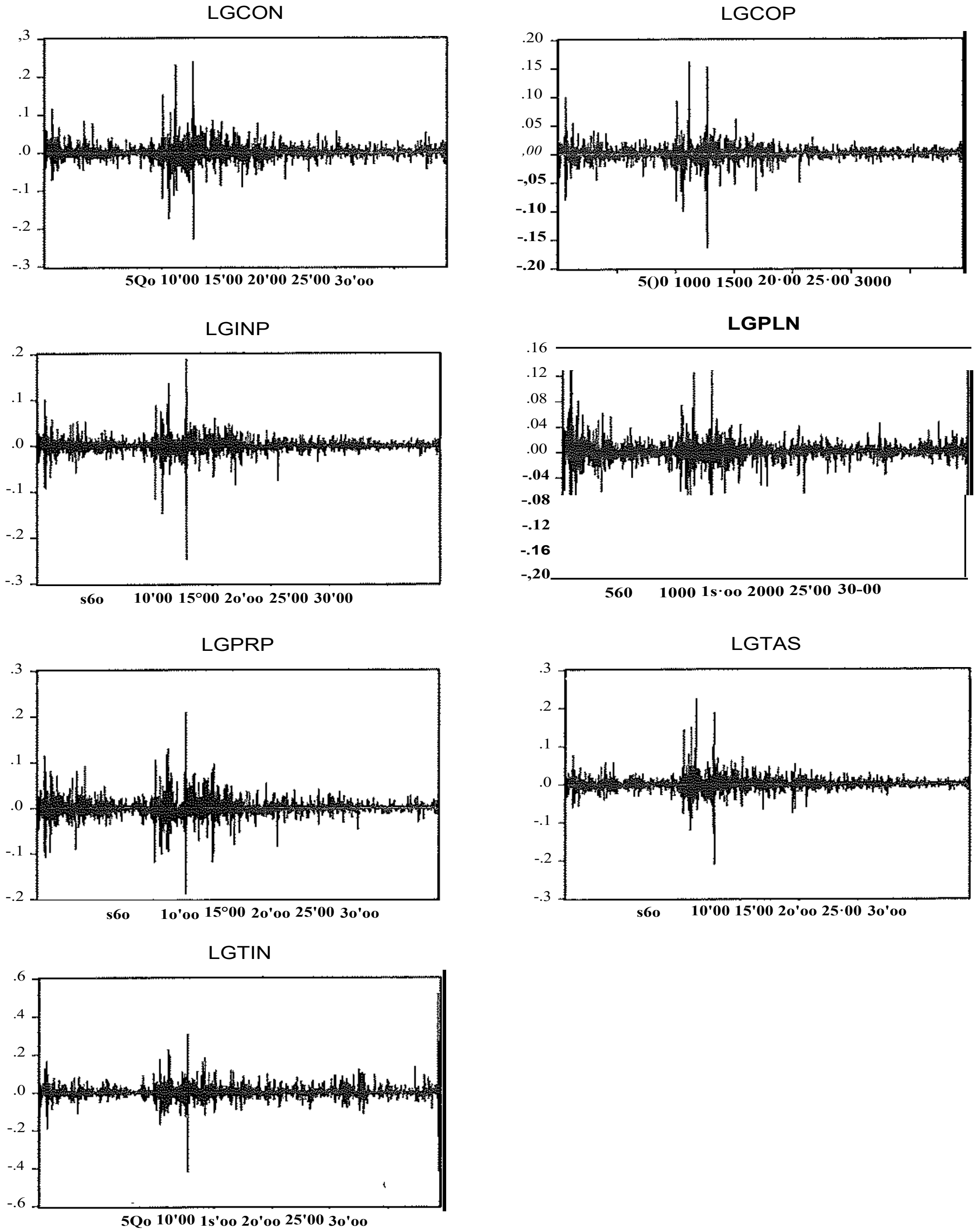

Figure 1: Returns of the Non-Financial Sectors

Figure 2: Kupiec Test of Model's Accuracy at 95%

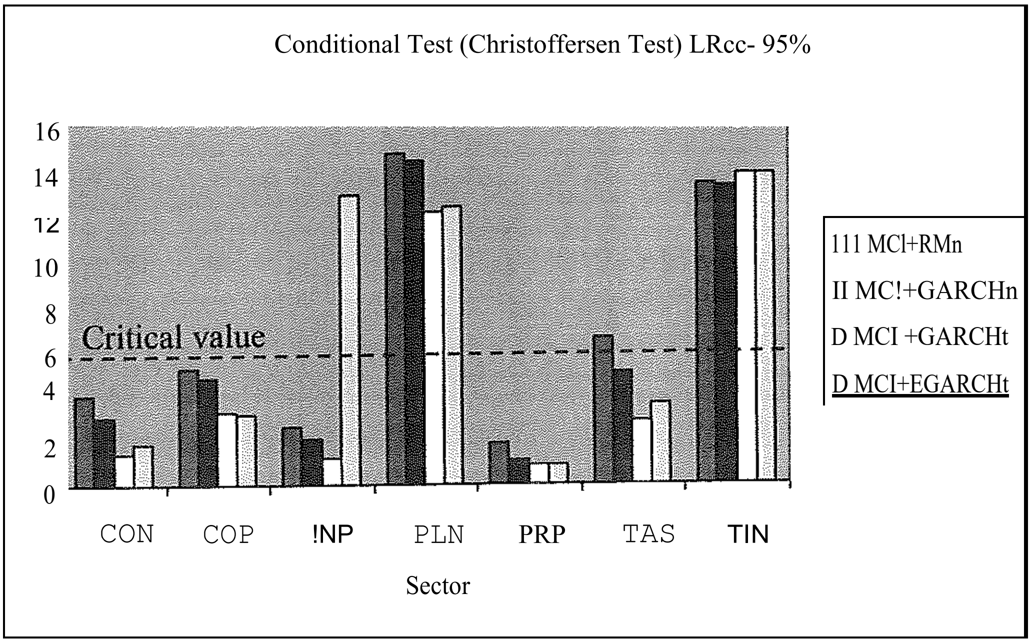

