ASSESSING THE ACCURACY OF RISK MODELS IN THE MALAYSIAN MARKET

Dr. Zatul Karamah Ahmad Baharul-Ulum
School of Business and Economics
Universiti Malaysia Sabah
88400 Kota Kinabalu, Sabah, Malaysia
E-mail : zatul@ums.edu.my

Prof. Dr. Ismail bin Ahmad
Faculty of Business Administration
Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia

Associate Prof. Dr. Norhana binti Salamudin
Faculty of Business Administration
Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia

ABSTRACT

This paper presents Value-at-Risk (VaR) models that are integrated with several volatility representations to estimate the market risk for the Malaysian non-financial sectors data. The models are used to obtain daily volatility forecasts and these volatilities are used to estimate the Value-at-Risk (VaR) for each sector based on the Monte Carlo Simulation (MCS) approach. In a sample over the years from 1993 until 2010 for three non-financial sectors sample namely Industrial Product (INP), Property (PRP) and Trade and Services (TAS) sectors, the expected maximum losses were quantified at 95% confidence level. Several accuracy tests namely the Kupiec, Christoffersen and Lopez tests are conducted to complement the estimates. The final results provide evidence that consideration of fat-tails and asymmetries are crucial issues when deciding to estimate VaR in managing financial risk.

Keywords: *Value-at-Risk, volatility modelling, accuracy test*

1. INTRODUCTION

The world business transactions have experience and contribute to diverse sources of financial uncertainty or risk since three decades ago. In today's competitive business environment, firms have to face several financial risks namely market, credit, liquidity, operational and legal risk. These uncertainty scenarios undoubtedly have its impact on the volatility level of the financial market thus influence the return of an investment. These conditions provide incentives for firms to find new and better ways to manage risk. To date one of the most widely used market risk measure is recognized as the Value-at-Risk or VaR methodology. VaR 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). In a basic form, JP Morgan (1996) states VaR as a technique to answers the question of "How much can an investor lose with x% probability over a given time horizon".

Despite the fact that the empirical testing has unveiled important issues pertaining to VaR methodologies and measurements, one should note the existing literatures on VaR models have been evolving on developed countries such as United States (US), European and Japanese market using mainly data from the financial sectors [see among others Hendricks, 1996; Ho et.al., 1996; Venkataraman, 1997; Hull & White, 1998; Kritzman & Risch, 2002; Lee & Saltoglu, 2002; Luciano & Marena, 2002]. Incredibly, the lack of VaR studies using emerging economies samples including Malaysia requires greater attention due to the fact that these markets are not less important plus being proven to be correlated with the developed ones (Brooks & Persand, 2003; Seymour & Polakow, 2003). In addition, one of the reasons to study these markets as highlighted by Sinha and Chamu (2000) is that it tends to show more volatile conditions and routinely produce risks with fat tails and asymmetry that are not consistent with well-behaved distribution. Thus, for the benefit of both academic and policy makers, research to evaluate risk forecast for the emerging markets must be further examined.

Within this manner, the main intention of this paper is to compare the accuracy of the VaR estimates based on three 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 the literature background. Section 3 briefly outlines the description of the data used in the study and the methodology employed to assess the VaR values. The final results are presented and interpreted in section 4. To conclude the paper, the summary of the findings and comments on its limitations and implications are addressed in the final part of this paper, section 5.

2. REVIEW OF LITERATURE

The concept of VaR is first introduced almost four decades ago by Baumol (1963) when the author evaluates the *Expected Gain-Confidence Limit Criterion* model. Dowd (2005) and Jorion (1997) testify the basic elements of a VaR system may include one investment portfolio, evaluation procedure towards portfolio investment, the analysis horizon, the identification of portfolio risk movers and a model which relates risk sources and portfolio characteristics on performance. Many techniques of VaR have since been developed by many researchers in an attempt to minimize risk. These include the variance-covariance method (VCV), historical simulation (HS) and Monte Carlo simulation (MCS).

