MARKET RISK ANALYSIS OF THE NON-FINANCIAL SECTORS IN MALAYSIA

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ABSTRACT

The objective of this study is to compare Value-at-Risk (VaR) numbers and behaviour patterns among non-financial sectors in Malaysia. The study applies the VaR full valuation approach namely the Monte Carlo Simulation (MCS) that are integrated with GARCH-based models as one of the parameter. The results indicate that the mining sector is most volatile while plantation sector has the lowest risk estimation in most circumstances as both the holding period and confidence level increases. The study also provides further evidences to existing literatures, which identify traditional economic sectors of a country, whether can generate the highest or the lowest level of risk.

Keywords: Value-at-Risk, Monte Carlo Simulation, GARCH models

INTRODUCTION

Over the years, several series of extreme events and financial turmoil have provided opportunities to evaluate the behaviour of various financial instrument's activities and outcomes. This situation triggers change in the development of financial measurements that may include risk measurement systems, volatility modelling and the introduction of new finance-related theories. Undoubtedly, since the introduction of the traditional measures and evaluation methods, the process has definitely evolved to suits current business environment in handling a portfolio's risk. In fact, some recent integration works with psychological theory have also created more enhanced modern portfolio theory. Even though it can be complicated, market users including practitioners and policy makers are required to adapt these challenging realities because such situations have direct consequences on the level of risk. Furthermore, since risk affects the outcomes of portfolios, the implementation of an effective risk measurement system is crucial due to the fact that it will finally affect the shareholders wealth.

One of the most recent valuation method used to monitor the behaviour of market risk is the Value-at-Risk (VaR). Along with the immense popularity, VaR have since become an integral risk management tool and a standard to monitor and control a firm's risk exposures. According to Butler (1999) and Jorion (1997), VaR summarizes the worst expected loss that an institution could suffer over a target horizon under normal market conditions at a given confidence level. On a global scale, VaR as a financial risk management tool has proven to be widely adopted due to the reason that it may signal inefficiency in capital charges.

The Issues

In-depth reviews from previous studies have found that less attention within the framework of VaR are given to test the effect of each individual sector traded within an equity market, especially the non-financial ones. Other than the stock market indices, alternative forms of financial instruments were used as the input namely, foreign exchange holdings (Bredin and Hyde, 2004; de Raaji and Raunig, 1998; Dunis and Chen; 2005; Jackson, Perraudin and Maude, 1998; Nath and Reddy, 2003; Zangari; 1996) or fixed income securities (Bolgun, 2004; Brooks and Persand, 2002; Busaramkamwong, Ng and Stamenoric, 2004; Lambardiaris, Papadopoulou, Skiadopoulos and Zoulis, 2003; Singh, 1997; Vlaar, 2000). In a volatile environment, these different sectors from diverse business backgrounds have the tendency to exhibit different VaR values (Hallerbach and Menkveld, 2004; Hotz, 2004; Wilson, Nganje and Hawes, 2007, Su, 1999). Thus further work is needed to address these dissimilarities (Danielson and de Vries, 1997).

Additionally, there are still inconclusive works on matters pertaining VaR methodologies and measurement, which over the last decade were mainly focusing on, developed nations such as the United States (US), European and Japanese markets (Hendricks, 1996; Ho, Chen and Eng, 1996; Hull and White, 1998; Kritzman and Risch, 2002; Lee and Saltoglu, 2002; Linsmeier and Pearson, 2000; Luciano and Marena, 2002; Venkataraman, 1997). Hence, there is a need to study VaR using emerging economies samples because these markets tend to show more volatile conditions and routinely produce risks with fat tails and asymmetry characteristics that are not consistent with well-behaved distribution (Sinha and Chamu, 2000). As a matter of fact, from the Malaysian perspectives, very few studies on VaR are identified such as those by Cheong (2008), Choong (2004), Su and Knowles (2006) and Zangari (1996). In sum, for the benefit of academic, practitioners and policy makers, research to evaluate risk forecast for the Malaysian economy must be further examined.

