Measuring Risk Models' Efficiency: The Case for the MALAYSIA Market

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Abstract

The intention of this paper is to determine the most efficient risk model which can be implemented in diverse business sectors of an economy. The methodology involved using Value-at-Risk (VaR) technique with the integration of GARCH-based representation on three selected non-financial sectors in Malaysia. Using time-series data from 1993 until 2010, the efficiency test namely the Mean Relative Scaled Bias (MRSB) is then conducted. The evidence showed that the VaR forecast integrated with t-distribution GARCH has better capabilities to track movements in true risk exposures thus suggesting it as the most efficient model within specific assumptions and constraints.

Keywords Value-at-risk, efficiency test, mean relative scaled biased (two more keywords)

INTRODUCTION

The tremendous evolution since the 1970s in risk management practices coupled with innovation of financial engineering instruments have several distinctive effects, depending on the nature of business (Basle Committee, 1994; Dowd, 2005; Fong & Vasicek, 1997; Gastineau, 1993; Holton, 2003; Ibrahim, 1994). One of the effects is that by combining fundamental and analytical techniques to create new risk evaluation approaches, the process will be in a much better form to prevent larger financial losses. As indicated by several observers such as Brooks and Persand (2002) and Rahl and Lee (2000), viewing different kinds of business and investment portfolios based on an effective risk measurement tool is crucial in order to maximize returns and minimize risk.

Nonetheless, JP Morgan (1996) highlighted that the absence of a common point of an efficient reference for market risks makes it difficult to compare different approaches towards the measurement of market risks. As noted by Nath and Reddy (2003), should the underlying risk not be properly estimated, it will lead firms to a lower profit level and jeopardize the financial stability condition, since less optimum capital is allocated throughout the organization. Thus, the growing need for better empirical investigations or modelling techniques to evaluate alternative measures of risk, says Brachinger (2002), should be further explored to avoid inappropriate policy decisions which can affect a firm stakeholders in particular investors.

With regards to this manner, the intention of this paper is to determine the most efficient risk model which can be implemented in diverse business sectors of an economy. To address the issue, a sample of three non-financial sectors from the Malaysia market is chosen and tested using Value-at-Risk (VaR) technique integrated with GARCH-based representations. The detail outline of the paper covers section 2 on the literature review. Section 3 highlights the research methodology while section 4 on the results. The conclusion as in section 5 summarizes the findings, limitations and suggestions for future research.

LITERATURE REVIEW

VaR can be defined theoretically as a summarization of the worst expected loss over a target horizon under normal market conditions at a given confidence level that an institution could suffer (Butler, 1999; Dowd, 2005; Jorion, 1997 & 2006). It basically links how confident an investor is on a particular investment on a certain holding period considering simultaneously any volatile movements in the market.

As cited by Urbani (2004), due to the urgent need for a single risk measure in order to establish the capital adequacy limits for banks and other financial institutions, VaR is slowly replacing standard deviation or volatility as the most widely used measure of risk. Johansson, Seiler and Tjarnberg (1999) 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.

Since the introduction of the simplest VaR models, a range of approaches to calculate VaR has expanded from two important perspectives; number and complexity. These include the variance-covariance method (VCV), historical simulation (HS) and Monte Carlo simulation (MCS). Nonetheless added Urbani (2004), as one of several alternatives to portray risk, VaR has so far not been exploited extensively in explaining financial assets' hazardous return behaviour within specific parameters, assumptions and data characteristics.

Evaluating Efficiency

Efficiency portrays that a good risk measure is to be strongly correlated with the portfolio's true risk exposure (Engel and Gizycki, 1999). It is the extent to which each model tracks movements in the true risk exposures. Both authors in a study of foreign-exchange portfolios of 54 banks in Australia highlight three aspects of model efficiency that need to be looked upon. First, the model's capacity in providing adequate risk coverage with the minimum average capital; second, the correlation between VaR measures and the size of profits and losses; and finally, the extent to which the distribution underlying each VaR model matches the observed profit and loss distribution. Engel and Gizycki (1999) also stressed that several quantitative applications can be employed to evaluate a model's efficiency level. The crucial one is mean relative scaled bias, while additional quantifications include correlation, uniform percentiles and the autocorrelation in percentiles.