However, the values provided by these techniques are greatly influenced by the changes in market values of portfolio due to several sources of risk namely equities, indexes, interest and exchange rates. Obviously, it may cause the computation of VaR to be inaccurate and sometimes can be potentially misleading for the uninformed. Thus using a wrong VaR model will increase the biasness of decision makers' behaviour and may exposed the firms to a higher risk than desired (Johansson et al., 1999). In fact, Artzner et al. (1999) further remind that an inaccurate assessment of VaR increases the (moral hazard) risk of an investment. This misspecification is subjected to various sources of model errors. These model errors says Beder (1995), are related with model specification, data used and methods employed during the parameter estimation. A number of studies have been done to address the issues of accuracy when evaluating VaR performances as in the following section.

2.1 Evaluating accuracy

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). According to Hendricks and Hirtle (1997) and Jorion (2002), due to the rising attention given by regulators and market users to implement VaR in financial institutions, the quest to evaluating the accuracy of underlying models becomes a necessity. Inability to undergo this process will definitely jeopardize the quality of the information provided thus misstate a firm's true risk exposures. A focal point according to both authors is inaccurate VaR models will reduce the main benefits of models-based capital requirements. Engel and Gizycki (1999), for example, present five accuracy measures: binary and quadratic loss functions, scaling factors to obtain sufficient risk coverage, and the average and maximum magnitude of losses not covered by the VaR estimates. Mixed results are recorded when these tests are handled both at the 95% and 99% confidence level. For the 95% percentile, the exponential VCV, exponential HS, the constant-correlation GARCH and OGARCH models show higher accuracy level while at 99%, models like the EVT, simple MCS and normal-mixture MCS, simple and antithetic HS demonstrate better accuracy. Clearly, as stressed by Engel and Gizycki (1999), model accuracy is important to all users of VaR models.

Lopez (1999) on the other hand has introduced several strategies which includes three hypothesis-testing methods in measuring VaR model accuracy level; 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 more superior than the other two in differentiating VaR from the actual and alternative models.

Another performance measures within this manner can also be conducted by using the Kupiec test and Christoffersen test. Giot and Laurent (2005) for instance take two steps; first, by computing the failure rate depicted in the left and right tails. Next they perform 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) basing his work on an earlier 2001 study, performed the Kupiec likelihood ratio and extended it by applying the Christoffersen independence and conditional coverage test. Based on the U.S market data 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. The study finally demonstrated that data volatilities are adequate inputs to market participants especially for managers who manage index funds. The degree of performance increase because the implied volatility pertaining to index tracking can be directly fed into the market risk model. Similar conclusions can also be referred in Ane (2005), Cifter and Ozun (2006) and Papadamou and Stephanides (2004).

3. DATA AND METHODOLOGY

3.1 Data

The data sample covers the time series indices of three non-financial sectors traded in the first board of the Bursa Malaysia over the period 1993 until 2010. The selections are based on the highest accumulated amount for market capitalization as at January, 2011. The data set is then divided into two parts. The first part, from 1993 until 2008, 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 2009 until 2010, is used for backtesting each estimated VaR models (Mohamed, 2005; Pederzoli, 2006). The non-financial industries are represented by sectors of Industrial Product (INP), Property (PRP) and Trade and Services (TAS) sectors.

3.2 VaR Theoretical Formula

In general, as stipulated by 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:

$$\Pr\left[r_{t+h} < VaR_t(h)\right] = \alpha \qquad \text{(Eq. 1)}$$

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:

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

Theoretically, VaR can be presented as:

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

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 Test of accuracy

To gauge the quality and accuracy of the VaR measurement, the Basle Committee stipulates that backtesting needs to be carried out. Three selected accuracy assessments are applied namely the Kupiec test, Christoffersen test and Lopez test. In short, 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 regard to better performance.