In this manner, the main intention of this paper is to compare VaR numbers and behaviour patterns among the non-financial sectors traded in Malaysia stock market based on the full valuation approach namely the Monte Carlo Simulation (MCS). The following section provides the review on previous literatures on VaR while Section 3 outlines the

data and methodology used to measure VaR values. Section 4 presents the final results and interpretations. For conclusions, the summary of the study's findings, implications and limitations are addressed in Section 5.

REVIEW OF RELEVANT LITERATURES

Cassidy and Gizycki (1997) conversely termed VaR as the earnings-at-risk or a potential loss amount. The main reason underlying its popularity lies in its simplicity of providing a single statistical figure summary of possible potential losses within a given time horizon. Since the introduction of the simplest VaR models, a range of approaches to calculate VaR has expanded from two important perspectives; number and complexity. Jorion (1997) classifies VaR into two groups; the local and full valuation. The essential characteristic, which differentiates both approaches, is the assumptions of normality of a portfolio's distribution. The local valuation consists of the variance-covariance, delta-normal and delta-gamma approach while full valuation mainly concentrates on either the historical or Monte Carlo simulation.

In accordance with its basic principles, Davis and Fouda (1999) state that VaR helps to monitor the frequency of loss occurrence. Additionally, Wirch (1998) clearly states that VaR aids investment risk evaluation, identifying asset allocation optimally, developing and evaluating portfolio strategies, measuring portfolio quality and evaluating portfolio managers. As a tool for monitoring management activities from the top levels to lowest levels of management, VaR is used to control traders and risk management staff in setting up position and trading limits, to determine capital requirements, performance evaluation and disclosure to both internal members (board of directors and/or senior management) and external constituencies such as the regulators and investors (Ju and Pearson, 1999). At least equally important, VaR is an estimation of market risk based on previous data and the fact that it can be measured in monetary value eases communication between market users in optimizing, selecting and also classifying portfolio. For example, practical research by Yu, Chin, Hang and Wai (2001) on firms that are situated in Hong Kong and Shanghai, confirmed that VaR was the most widely used risk management technique.

Due to the fact that VaR combines several parameters such as volatility, holding period and confidence level in its quantification, VaR provides better platform and more practical maximum loss estimates. This will help to identify the safest investment and to allocate adequate capital, which then maximizes the profitability of an investment. This in turn will articulate the wealth increment of the shareholders. To reach an adequate and efficient capital allocation, affirms Tardivo (2002b), the firm's management must consider several operative elements. These include; a suitable amount of capital to be allocated accordingly to firm's activities or division, right and proper risk management structures, and a reconciliation process between the allocation process and assets constraints.

Berkalaar, Cumperayot and Kouwenberg (2002), in their study on stock price and options, concluded that VaR offers good risk management practice throughout a firm and performs well most of the time. Any reduction in stock return volatility can have an adverse effect on the likelihood of extremely negative returns. This is because, empirically, during a bad state of optimal investment strategy, risk managers will be forced to take a large exposure to stocks, thus pushing up market risk and exploiting the price equilibrium. Thus by using VaR, it helps to reduce stock return volatility by setting a limit on probability of losses.

Concisely, VaR can be very useful for risk management practices; risk supervision, risk reporting and division of resources. It is an indicator, says Tardivo (2002a) that can be categorized under the utility-based performance group. The fact is its function depends on the amount of investment and the risk tolerance level of an investor. On a daily basis, according to Simons (2001), the characteristics of VaR are based upon the fact that VaR can be calculated using current portfolio composition rather than the portfolio's historical returns and it can also be aggregated across various asset categories. This condition offers institutional investors extra advantage since the previous traditional risk measures like beta for stocks and duration for bonds have only one or other of these characteristics.

DATA AND METHODOLOGY

Data

The time series indices of seven non-financial sectors traded in the first board of the Bursa Malaysia from year 1993 to 2010 are used. This sample size is chosen because it covers different economic conditions besides having complete data information; appreciation, depreciation and unchanged values. The construction, consumer product, industrial products, plantation, properties, trading and services, and mining sectors represent the non-financial industries. All the data were obtained from Data stream. Two other non-financial sectors, namely technology and hotels, have been omitted from this study because the former started its index listing only in year 2000, while the latter is not represented by a specific index on Bursa Malaysia.