Figure 3: Christoffersen Test of Model's Accuracy at 95%

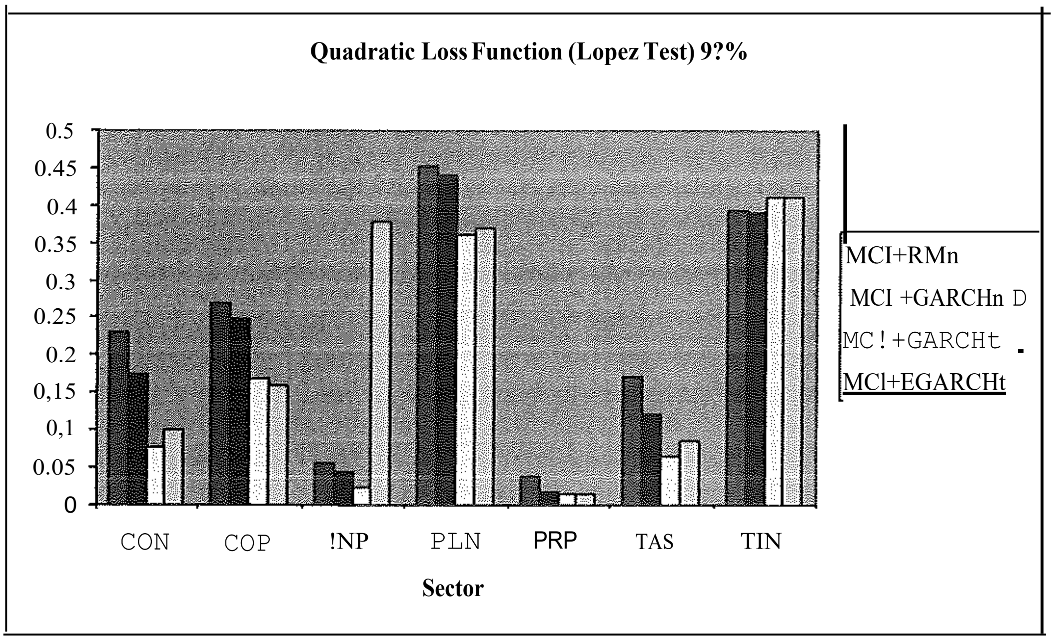

Figure 4: Lopez Test of Model's Accuracy at 95%