The 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.

$$f(x) = \binom{T}{x} p^x (1-p)^{T-x} \quad \text{(Eq. 4)}$$

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:

$$LR_{uc} = -2\ln\left((1-p)^{T-x} p^x\right) + 2\ln\left((1-\hat{p})^{T-x} \hat{p}^x\right) \quad \text{(Eq. 5)}$$

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 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:

$$I_t = \begin{cases} 1, if & \Delta P_{i,t} < VaR_{t|t-1} \\ 0, if & \Delta P_{i,t} \geq VaR_{t|t-1} \end{cases} \quad \text{(Eq. 6)}$$

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

$$LR_{ind} = -2\ln\left(\frac{(1-\pi)^{(T_{00}+T_{10})}\pi^{(T_{01}+T_{11})}}{(1-\pi_0)^{T_{00}}\pi_0^{T_{01}}(1-\pi_1)^{T_{10}}\pi_1^{T_{11}}}\right) \sim \chi_1^2 \quad \text{(Eq. 7)}$$

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:

$$LR_{cc} = -2\ln\left(\frac{(1-P)^{T_1} P^{T_0}}{(1-\pi_0)^{T_{00}} \pi_0^{T_{01}} (1-\pi_1)^{T_{10}} \pi_1^{T_{11}}}\right) \sim \chi_2^2 \qquad \text{(Eq. 8)}$$

Quadratic Loss Function (Lopez, 1999): The third accuracy test is introduced by Lopez (1999) who suggests that 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.

$$L_{i,t+1} = \begin{cases} 1 + \left(\Delta r_{i,t+1} - VaR_{i,t}\right)^2, & if \Delta r_{i,t+1} < VaR_{i,t} \\ 0, & if \Delta r_{i,t=1} \geq VaR_{i,t} \end{cases} \qquad \text{(Eq. 9)}$$

4. RESULTS

4.1 Descriptive Statistical Analysis

The descriptive statistics presented in Table 4.1 illustrate the basic statistical characteristics of the return series (i.e. in log-differenced form). The sample mean for the observations is close to zero where the means are negative for all the sectors. This shows that INP, PRP and TAS have commonly more negative returns. 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 -0.5700 (INP) to a high of 0.8322 (TAS) 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 4.1 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, it is appropriate to consider the application of volatility models in further analysis. Three models for single variable: GARCH(1,1)$_N$, GARCH(1,1)$_t$ and EGARCH(1,1)$_t$ will be estimated and compared in the next subsections.

4.2 Implementing GARCH-based Model

The GARCH-based models are estimated by maximum likelihood method and the results are presented in Table 4.2. Subsequently, Table 4.3 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 4.2). 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 α and β, which is the persistence coefficient, is very close to unity. This indicates shocks to the conditional variance will be highly persistent. The coefficients on all three terms in the conditional variance equation too are highly statistically significant. For this particular model, the residual based diagnostic tests (Table 4.3) provide evidence that the squared standardized returns present no significant autocorrelation, consistently with the LB. This LB statistic verifies the ability of GARCH(1,1)$_N$ to capture the non-linear dependence: the squared standardized returns are in fact independent. The ARCH tests also confirm that there are no residual ARCH effects in the standardized return. This implies that the models are well-specified.

Due to the fact that the normality condition fails to capture any existence of fat-tailed property, a non-normal distribution, most commonly the Student-t distribution is applied to model the excessive third and fourth moment of the sample. Panel B of Table 4.2 demonstrates the results for GARCH$(1,1)_t$ and Panel C exhibits an asymmetric GARCH model, the EGARCH$(1,1)_t$.

Similar to GARCH$(1,1)_N$, the parameters for GARCH$(1,1)_t$ 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. In this case, values of intercept 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 also illustrates values that are very close to one, which portrays a high persistence level of volatility. Viewing the diagnostic test results in Table 4.3, the Ljung-Box statistics test shows no evidence of non-linear dependence in standardized squared residuals at lag 20. Furthermore, Engle's first-order LM test for ARCH residuals found no evidence of time-varying volatility for all series, thus the model is well-specified.