VaR Theoretical Formula

In general, VaR is a specific quantile of a portfolio's potential loss distribution over a given holding period. From Dowd (2005), assuming r_t follows a general distribution, f_t, VaR under a certain chosen h and α gives:

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

Theoretically, VaR can be presented as:

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

Volatility Modelling Under t-Distribution

The student t-distribution [$v_t \sim t(0,1,\upsilon)$] is implemented to adjust and accommodate a reasonable amount of fat tail or asymmetric biases (in other words any presence of excess kurtosis) observed in the data analysis. Engel and Gizycki (1999) concluded that estimating VaR under the t-distribution gives better results compared to the normal distribution in that it captures the downside risk measure more efficiently. Other than that, student t-distribution as compared to the normal distribution provides more flexible way to estimate the probability density function should less information be gathered about the population. Plus, it is more capable of capturing any downside swing, which in turn will provide better prediction (Danielsson & de Vries, 1997).

The t-distribution is:

$$f(t \mid v) = \Gamma\left(\frac{v+1}{2}\right) / \sqrt{\pi(v-2)} / \Gamma(v/2)\left(1+\frac{t^2}{v-2}\right)^{-(v+1)/2}$$
(Equation 3)

As an input parameter to VaR, two volatility models namely GARCH and EGARCH are chosen to be applied under the t-distribution. These models are tested and then through Monte Carlo Simulation, one best suited for every sector is identified.

GARCH t-distribution

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

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + ... + \alpha_p \varepsilon_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + ... + \beta_q \sigma_{t-q}^2$$
(Equation 4)

Where $\omega > 0$; $\alpha_1, ..., \alpha_p$; $\beta_1, ..., \beta_q \geq 0$

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

$$\sigma_t^2 = \omega + \alpha\ \varepsilon_{t-1}^2 + \beta\ \sigma_{t-1}^2 \qquad \text{(Equation 5)}$$

where $\omega > 0$ and $\alpha, \beta \geq 0$. Commonly, most researchers apply GARCH (1,1) model due to the fact that it is relatively easier to estimate and more parsimony (Bollerslev, 1986; Mat Nor, Yakob & Isa, 1999). According to Alexander (1998), a leptokurtic (fatter tails than normal) of unconditional returns distribution is due to the changing conditional variance that allows more outliers or unusually large observation.

From Equation 4, the GARCH-t is then expressed according to Equation 3 for which

$\mu = v_t \sqrt{h_t}$ where $v_t \sim t(0,1,\upsilon)$ is a student t-distribution with a mean equal to zero, variance unity, υ degrees of freedom and h_t, a scaling factor that depends on the squared error term at time t-1.

EGARCH

The development of other types of GARCH models is prompted due to the fact that stock return volatility is often found to be greater following a negative return than a positive return of equal size. EGARCH was introduced by Nelson (1991) with the special intention to reduce the volatility asymmetric effect, besides eliminating the non-negativity constraints of the GARCH model. This constraint may restrain the dynamics of the obtained conditional variances (Alexander, 1998). EGARCH is generated by taking the exponential function of conditional volatility. Through this volatility log formulation, the impact of the lagged squared residuals is exponential

$$\ln\sigma_t^2 = \alpha + g(z_{t-1}) + \beta\ \ln\sigma_{t-1}^2 \qquad \text{(Equation 6)}$$

where

$$g(z_t) = \omega z_t + \lambda\left(|z_t| - \sqrt{\frac{2}{\pi}}\right) \qquad \text{(Equation 7)}$$

Other VaR Parameter Settings

This study has chosen three different holding periods: 1-day, 10-day (two weeks and 25-day (one-month). Besides that for the purpose of reporting and comparing VaR numbers, this research has selected confidence intervals that are set at 95 per cent and 99 per cent. The chosen holding periods and confidence levels are based on the definition given by RiskMetrics and the Basle proposal. Using all the parameter as inputs to quantify the

VaR, MCS was used to handle the non-normal distribution. Overall, 10,000 iterations were conducted for each simulation of the stated GARCH-based models.

RESULTS

Volatility Model Summary

Table 1 displays the estimated results of GARCH-based model. The parameters for GARCH $(1,1)_t$ are found to satisfy the restriction that $\omega > 0$ and $\alpha, \beta \geq 0$ [Panel A]. The coefficients on all three terms in the conditional variance equation are proven 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.

