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MALAYSIAN STOCK MARKET AND MARKET RISK MODELS

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ABSTRACT

The objective of this study is to test the conservatism level of Value-at-Risk (VaR) models that are integrated with several volatility representations in estimating the market risk for the Malaysian stock market. By applying to the non-financial sectors data, the expected maximum losses and conservatism degree were quantified for VaR models at 95% confidence level. In summary, this study indicates that consideration of volatility modelling is important when deciding the appropriate VaR models in managing market risk.

KEYWORDS: Value-At-Risk, Volatility Modelling

INTRODUCTION

Value-at-Risk (VaR) summarizes the worst expected loss that an institution could suffer over a target horizon under normal market conditions at a given confidence level (Dowd, 2005; Jorion, 2006). Since the introduction of the simplest VaR models, a range of approaches to calculate VaR has expanded from two important perspectives; number and complexity. Many techniques of VaR have been developed by many researchers in an attempt to minimize risk. The traditional ones are the Risk Metrics variance-covariance method (VCV), historical simulation (HS) and non-volatility based Monte Carlo simulation (MCS).

Despite the widespread use of VaR to evaluate risk of portfolio, the traditional VaR approaches have several shortcomings, most noticeably when VaR modelling is very much influenced by main sources of bias; heavy-tails and volatility clustering. However, the extent to which the VaR behaviours are affected by these circumstances is not known. Heavy-tailed circumstances as cited by Bali and Cakici (2004) and Cotter (2004) will happen more frequently than would be predicted by the normal distribution (sometimes referred to as the Gaussian distribution). These authors highlighted that 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. However, maintaining a normality assumption and failure to account for any financial time series imperfection will undoubtedly lead to underestimating or overestimating VaR (Danielson & de Vries, 1997; Kritzman & Risch, 2002; Mohamed, 2005).

In addition, as noted by Danielson (2002) it has been widely agreed that VaR models should be used cautiously by means of integrating several backtesting procedures. This approach is essential because it can, not only quantify which is the best model, it can also help to determine the conservatism level of a chosen VaR methodology. An example from Christoffersen (2003) shows that daily historical VaRs plus the profits and losses exhibit a strong tendency for VaR violations (i.e. losses larger than the true VaR) to occur on adjacent days. This clustering of VaR violations is a sign of serious model misspecification. Thus observations must be complemented with a rigorous conditional backtesting approach.

In line with the above statements, this study is carried out with the intention to compare the performances of VaR models from the perspective of conservatism level in particular for the non-financial sectors in the Malaysian market. The flow of the paper covers section 2 which provides the literature review of the study. Section 3 describes the dataset and methodology of the study which include the technical approaches used to test the conservatism of the model. Section 4 highlights the results and finally section 5, on the summary of the study's findings as well as limitations.

LITERATURE REVIEW

The study of VaR has been experiencing rapid development since its formal introduction to market users by Risk Metrics in 1994. The main reason underlying this awareness is the growing concern of risk among market participants and financial institutions. The diverse estimation techniques of VaR to represent an adequate differentiation analysis are the focal point of attempts to assist financial risk management practices. Thus, many techniques of VaR have been developed by many researchers in an attempt to minimize risk. These include the variance-covariance method, historical simulation and Monte Carlo simulation.

The reasoning behind the application of VaR to financial risk is highlighted by several studies; among others, Alexander (1998), Dowd (2005), JP Morgan (1996) and Rahl and Esseghaier (2000). Collectively, their main concerns were to measure and manage the market risk within certain parameters and selected conditions. Urbani (2004) report that the most important strength of VaR is its ability to aggregate several market risk sources into one quantitative measure of a portfolio's potential value change. This single number is able to explain specifically the probability of adverse movement and a firm's exposure to downside market risk. Unlike beta estimation, standard deviation, duration or surplus ratio, VaR is measured in monetary value (Panning, 2001). And even though VaR may not be used directly as a preferred risk measure, Dowd (2005) adds that estimating these quantile can be an important input to alternative risk measure, such as coherent and other risk measures based on weighted average of quantile.