Alternatively as in EGARCH$(1,1)_t$, all the conditional variance equation coefficients, inclusive of the results of asymmetry coefficient δ, are significantly different from zero. This condition supports the existence of asymmetric impacts of returns on conditional variance. The results of the diagnostic tests confirm that this model has approximately zero mean and unit variance. 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.

4.3 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 4.4. Figures 4.1, 4.2 and 4.3, display visual adaptations from the following tables in accordance with the three tests.

4.3.1 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 in order 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. All VaR models for PRP and TAS pass LR_{uc} test at 95% confidence level (Table 4.4 and Figure 4.1). Thus, the null hypothesis is not rejected and it also illustrates that these models generate reasonable unconditional coverage probabilities. For 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. Though the demonstrated results are rather mixed, when comparing between normal distribution and t-distribution models, the former distribution give more accurate combination than the latter.

4.3.2 Conditional Testing (Christoffesen Test)

The next accuracy test is suggested by Christoffersen (1998). At 95%, all models for PRP and TAS sector pass the LR_{cc} test (refer column 4, Table 4.4). The results for INP indicate that MC_1+EGARCH$_t$ fail to pass the LR_{cc} test. The failure of the model as reported in Table 4.4 is because values of both LR_{uc} and LR_{ind} exceeded the critical values. Visible illustration for the Conditional Testing can also be referred to Figure 4.2.

4.3.3 Quadratic Loss Function (Lopez Test)

From the observation, it is also learnt that for all sectors, the model with the highest accuracy value is the MC_1+$GARCH_t$ in that the values of AQLF are the lowest as compared to MC_1+$GARCH_N$ and MC_1+$EGARCH_t$ (refer to column 5, Table 4.4). And by studying the 95% level of confidence as presented in the subsequent Figure 4.3, according to Lopez QLF test, the most inaccurate model is MC_1+$GARCH_N$ except for the INP sector.

In all, as proven in preceding subsection 4.3.1 to 4.3.3, 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_1+$GARCH_t$.

5. CONCLUSIONS

In the matter of accuracy, it can be observed that according to Kupiec test, almost all models as applied in the Malaysian market were found to be accurate at 95% level of confidence, whether the evaluation was quantified in a normal or t-distribution circumstances (Table 4.4, 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).

The Christoffersen test also gives almost similar conclusions as in the Kupiec test using the Malaysian data. Almost all models assessed under normal and t-distribution, were estimated to be accurate (Table 4.4, Column 4). Model MC_1+$EGARCH_t$ is not consistent for all observations thus considered to be rejected or inaccurate. 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 4.4, Column 2 and 3). Again, models that fail $LR_{uc,}$ produce coverage probabilities statistically different from the theoretical coverage probabilities. For models that fail $LR_{ind,}$ this is because they fail to capture the volatility dynamics of the return process (Christoffersen, 1998; Christoffersen, Hahn & Inoue, 2001). However, the findings based on Kupiec test and Christoffersen test contradict the findings of studies by Artzner, Delbaen, Eber and Heath (1999), Basak and Shapiro (2001) and Sadorsky (2005) who found that all models filed as normal reject the conditional coverage test.

In the case when the magnitude of the exceptions impact on different VaR models is taken into consideration, the best model to produce superior risk forecast is revealed (Table 4.4, Column 5). As a general conclusion drawn from the Lopez test, the most accurate model under the single variable circumstance is the MC_1+$GARCH_t$. This 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 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. 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. Capabilities of the $GARCH_t$ based model to give the most adequate risk forecast have also been recognized earlier by Lee and Saltoglu (2002), Lin and Shen (2006) and Mohamed (2005).

By examining model-to-model basis, it can be said that MC_1+$GARCH_t$ has better capability to produce superior risk forecasts for the Malaysian non-financial sectors than the other models, particularly more conventional VaR models such as those of $GARCH_N$. The reason for rejecting this normally distributed model 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 normally distributed models are unsuitable modelling approaches and perform quite poorly in the above-mentioned manner (refer among others Giot & Laurent, 2005; Lopez, 1999).