For EGARCH $(1,1)_t$ as in Panel B, 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.

Output of VaR Estimation

The results of estimated VaR are shown in Table 2 and Table 3. Next, each simulated value in each table is further illustrated as line-charts as in Figure 1 and Figure 2. Let VaR ($MC+GARCH_t,h,\alpha$) and VaR ($MC+EGARCH_t,h,\alpha$) be respectively the VaR based on MCS combined with GARCH under t-distribution at h holding period plus $\alpha\%$ confidence level and of VaR derived from MCS combined with EGARCH under t-distribution. In both situations, the VaR increases as investment holding periods are longer. Besides that for all sectors, the calculated expected maximum loss figures also show some increment when the level of confidence is shifted from 95% to 99%.

To be precise, the lowest VaR for t-distribution with GARCH integration is 1.25%, which is recorded by sector PLN. The highest point is accounted for by TIN (24.95%). For t-distribution with EGARCH integration, the trade and service (TAS) sector provides the minimum value of VaR of 1.09% while TIN maintains its position as the riskiest sector with an estimated maximum VaR value of 22.90%. Interactively as in Figure 1, when both holding period and confidence level move to a higher point, the individual deviation from the basic level 1-day (95%) to the higher end (25-days; 99%) for sectors, which include CON, COP, INP, PLN and TAS, is found to be not so widely dispersed which means the riskiness level for is somehow quite stable. In contrast, both PRP and TIN exhibit (particularly in the case of TIN) a much wider dispersion.

Table 1 Estimation Results of GARCH-based Model

Panel A: GARCH(1,1)$_t$

	ω	α$_1$	β$_1$	α+β
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 B: 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.

In the next situation, MC+EGARCH$_t$, displayed as in Figure 2 shows more intense behaviour. For the most part, in all six cases of possible pairs between the holding period and confidence level, the VaR differences among seven non-financial sectors are found

to be more inconsistent. Compared to 1-day basis, the 10-day and 25-day predictions are much more volatile. CON, INP and TIN continue to illustrate higher VaR as the holding period and confidence level increases.

Table 2 Monte Carlo Simulated VaR *(MC+GARCH$_t$)*

	1-d		10-d		25-d	
	95%	**99%**	**95%**	**99%**	**95%**	**99%**
CON	-0.0215	-0.0344	-0.0422	-0.0674	-0.0652	-0.1047
COP	-0.0140	-0.0230	-0.0431	-0.0722	-0.0635	-0.1056
INP	-0.0126	-0.0200	-0.0401	-0.0640	-0.0636	-0.1041
PLN	-0.0125	-0.0205	-0.0372	-0.0630	-0.0560	-0.0967
PRP	-0.0134	-0.0226	-0.0430	-0.0694	-0.0741	-0.1158
TAS	-0.0137	-0.0221	-0.0415	-0.0678	-0.0666	-0.1056
TIN	**-0.0316**	**-0.0500**	**-0.0988**	**-0.1583**	**-0.1554**	**-0.2495**

Notes:
1. MC+GARCH$_t$ denote single variable simulation integrated with GARCH model.
2. Subscript t for student-t distribution.

Table 3 Monte Carlo Simulated VaR *(MC+EGARCH$_t$)*

	1-d		10-d		25-d	
	95%	**99%**	**95%**	**99%**	**95%**	**99%**
CON	-0.0202	-0.0327	-0.0733	-0.1344	-0.1012	-0.1601
COP	-0.0145	-0.0236	-0.0451	-0.0724	-0.0700	-0.1107
INP	-0.0253	-0.0399	-0.0800	-0.1307	-0.1205	-0.1918
PLN	-0.0121	-0.0198	-0.0353	-0.0626	-0.0538	-0.0870
PRP	-0.0137	-0.0221	-0.0441	-0.0738	-0.0730	-0.1093
TAS	-0.0109	-0.0193	-0.0367	-0.0596	-0.0581	-0.0944
TIN	**-0.0284**	**-0.0466**	**-0.0857**	**-0.1400**	**-0.1294**	**-0.2290**