Back Testing

The term backtesting is also referred to as 'financial risk model evaluation' (Christoffersen, 2003). Backtesting is used to investigate the performance of various VaR methods with respect to specific parameters. It is one of the required procedures made compulsory by regulators to be carried out by financial institutions. As reflected in Teker and Akcay (2004), this procedure helps to test and compare the quality of alternative VaR estimation approaches. An earlier study by de Raaji and Raunig (1998) who back tested the relationship between underestimated VaR values and the methodology, also reached similar intentions. They used VCV, HS and MCS as models representing the methodology. By using the data of an equally weighted portfolio of thirteen foreign exchanges, from 1986 to 1998, the backtesting results were consistent with earlier notions that methods which do not incorporate excess kurtosis tend to underestimate VaR with respect to the specified confidence level.

Jorion (2002) agreed that backtesting is an important procedure to support VaR quantification. Highlighting five models, namely the normal, student-t, HS, EWMA-Normal and EWMA-HS for daily US market data ranging from 1980 until 2001, he showed that backtesting is essential to help reduce a model's biasness which can accumulate low average VaR. With the lowest bias, the best overall model in this study was the student-t model. Besides that, there were also prior literatures that looked into the importance of associating backtesting practices and the length of data. Lin and Chien (2006) and Lin, Chien and Chen (2005) for examples stressed that model evaluation must accommodate VaR estimation if the data covers a long horizon. This is because the evaluation result may explain the performance of respective models sufficiently under different market structures.

A comprehensive study conducted by Engel and Gizycki (1999) have identified one of the important perspective that need to be highlighted when VaR evaluations are made; level of conservatism. Among the main intention to execute this procedure, is to identify VaR model that is best suited when used to measure risk exposures. Their in-depth observation of performance assessment which covers four classes of VaR models (namely, the VCV, HS, MCS and extreme value), can be seen as a breakthrough study that verifies conservatism test is crucial to support the process of determining the best VaR models.

Conservatism Test

Conservative models are those with relatively high-risk estimate sizes. Among the studies that emphasized this test are those done by Engel and Gizycki (1999), Bredin and Hyde (2004), Lin et al. (2005) and Lin and Chien (2006). The study by Engel and Gizycki (1999) attempts to measure each model's relative size and variability according to both the mean relative bias and root mean squared relative bias. The study illustrates that although the normal mixture based MCS requires higher computing power, it is more conservative than other VaR models. Bredin and Hyde (2004) for example adopted similar methodology and found that the EWMA was more conservative compared to other selected VaR forecasts models namely the EQMA, Orthogonal GARCH (OGARCH) and HS. They concluded that the high underlying values of VaR and the suitability of the method are the reasons for this outcome.

By applying an updating technique on HS for several indices data ranging from 1990 until 2001, Lin et al. (2005) revealed that considering volatility as an additional parameter when selecting VaR model is critical. This is because deciding whether a model is statistically conservative can be influenced by the estimated volatility of the model.

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 the non-financial sectors as indicated by Sanders and Manfredo (1999) is due to the fact that limited studies on VaR are done from the perspectives of non-financial firms. Besides that, the reason to examine sectorial behaviour as indicated by Darrat and Mukerjee (1995) is because 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).

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

According to Dowd (2005), given the degree of confidence level α, holding period h and considering the return series r_{t+h} of a financial asset which denotes the portfolio wealth at time t and the portfolio return at time $t + h$, $VaR_t(h)$, can be defined as the conditional quantile as follows:

$$\Pr [r_{t+h} < VaRt(h)] = \alpha \tag{3.1}$$

Theoretically, VaR can be presented as:

$$VaR_t = W_t \alpha \sigma \sqrt{\Delta t} \tag{3.2}$$

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

The study is conducted based on two cases. First, for normal distribution, the study will implement two groups of conditional volatility models; the Risk Metrics Exponentially Weighted Moving Average (EWMA) and the Generalized Autoregressive Conditional Heteroscedasticity (GARCH). Second, for t-distribution the study applies the GARCH (t-distribution) and the Exponential GARCH (EGARCH) model.

Risk Metrics EWMA

This model 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). 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:

$$\hat{\sigma}_t^2 = (1-\lambda)\sum_{i=0}^{\infty} \lambda^{i-1} x_{t-i} \tag{3.3}$$

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

GARCH Normal-Distribution

To capture inadequate tail probability as portrayed in Risk Metrics 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 σ_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:

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

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:

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

where $\omega > 0$ and α, $\beta \geq 0$. 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 3.5, the GARCH-t is then expressed according to equation 3.6 for which $\mu = v_t \sqrt{h_t}$ where $v_t \sim \boldsymbol{t}(0,1,\upsilon)$ 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).