In a more advance manner where the models are integrated with several volatility representations, Chiu, Lee and Hung (2005) compared the efficiency level between jump-dynamics (GARJI, ARJI) and GARCH on Dow Jones industry index, S&P stock index plus Japanese yen from January 1990 to December 2003. The outputs suggested that the most efficient model was GARJI because it contained jump-component in the price evolving process. Another study on foreign exchange rates by Dunis and Chen (2005) clearly provide evidence that VaR efficiency can be improved when design choices such as combination of several time series model and market data volatility are included (see also Lin & Chien, 2006; Lin, Chien and Chen, 2005; Venkatesh, 2003).

RESEARCH METHODOLOGY

Theoretical Formula of VaR

From Dowd (2005), VaR measures the market risk for a portfolio of financial assets with a given degree of confidence level a 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 $\text{VaR}_t(\text{h})$, can be defined as the conditional quantile as follows:

$$\Pr\left[rt+h < \text{VaRt}(h)\right] = \alpha \qquad \text{(Equation 1)}$$

Assuming r_t follows a general distribution, f_t, VaR under a certain chosen *h* and a gives:

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

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. Thus,

$$VaR_t = W_t \alpha\sigma\sqrt{\Delta t} \qquad \text{(Equation 3)}$$

VaR Generating and Evaluation Process

Figure 1 summarizes the overall process involved in generating and evaluating VaR based on the Monte Carlo Simulation (MCS).

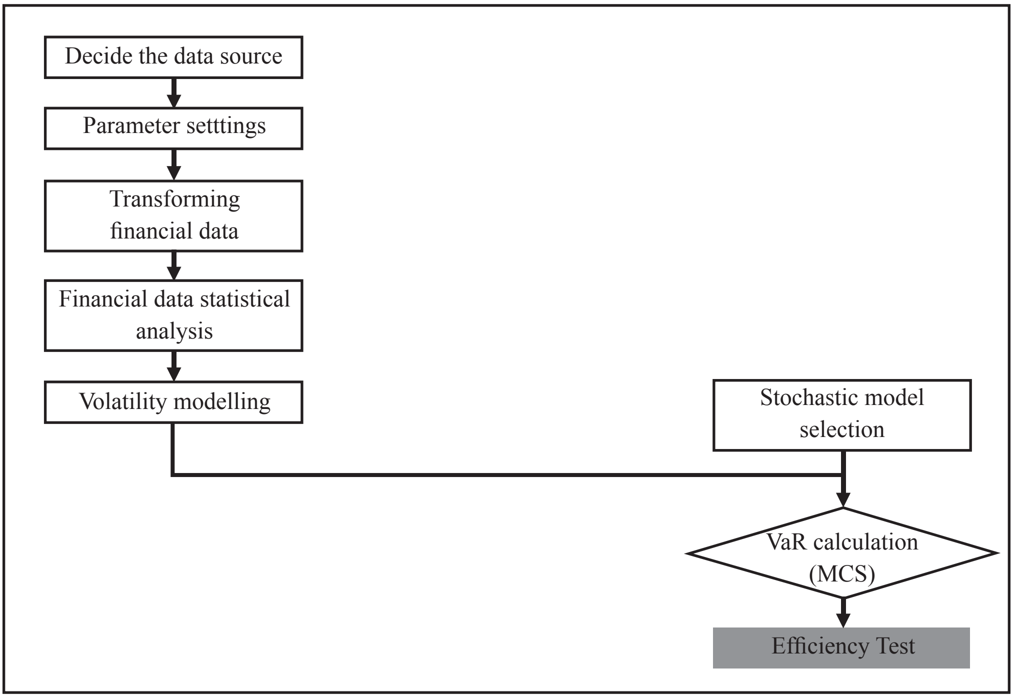

Figure 1 Overview of the Quantification and Evaluation Process of VaR based on MCS. [An adaptation from Jorion (2006) page 200]