Although 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_1+$GARCH_t$. Perhaps it is due to the fact that assuming EGARCH will work with a t-distribution may not maximize its potential in VaR estimation. Thus, applying other forms of statistical distribution like the Generalized Error Distribution (GED) may be an alternative solution to increase the EGARCH-based model's accuracy. Past research that acknowledges the superiority of EGARCH over EWMA and GARCH include those by Pederzoli (2006) who looked into UK stock data and also Yao, Li and Ng (2006) who concentrated on the Shanghai Stock Exchange Share Index. An almost comparable study which combined a student-t distribution with EGARCH but established this model as being the most adequate VaR forecast was carried out by Angelidis et al. (2003) for five equity indices (CAC40, DAX 30, FTSE100, NIKKEI 225, S&P500). Thus, similar to previous research, this study admits the important role of the characteristics of the volatility process in terms of asymmetry in estimating VaR.

This study is not without any limitations. Firstly, the statistical distributions assumed are limited to normal and student-t distributions. Although each has its own unique capabilities, their ability can be different if used under more extreme conditions. There are other specified statistical distributions to handle these cases (particularly when extreme economic conditions appeared in the data). In this respect, for future research, results can be more robust if distribution classes like Frechet, Weibull and Gumbel distribution are included. This study also focuses on two types of volatility models namely; the GARCH(1,1) and EGARCH(1,1). 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. However, there are also conditions like leverage effect and jump-dynamics that could be considered for extended studies.

As a summary, applying adequate MCS plus volatility models like the MC_1+$GARCH_t$ in various sectors in the Malaysian stock market can deliver better accurate VaR forecasts. Furthermore, where accurate forecasted VaRs are obtained, the prerequisite of the Basel Commitment in backtesting criteria is satisfied. This will enhance investment decision and improve risk estimation particularly for Malaysian investors. Nevertheless, these concluding remarks are very much dependent on the VaR settings; the statistical distribution properties, type of sectors, level of confidences and models involved to measure accuracy.

REFERENCES

Ane, T. (2005). Do Power GARCH models really improve VaR forecasts? *Journal of Economics and Finance, 29*(3), 337-358.

Artzner, P., Delbaen, F., Eber, J. M., & Heath, D. (1999). Coherent measures of risk. *Mathematical Finance, 9*(3), 203-228.

Basak, S. & Shapiro, A. (2001). A value-at-risk based risk management: Optimal policies and asset prices. *Review of Financial Studies.* 14:371-405.

Baumol, W. (1963). An expected gain-confidence limit criterion for portfolio selection. *Management Science.* 10:174-182

Beder, T. (1995). VaR: Seductive but dangerous. *Financial Analysts Journal, 51* (September/October), 12-24.

Brooks, C., & Persand, G. (2003). The effect of asymmetries on stock index return VaR estimates. *The Journal of Risk Finance*(Winter), 29-42.

Christoffersen, P.F. (1998). Evaluating interval forecasts. *International Economic Review.* 39: 841-862

Christoffersen, P.F., Hahn, J., & Inoue, A. (2001). Testing and comparing VaR measures. *Journal of Empirical Finance.* 8: 325-342.

Cifter, A., & Ozun, A. (2007) The Predictive Performance of Asymmetric Normal Mixture GARCH in Risk Management: Evidence from Turkey. Retrieved September 10, 2007, from http://www.gloriamundi.org

Dowd, K. (2005). *Measuring Market Risk.* West Sussex, England: John Wiley & Sons.

Engel, J., & Gizycki, M. (1999). *Conservatism, accuracy and efficiency: Comparing value-at-risk models.* Retrieved September 1, 2005, from http://www.gloriamundi.org

Giot, P. (2005). Implied volatiltiy indexes and daily Value at Risk models. *The Journal of Derivatives*(Summer), 54-64.