$$f(t \mid \nu) = \Gamma\left(\frac{\nu+1}{2}\right) / \sqrt{\pi(\nu-2)} / \Gamma(\nu/2)\left(1 + \frac{t^2}{\nu-2}\right)^{-(\nu+1)/2} \tag{3.6}$$

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

$$\ln \sigma_t^2 = \alpha + g(z_{t-1}) + \beta \ln \sigma_{t-1}^2 \tag{3.7}$$

Where

$$g(z_t) = \omega z_t + \lambda\left(|z_t| - \sqrt{\frac{2}{\pi}}\right) \tag{3.8}$$

Test of Conservatism

The test is conducted to determine VaR models with relatively high-risk estimates size (Engel & Gizycki, 1999). The first measuring degree is the mean relative bias and secondly, the root mean squared relative bias [refer also Hendricks (1996)].

Mean Relative Bias (MRB)

Given T is the time periods, N is the number of risk assessment models to be measured, the MRB of model i is given by the following equation:

$$MRB_i = \frac{1}{T}\sum \frac{VaR_{it} - \overline{VaR_i}}{\overline{VaR_t}} \quad \text{where} \quad \overline{VaR_t} = \frac{1}{N}\sum_{i=1}^{N} VaR_{it} \tag{3.9}$$

The larger the value of MRB, the more conservative a model is.

Root Mean Squared Relative Bias (RMSRB)

RMSRB is an elaboration of the MRB measure (Hendricks, 1996). Similar to the standard deviation concept, RMSRB measures the degree or risk measurement deviation from the mean VaR of all models. The equation is computed as follows:

$$RMSRB_i = \sqrt{\frac{1}{T}\sum_{i=1}^{T}\left(\frac{VaR_{it} - \overline{VaR_t}}{\overline{VaR_t}}\right)^2} \quad \text{where } \overline{VaR_t} = \frac{1}{N}\sum_{i=1}^{N} VaR_{it} \tag{3.10}$$

The larger the value of RMSRB, the larger will be the degree of risk measurement deviation.

RESULTS

Volatility Model Summary

Table 1 displays the results of estimated future volatility or σ_t^2 for Risk Metrics 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.

For GARCH$(1,1)_N$ the overall results of parameter ω,α and β are found to satisfy the condition; ω>0 and α, $\beta \geq 0$ (Panel A, Table 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 (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, $\beta \geq 0$. 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.

Looking at EGARCH$(1,1)_t$, all the conditional variance equation coefficients, inclusive of the results of asymmetry coefficient δ, are significantly different from zero. This supports the existence of asymmetric impacts of returns on conditional variance.

Back Testing Result: Conservatism Test

The idea of testing the conservatism level between various models is to examine whether a model produces higher risk relative to other alternative models. The more conservative is the model, the higher the risk (Hendricks, 1996). Table 3 provides the output details.

Mean Relative Bias (MRB)

At the 95% confidence level, the MRB for each of the non-financial sectors tends to fall between -0.006 and 0.006, indicating that there is slight difference in the magnitude of risk estimates across most of the models. Outstanding exceptions are PRP (MCS_1+$EGARCH_t$) and TAS (MCS_1+$GARCH_t$) that produce larger MRB, while COP (MCS_1+$EGARCH_t$) and TAS(MCS_1+$EGARCH_t$) recorded MRB at lower values. On a sector-by-sector basis, starting from CON, the most conservative is MCS_1+$EGARCH_t$. A similar condition also applies to sector PRP. The INP, PLN, TAS and TIN share a similar model; that is MCS_1+$GARCH_t$, while for COP, on the other hand, all its models produce low risk estimates. Nonetheless for COP, MCS_1+RM_n have the highest point compared with other alternative models. Overall for 95%, MCS_1+$GARCH_t$ has the tendency to produce more conservative risk estimates in comparison with other simulated models, even though in a certain case MCS_1+$EGARCH_t$ portrays similar traits. These results suggest that though t-distribution theoretically is appropriate for handling any reasonable amount of fat tail or asymmetric biases it, however, is more conservative compared to a normal distribution when making any prediction for an investment's worst loss. Generally, the outputs across the seven non-financial sectors indicate that the t-distribution models perform better where the most variable result at 95% is produced by MCS integrated with $GARCH_t$.