Data

The data covers time series indices of three non-financial sectors traded in the first board of Bursa Malaysia from year 1993 until 2010. The non-financial industries are represented by sectors of Industrial Product (INP), Property (PRP) and Trade and Services (TAS) sectors. The three non-financial sectors are selected based on the highest accumulated amount for market capitalization documented on January, 2011. Only non-financial sectors are considered due to the fact that firms underlying the financial sector in an economy have different regulatory background (Ibrahim & Mazlan, 2006). By nature, the financial based firms can be very volatile, apart from having accounting variables' presentation which is dissimilar to other industries (Abdullah & Nordin, 2006; Baharumshah & Almasaied, 2005).

The data set is then divided into two parts. The first part, covering the years from 1993 until 2008, is used to estimate the volatility parameters. This sample period is chosen because it includes different economic conditions and includes complete data information; appreciation, depreciation and unchanged values. The second part; 2009 until 2010, is used for VaR models' efficiency testing (Mohamed, 2005; Pederzoli, 2006).

VaR Parameter Settings

Holding Period: Holding period refers to the trading horizon for buying and selling transactions for each stock (e.g. if a stock is bought yesterday and sold today, the holding period is 1-day). A 1-day holding period is selected to include portfolios that show rapid turnover (Jorion, 2006).

Confidence Level: Given the definition by RiskMetrics and the Basle proposal, for the purpose of reporting and comparing VaR numbers, this research has selected confidence interval that is set at 95 percent.

Transforming Financial Data

The daily stock return is defined as natural log return of its gross return.

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) \quad \text{(Equation 4)}$$

Where; P_t – price of a security at date t,
t – represents one business day
r_t – log price change (or continuously compounded return)

Financial Data Statistical Analysis

Testing for Stationarity:

Two unit root tests to determine data stationarity are the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test.

Measure and Test of Moment Significance:

A further measure is the testing of sample statistics' significance level to see if the statistics are significant from the null hypotheses test: Mean (μ) = 0, Skewness (Sk) = 0 and kurtosis (Ku) = 0.

Testing for Departures from Normality:

The Jarque-Bera test is a joint test of skewness and excess kurtosis (third and fourth moment respectively) for departures from normality. This test will to determine whether the coefficient of skewness and excess kurtosis are jointly zero.

Volatility Modelling

Three volatility models are used in the study as being part of the parameters for VaR; GARCH$(1,1)_N$ under the assumption of normal distribution and for t-distribution both GARCH$(1,1)_t$ and EGARCH$(1,1)_t$.

Stochastic Model Selection

The next step involves selecting the stochastic model that underlies the VaR estimation using the MCS. This process is essential since it governs the asset pricing dynamics. In this matter, one of the most common characteristics of the Monte Carlo method according to Dowd (2005) and Jorion (1997) involves the assumption that the market rates follow a joint geometric Brownian motion (GBM) process with the characteristics of a constant drift and volatility parameters as follows,

$$dp(t) = \mu(t)p(t)dt + \sigma(t)p(t)dZ(t) \qquad \text{(Equation 5)}$$

and, implying the stochastic integral

$$p(t+\Delta t) = p(t)^{*} \exp\left[\int_{\Delta t} \mu(s)\,ds + \left(\int_{\Delta t} \sigma(s)\,ds\right)\sqrt{\Delta t}\,\omega\right] \qquad \text{(Equation 6)}$$

where $\mathbf{p}(t)$ is the Nx1 vector of market rates at time t, $\mu(t)$ is the Nx1 vector of instantaneous drift terms at time t, $\sigma(t)$ is the Nx1 vector of instantaneous, annualized volatilities of the process, d**Z** is an Nx1 serially independent standard Wiener process with correlation matrix $\sum$ and $\omega \sim \mathbf{N}(\mathbf{0}, \sum)$.

VaR Calculation by Monte Carlo Simulation

For this study, the chosen Monte Carlo method is the typical structured Monte Carlo simulation. An overall 10,000 iterations were conducted for each simulation.