Giot, P., & Laurent, S. (2005). Modelling daily value-at-risk using realized volatility and ARCH type models. *Journal of Derivatives*.

Hendricks, D. (1996). Evaluation of value-at-risk models using historical data. Federal Reserve Bank. *Economic Policy Review, 2*(April), 39-70.

Hendricks, D. & Hirtle, B. (1997). Bank capital requirements for market risk: The internal models approach. *FRBNY Economic Policy Review* (December): 1-12

Ho, T. S. Y., Chen, M. Z. H., & Eng, F. H. T. (1996). VAR analytics: Portfolio structure, key rate convexities and VAR betas. *Journal of Portfolio Management, 23*(1), 89-98.

Hull, J., & White, A. (1998). Value at risk when daily changes in market variables are not normally distributed. *Journal of Derivatives, 5*(3), 9-19.

JP Morgan. (1996). *RiskMetrics Technical Document*. New York.

Johansson, F., Seiler, M., & Tjarnberg, M. (1999). Measuring downside portfolio risk. *Journal of Portfolio Management, 26*(1), 96-107.

Jorion, P. (1997). In defense of VaR. *Derivatives Strategy*. 20-23.

Jorion, P. (2002). How informative are Value-at-Risk disclosure. *Accounting Review, V77*(4), 911-931

Kritzman, M., & Risch, D. (2002). The mismeasurement of risk. *Financial Analysts Journal*(May/June), 91-99.

Kupiec, P. (1995). Techniques for verifying the accuracy of risk management models. *Journal of Derivatives*. 3:73-84.

Lee, T.-H., & Saltoglu, B. (2002). Assessing the risk forecasts for Japanese stock market. *Japan and the World Economy, 14*, 63-85.

Lin, C.H., & Shen, S.S. (2006) Can the student-t distribution provide accurate Value at Risk? *The Journal of Risk Finance,* 7(3), 292-300.

Lopez, J.A. (1999). Regulatory evaluation of value-at-risk models. *Journal of Risk* 1: 37-64.

Luciano, E., & Marena, M. (2002). Portfolio value at risk bounds. *International Transactions in Operational Research*(9), 629-641.

Mohamed, A. R. (2005). *Would Student's t-GARCH Improve VaR Estimates.* University of Jyvaskyla. Retrieved August 2, 2006, from http://www.gloriamundi.org

Papadamou, S., & Stephanides, G. (2004). Evaluating the styled-based risk model for equity mutual funds investing in Europe. *Applied Financial Economics*(4), 751-760.

Pederzoli, C. (2006) Stochastic volatility and GARCH: A comparison based on UK stock data. *The European Journal of Finance,* 12(1), 41-59.

Sadorsky, P. (2005). Stochastic volatility forecasting and risk management. *Applied Financial Economics*(15), 121-135.

Seymour, A. J., & Polakow, D. A. (2003). A coupling of extreme-value theory and volatility updating with Value-at-Risk estimation in emerging markets: A South African test. *Multinational Finance Journal, 7*(1&2), 3-23.

Sinha, T., & Chamu, F. (2000). *Combining Different Methods of Calculating Value at Risk*. Retrieved September 1, 2005, from http://gloriamundi.org

Venkataraman, S. (1997). Value at risk for a mixture of normal distribution: The use of Quasi-Bayesian estimation techniques. Federal Reserve Bank of Chicago. *Economic Perspectives*(March/April), 2-3.