Notes:
1. MC+EGARCH$_t$ denote single variable simulation integrated with EGARCH model.
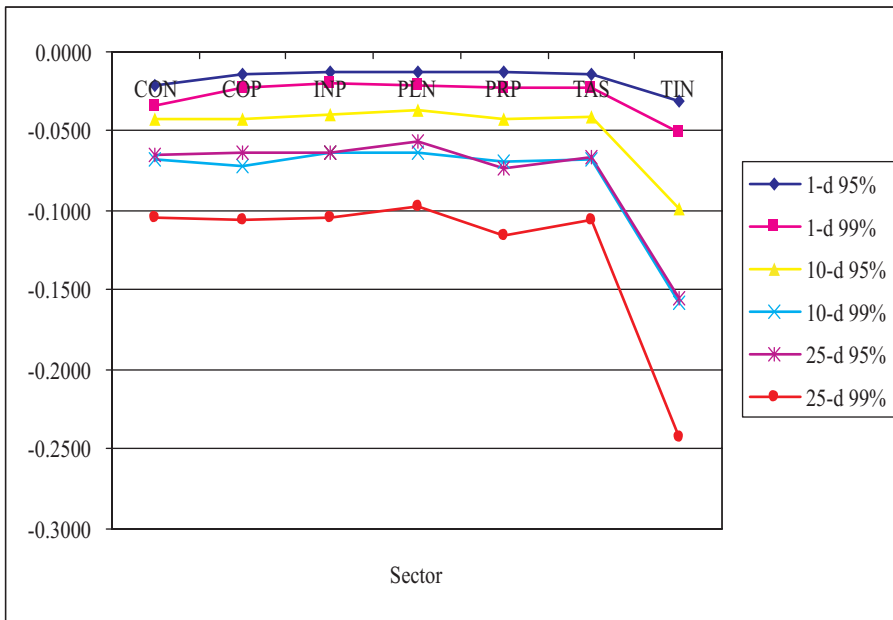
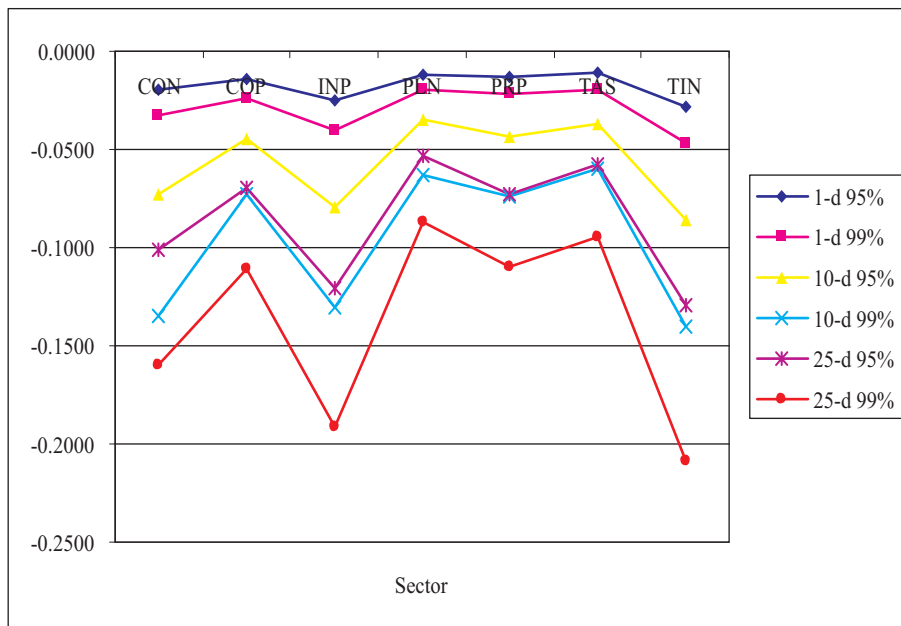**Figure 1** Monte Carlo Simulated VaR *(MC+GARCH$_t$)*

Figure 2 Monte Carlo Simulated VaR *(MC+EGARCH$_t$)*

VaR Behaviour Patterns of Non-Financial Sectors in Malaysia

Among all the sectors, mining illustrates the most extreme VaR while plantation in most combinations shows the mildest position, particularly as both the holding period and confidence level increases. This means mining has the highest absolute downside risk and plantation the opposite. These situations could be the consequences of high peaked ness of the mining sector and minor extreme events effect on the plantation sector that indirectly provides lesser influence to the level of profit or loss (Zain, 2005). In other words, the increasing/decreasing contribution of risks in this sector is mostly caused by the rising/declining exposures and volatilities (Au, 2002; Choong, 2004; Lambadiaris et al., 2003). These can be attributed to different industrial characteristics and practices, which indirectly have an effect on the economic growth rates of each sector.