Test of Efficiency

From Hendricks (1996), determination of Mean Relative Scaled Bias (MRSB) value involves two levels: first, to find the scaling factor, X_i using the calculation:

$$F_i = T_i(1-\alpha), F = \sum_{i=1}^{T_i} \begin{cases} 1 & if \quad \Delta P_{i,t} < VaR_{i,t} \\ 0 & if \quad \Delta P_{i,t} \geq VaR_{i,t} \end{cases} \qquad \text{(Equation 7)}$$

where F_i is the total number of failure ΔP_t with T_i as the actual loss sample size on the tth day and a as the model significant level. The second level is to use MRSB to determine the scaling factor with the respective model by referring to its degree of deviation. It actually compares the scaled VaR numbers with its relative average sizes by using the following equation,

$$MRSB_i = \frac{1}{T}\sum_{i=1}^{T}\frac{Y_{i,t}-\overline{Y}_t}{\overline{Y}_t} \quad \overline{Y}_t = \frac{1}{N}\sum_{i=1}^{N} Y_{i,t} \quad Y_{it} = X_i VaR \qquad \text{(Equation 8)}$$

where $MRSB_i$ is the squared MRSB of the *i*th risk assessment model, T is the sampling period, N is the number of risk assessment models to be evaluated and Y_{it} is the VaR after scaling. Being a negative model evaluation indicator, the smaller the relative bias, the more efficient the model will be.

RESULTS

Descriptive Statistic

Table 1 illustrates the statistical characteristics of the return series in log-differenced form. The sample mean for the observations is close to zero where the means are negative for all the sectors.

Table 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)

It interprets that the three sectors have in common more negative returns. The values of skewness ranging from a low of -0.5700 (INP) to a high of 0.8322 (TAS) are suggesting the series distributions are skewed. The high kurtosis compared to the normal distribution which is 3, implies the distributions of series are leptokurtic or fat-tailed. The large values of the JB statistics provide strong evidence of non-normality while Ljung-Box Q tests reject the null hypothesis in all series, which shows that the squared returns have serial correlation. And with reference to the large values of chi-square statistics and small values of probability statistics, it indicates the hypothesis that the series is not heteroscedastic is rejected at the 1% significance level. This signifies the presence of ARCH effect in the data. In all, based on evidences 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.

GARCH-based Model Estimation Analysis

For GARCH $(1,1)_N$ the overall results of parameter ω,a and β are found to satisfy the condition; ω>0 and a, β ≥ 0 (Panel A, Table 2).

Table 2 Estimation Results of GARCH-based Model

Panel A: GARCH$(1,1)_N$				
	ω	α_1	β_1	α+β
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	α+β
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. a refers to the lagged squared error. β coefficient refers to the lagged conditional variance and δ coefficient is the EGARCH asymmetric term.

Precisely, the intercept term 'ω' is very small while the coefficient on the lagged conditional variance, β is approximately 0.9. In all three sectors, the sum of the estimated coefficient of the variance equations a 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 are also highly significant. For this particular model, the residual based diagnostic tests (Table 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.

Table 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.

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

For 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. 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, this proves that the estimated model is also well-specified.

Testing for Efficiency

The following Table 4 and Figure 2 summarize the findings for the efficiency test using MRSB.

Table 4 Efficiency Test - Forecasting Performance Summary for Different VaR Models at 95% Confidence Level

	INP	PRP	TAS
MC_1+$GARCH_N$	0.3872	1.1771	0.2091
MC_1+$GARCH_t$	-0.2243	-0.6155	-0.1345
MC_1+$EGARCH_t$	0.0118	0.2147	0.0406

Notes:
1. MC_1+$GARCH_N$ and MC_1+$GARCH_t$ denote variable simulation integrated with GARCH model.
2. MC_1+$EGARCH_t$ denote variable simulation integrated with EGARCH model.
3. Subscript N and subscript t are for normal and student-t distribution respectively.