Yao, J., Li, Z.S., & Ng, K.W. (2006) Model risk in VaR estimation: An empirical study. *International Journal of Information Technology & Decision Making.*

Table 4.1: Basic Statistics of the Full Sample

	INP	**PRP**	**TAS**
Mean	-0.0002	-0.0004	-3.99E-05
Std Dev	0.0154	0.0187	0.0169
Skewness	-0.5700	0.6349	0.8322
Kurtosis	41.7549	21.0114	32.9321

JB	215402.20 *(0.0000)* ***	46731.86 *(0.0000)* ***	128776.00 *(0.0000)* ***
LB(20)r^2	1721.00 *(0.0000)* ***	1732.7 *(0.0000)* ***	1370.10 *(0.0000)* ***
ARCH-LM(1)	1433.05 *(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 (Symbol used): Industrial Product (INP), Property (PRP), Trade & Service (TAS*

Table 4.2: Estimation Results of GARCH-based Model

Panel A: GARCH(1,1)$_N$				
	ω	α_1	β_1	$\alpha+\beta$
INP	2.31E-06 (7.68E-07)***	0.1154 (0.0191)***	0.8644 (0.0153)***	0.9798
PRP	3.95E-06 (1.10E-06)***	0.1400 (0.0258)***	0.8494 (0.0204)***	0.9894
TAS	1.64E-06 (7.50E-07)**	0.0969 (0.0146)***	0.9030 (0.0149)***	0.9999
Panel B: GARCH(1,1)$_t$				
	ω	α_1	β_1	$\alpha+\beta$
INP	2.77E-06 (6.78E-07)***	0.1188 (0.0177)***	0.8673 (0.0126)***	0.9861
PRP	4.02E-06 (5.95E-07)***	0.1626 (0.0115)***	0.8291 (0.0101)***	0.9917
TAS	3.33E-06 (8.15E-07)***	0.1188 (0.0152)***	0.8789 (0.0119)***	0.9977
Panel C: EGARCH(1,1)$_t$				
	ω	α_1	β_1	δ
INP	-0.3306 (0.0460)***	0.2362 (0.0239)***	0.9809 (0.0043)***	-0.1055 (0.0337)***
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)***

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 4.3: 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)
INP	GARCH(1,1)$_N$	-0.0491	0.9993	10.5060 (0.9580)	2.9412 (0.8644)
	GARCH(1,1)$_t$	-0.0185	0.9701	10.1040 (0.9660)	3.7316 (0.5349)
	EGARCH(1,1)$_t$	0.0141	0.9700	13.6440 (0.8480)	1.3097 (0.2568)
PRP	GARCH(1,1)$_N$	-0.0164	1.0003	18.4780 (0.5560)	4.4864 (0.3425)

	GARCH(1,1)$_t$	-0.0114	1.0579	15.6070 (0.7410)	2.2918 (0.1302)
	EGARCH(1,1)$_t$	0.0398	0.9710	21.8980 (0.3460)	7.3816 (0.6628)
TAS	GARCH(1,1)$_N$	-0.0328	1.0004	15.1470 (0.7680)	1.6143 (0.2040)
	GARCH(1,1)$_t$	-0.0114	0.9788	12.8250 (0.8850)	0.4745 (0.4909)
	EGARCH(1,1)$_t$	0.0194	0.9804	13.0830 (0.8740)	2.0477 (0.1525)

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.*

Table 4.4: Accuracy Test - Forecasting Performance Summary for Different VaR Models at 95% Confidence Level

	LRuc	LRind	LRcc	AQLF
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
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 and LRind follow asymptotically x(1) with critical value 3.84. LRcc is asymptotically x2 distributed with critical value 5.99.*