Root Mean Squared Relative Bias (RMSRB)

An extension to MRB as suggested by Hendricks (1996) is the RMSRB that captures the variability of a model's risk estimates as well as the extent to which a model's average differs systematically from all model averages. From Table 3, it can be observed that the RMSRB of 95% falls between 0.01 and 0.025. Of all the four VaR models, two models under t-distribution (MCS_1+$GARCH_t$ and MCS_1+$EGARCH_t$) demonstrate a more conservative position. This is in accordance with earlier findings of MRB (Bredin & Hyde, 2004; Engel & Gizycki, 1999).

CONCLUSIONS

The main conclusion is that the selection of a suitable model to compute and forecast VaR is very crucial. The empirical results showed that the GARCH-based models are the most conservative model at 95% level of confidence of MRB and RMSRB (Table 3). This study indicates that the VaR has higher values when it is calculated using MCS simulated with GARCH-based than MCS simulated with Risk Metrics EWMA. Thus, higher MRB and RMSRB are obtained. Following the statistical evaluation measures, these models have higher tendency to vary around the all-models average. The relative conservatism of these models is very much dependent on the composition of the VaR values of each non-financial sector traded within the equity market (Engel & Gizycki, 1999; Pederzoli, 2006). These findings however are not in line with the study of Bredin and Hyde (2004) who stipulated that the Risk Metrics EWMA model (using Irish FOREX trading data) has a higher degree of conservatism compares to the GARCH-based models.

This study is not without any limitations. Firstly, the statistical distribution assumed is limited to only normal and student-t distributions. Future study can be more robust if distribution classes like Frechet, Weibull and Gumbel distribution were included to handle more extreme conditions. This study also focuses on two types of volatility models namely; 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 circumstances like leverage effect and jump-dynamics that could be considered. In short, adopting backtesting such as conservatism test helps minimize model risk which makes it possible to increase the efficiency of the financial risk management process. Furthermore, this study indicates that consideration of volatility modelling is important when deciding the appropriate VaR models in managing market risk.

REFERENCES

1. Alexander, C. (1998). Risk Management and Analysis: Measuring and Modelling Financial Risk (Second ed. Vol. 1). England: John Wiley & Sons, Ltd.

2. Bali, T. G., & Cakici, N. (2004). Value at Risk and expected stock returns. Financial Analysts Journal (March/April), 57-73.

3. Bollerslev, T. (1986). Generalized autoregressive conditional heteroscedasticity. Journal of Econometrics, 31, 307-327.

4. Bredin, D., & Hyde, S. (2004). FOREX risk: Measurement and evaluation using VaR. Journal of Business Finance & Accounting, 31(9&10), 1389-1417.

5. Christoffersen, P. F. (2003). Meaningful risk measures. Canadian Investment Reviews (Winter), R15.

6. Cotter, J. (2004). Downside risk for European Equity Markets. Applied Financial Economics (14), 707-716.

7. Damodaran, A. (2005). Value and risk: Beyond betas. Financial Analysts Journal, 38-43.

8. Danielsson, J., & de Vries, C. G. (1997). Value-at-Risk and extreme returns. Retrieved July 14, 2000, from http://www.gloriamundi.org

9. Darrat, A.F., & Mukherjee, T.K. (1995) Inter-industry differences and the impact of operating and financial leverages on equity risk. Review of Financial Economics, 4, 141-156

10. De Raaji, G., & Raunig, B. (1998). A comparison of Value at Risk approaches and their implications for regulators. Focus on Austria (4), 57-71.

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

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

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

14. JP Morgan. (1996). Risk Metrics Technical Document. New York.

15. Jorion, P. (2002). Fallacies about the effects of market risk management systems. Financial Stability Review, 115-127.

16. Jorion, P. (2006). Value at Risk: The New Benchmark for Controlling Market Risk. (Third ed.) Chicago: Irwin.

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

18. Lin, C, H., & Chien, C.C.C. (2006) Incorporating a GED model into the historical simulation for Value-at-risk. Review of Pacific Basin Financial Markets and Policy, 9(2), 257-274

19. Lin, C. H., Chien, C. C. C., & Chen, S. W. (2005). A general revised historical simulation method for portfolio VaR. The Journal of Alternative Investments (Fall), 87-103.

20. Mat Nor, F., Yakob, N. A., & Isa, Z., (1999). ARCH and GARCH based tests on the Malaysian stock market, interest rate and exchange rate before and during the currency turmoil. Capital Markets Review, 7, 87-99.