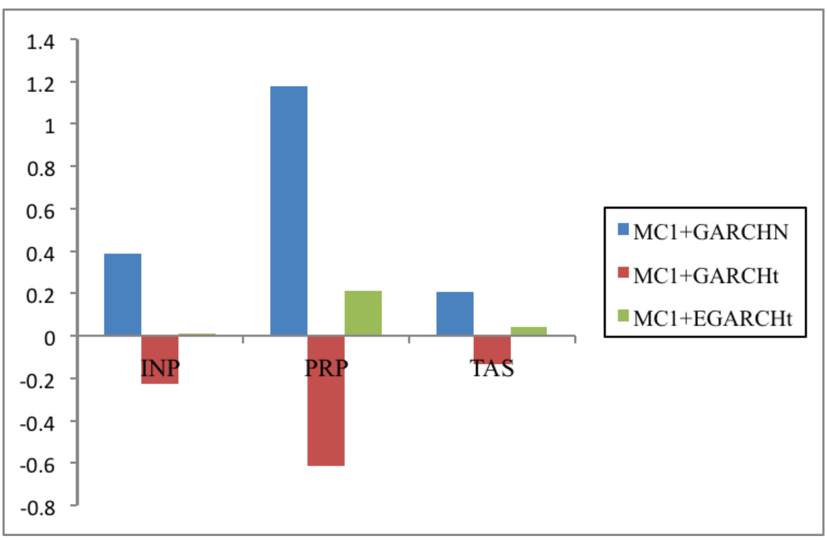

Figure 2 Mean Relative Scaled Bias - 95% Confidence Level

The most efficient model in accordance to MRSB is determined by the smallest number (Hendricks, 1996). With the exception of the most extreme case, the 95% MRSB numbers range from approximately -0.2 to 0.4 percent. This suggests that a small distinction exists between the efficiency positions of various models. Referring to Figure 2, the type of model which provides the highest or lowest efficiency position is consistent across the three non-financial sectors. At the 95% level, VaR quantification represented by MC_1+$GARCH_t$ is the most efficient and favourable for the sectors. The MC_1+$EGARCH_t$ though provide positive values at all circumstances have better position than MC_1+$GARCH_N$ which is quantified as the least efficient.

CONCLUSIONS

In line with the objective of this paper, the evidences have shown that VaR forecast integrated with t-distribution GARCH is the most efficient risk model. Across three non-financial sectors, consistent facts suggest the model portrays strong correlation with a portfolio's true risk exposure. In other words, within stipulated assumptions as compared to EGARCH and normal distribution GARCH, VaR integrated with t-distribution GARCH has better capabilities to track movements in actual risky circumstances (Engel & Gizycki, 1999). Though integration with EGARCH model theoretically is able to handle any asymmetry properties in a distribution, this present study has found it otherwise. Perhaps this condition is due to the fact that assuming EGARCH to perform within t-distribution constraint may not maximize its potential in VaR estimation. As for model under normal distribution, the rejection for it is common since the return distribution portrays non-normal traits thus making the VaR model less tolerable to accommodate issues of abnormalities such as fat-tails and asymmetries which finally underestimate true VaR. Similar inferences are found consistent with previous analysis done by Caporin (2003), Chiu et al. (2005), Hendricks (1996) and Lin et al. (2005).

This study is not without any limitations. Firstly, the statistical distributions are limited to normal and student-t distributions. Under more extreme circumstances, the results can be more robust if distribution classes like Frechet, Weibull, Gumbel or even Generalized Error Distribution (GED) distribution are included. These suggested distributions may maximize the performance in particular VaR integrated with EGARCH model. Secondly, the study only combines VaR quantification with GARCH (1,1) and EGARCH (1,1). Perhaps other types of GARCH-based models can be used when leverage effect or jump-dynamics are to be assumed. Apart from that, only three non-financial sectors are technically applied. And should all non-financial sectors and/or financial sectors are to be included together the outcomes may possibly lead to different conclusions.

As a summary, using an efficient risk model is important as it can generate better VaR forecasts which subsequently explain thorough correlation with actual risk exposure. Still this concluding remark is very much dependent on the VaR settings; the statistical distribution properties, type of sectors and the adjustments of VaR parameters involved in measuring risk models efficiency in diverse business sectors of an economy.

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