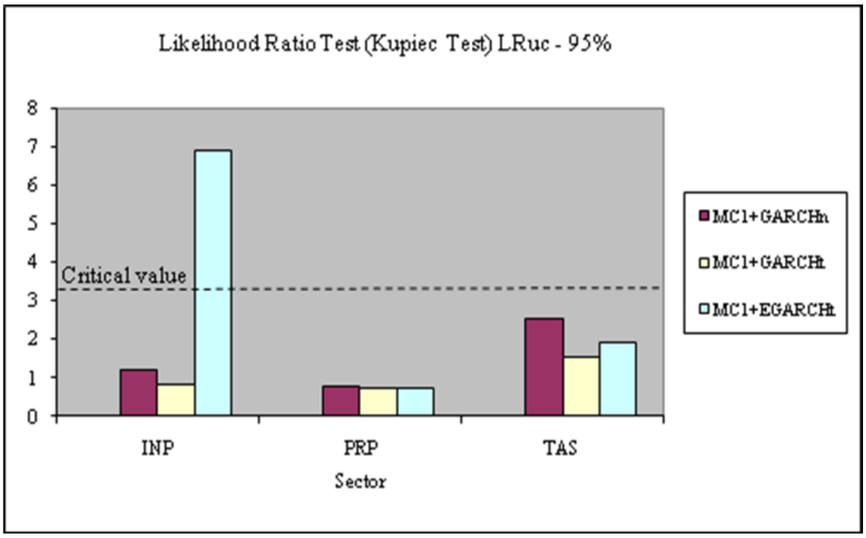

Figure 4.1: Likelihood Ratio Test (Kupiec Test) LR_{uc} – 95%

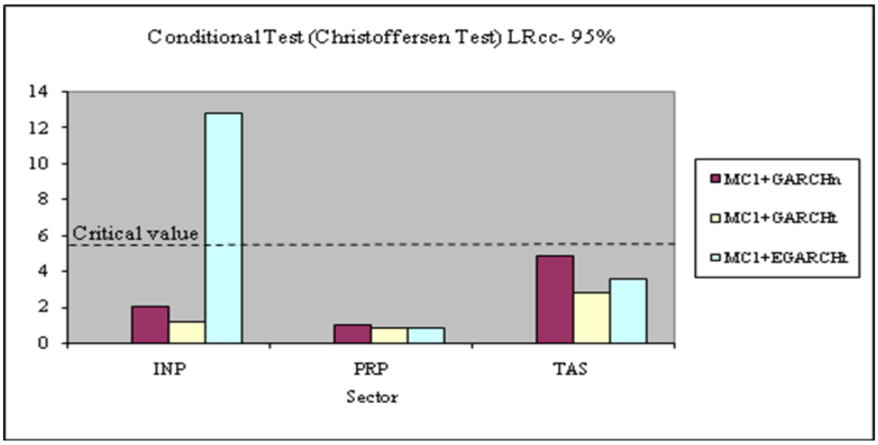

Figure 4.2: Conditional Test (Christoffersen Test) LR_{cc} – 95%

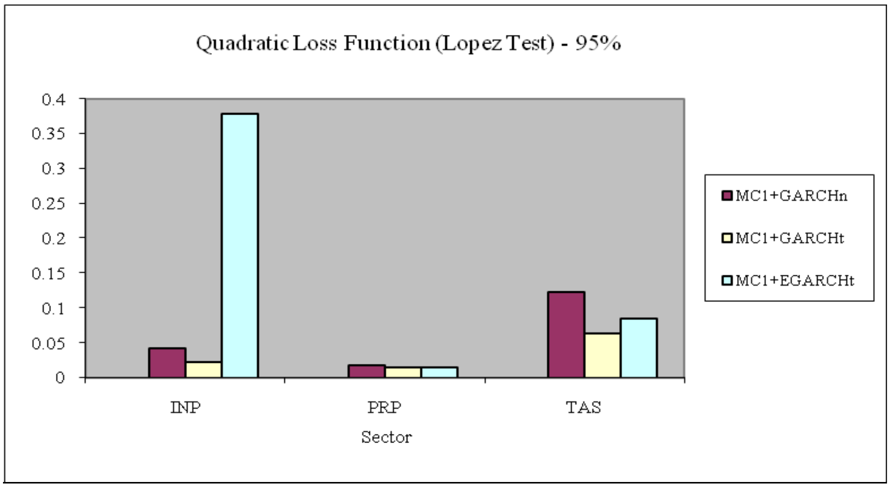

Figure 4.3: Quadratic Loss Function (Lopez Test) – 95%