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

22. Nelson, D.B. (1991). Conditional Heteroscedasticity in asset returns: A new approach. Econometrica. 59(2): 347-370.

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

24. Rahl, L., & Esseghaier, Z. (2000). Measuring financial risk in the 21st century. Bank Accounting and Finance, 45-54.

25. Teker, S., & Akcay, B. (2004). Value at Risk (VaR) computation under various VaR models and stress testing. Journal of Transnational Management Development. 47-67.

26. Urbani, P. (2004). All about Value at Risk. Finance Week (Summer), 12-13.

Table 1: Estimation and Diagnostic Tests Results of Risk Metrics EWMA

	λ = 0.94	Mean of Conditional Volatility $E(\mu_1/\sigma_1)$	Variance of Conditional Volatility $E(\mu_1/\sigma_1)^2$	Volatility Skewness	Volatility Kurtosis
CON	0.0056	-0.0430 (0.9875)**	0.9743	0.2671	5.6283
COP	0.0032	-0.0171 (0.9991)	0.9974	0.3088	11.3493
INP	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 parentheses.

2. *, ** and *** denote significance at 10%, 5% and 1% levels.

3. λ, represents the decay factor.

Table 2: Estimation Results of GARCH-Based Model

Panel A: GARCH(1,1)$_N$				
	ω	α_1	β_1	α+β
CON	4.64E-06 (1.79E-06)***	0.0900 (0.0142)***	0.9017 (0.0146)***	0.9917
COP	6.19E-07 (1.17E-06)	0.0691 (0.0223)***	0.9305 (0.0332)***	0.9996
INP	2.31E-06 (7.68E-07)***	0.1154 (0.0191)***	0.8645 (0.0153)***	0.9799
PLN	2.81E-06 (9.04E-07)***	0.1431 (0.0197)***	0.8542 (0.0195)***	0.9973
PRP	3.95E-06 (1.10E-06)***	0.1400 (0.0258)***	0.8495 (0.0204)***	0.9895
TAS	1.64E-06 (7.50E-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
Panel B: GARCH(1,1)$_t$				

	ω	α_1	β_1	$\alpha+\beta$
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
INP	2.77E-06 (6.78E-07)***	0.1188 (0.0177)***	0.8674 (0.0126)***	0.9862
PLN	3.67E-06 (8.51E-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	2.18E-05 (5.60E-06)***	0.1798 (0.0354)***	0.8072 (0.0158)***	0.9870
Panel C: EGARCH(1,1)$_t$				
	ω	α_1	β_1	δ
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)***
INP	-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.

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 3: Conservatism Test - Forecasting Performance Summary for Different VaR Models at 95% Confidence Level

		MRB	**RMSRB**
CON	MC_1+RM_N	0.0038	0.0123
	MC_1+$GARCH_N$	0.0029	0.0128
	MC_1+$GARCH_t$	-0.0031	0.0164
	MC_1+$EGARCH_t$	0.0048	0.0165
COP	MC_1+RM_N	-0.0001	0.0169
	MC_1+$GARCH_N$	-0.0006	0.0169
	MC_1+$GARCH_t$	-0.0024	0.0221
	MC_1+$EGARCH_t$	-0.0069	0.0217
INP	MC_1+RM_N	-0.0018	0.0156
	MC_1+$GARCH_N$	-0.0047	0.0170
	MC_1+$GARCH_t$	0.0037	0.0225
	MC_1+$EGARCH_t$	0.0023	0.0216
PLN	MC_1+RM_N	-0.0038	0.0175
	MC_1+$GARCH_N$	-0.0032	0.0169

	MC_1+$GARCH_t$	0.0041	0.0216
	MC_1+$EGARCH_t$	0.0004	0.0224
PRP	MC_1+RM_N	0.0041	0.0165
	MC_1+$GARCH_N$	0.0016	0.0164
	MC_1+$GARCH_t$	-0.0036	0.0218
	MC_1+$EGARCH_t$	0.0068	0.0215
TAS	MC_1+RM_N	0.0022	0.0166
	MC_1+$GARCH_N$	0.0026	0.0166
	MC_1+$GARCH_t$	0.0068	0.0232
	MC_1+$EGARCH_t$	-0.0059	0.0218
TIN	MC_1+RM_N	0.0012	0.0167
	MC_1+$GARCH_N$	-0.0009	0.0171
	MC_1+$GARCH_t$	0.0038	0.0224
	MC_1+$EGARCH_t$	-0.0051	0.0220