Other than that, the reason why mining (which is one of the traditional sectors other than plantation) has the most extreme VaR is because it has been experiencing lesser demand in the domestic and global market which indirectly led to many tin mines discontinued its operation. This causes sudden decrease in its activities especially in the year 2004 and 2005. On the mildest position, plantation did not absorbed too much of any extreme events effect although the Malaysian economy faced some turbulences along the observation period. One of the reasons is that the agricultural sector received strong and continuous supports from the government with various policies for example biotechnology policy and subsidies.

In between those two sectors are the interchangeable positions between manufacturing, construction and services. The rising or declining exposures for manufacturing can be attributed to several circumstances; a sharp decline from 2001 to 2002 which are influenced by main industrial countries electronic product cycle, a strong domestic demand enhanced by export-oriented industries and significant improvement in global economy (2002 – 2003) and also a downward trend in global semiconductor industry in year 2005. On the other hand, although the construction sector was badly affected by the recession, continuous government stimulus programs in particular for developing infrastructure projects and residential properties helped to lower the risk exposures. As a matter of fact, extensive backups given by local financial institutions by offering many attractive financing packages also created higher purchasing power and consequently reducing the sectorial risk. Thus, in some VaR estimation values, construction and property in this manner illustrated lower VaR numbers. For services sector even if it also encountered slower growth particularly after the financial crisis, the final outcomes are not as bad as the mining sector. Some of the related factors are strong domestic support and consumption in the tourism industry plus the nature of services that is to provide support for other sectors.

CONCLUSION

In line with the objective of this paper, it is found that among the studied non-financial sectors in Malaysia, the mining sector is most volatile while plantation has the lowest risk estimation in most circumstances. This study provides supporting evidence that traditional sectors may generate either the highest or the lowest values of VaR (Su, 1999).

The findings also reveal that integrating the most accurate confidence level, holding period and investment position are important. However, quantifying the volatility model for VaR is even more crucial. In this sense, within acceptable assumptions, a GARCH-based model can be a suitable model to be allocated as an input in VaR estimation. These findings highlight that it is very important for practitioners and policy makers to find the best method or model which suit the challenges to alleviate excessive risk caused by volatile market environment. In fact, efficient reserves need to be identified and accumulated to overcome any possible loss. Thus, should a potential financial crisis occurs, the firm may minimize the impact and indirectly saves the cost of all stakeholders especially the owners.

Further related implication from this study towards better understanding of managing market risk in various economic sectors is to have a sound risk management practice. Good coordinating and consistent reviews on quantitative components and qualitative components can avoid major failure in any investment positions. For instance, a firm which coordinates quantitative elements like VaR, stress testing, risk-adjusted performance measures, back testing, model review in daily activities and qualitative elements based on experience or judgement, will experience better governance and more transparent in daily operations and procedures decision making. By doing this according to Brachinger (2002) and Damodaran (2005), the firm will most likely to strategize more profitable activities for the sake of all the firm's stakeholders.

Although the study draws some essential facts, it is not without any limitations. First, the data embedded in the VaR models is taken as a whole although it actually experienced different economic conditions. A more vigorous output can be expected should each economic phase is examined individually and/or compared between one phase and another. As mentioned by Lee and Saltoglu (2002), different VaR interpretations will be observed if separate time periods such as before recession, in-recession and post recession are taken into considerations. Secondly, throughout the analysis and evaluation process, only Structured MCS was being used. Since MCS is highly dependent on a stochastic model that underlies the VaR estimation, MCS can be influenced by model risk. Thus, other VaR generating procedure like the Extreme-Value Theory can be applied. And finally, this study only focuses on GARCH (1,1) and EGARCH (1,1) model. The three main reasons for choosing these two models are either [1] to capture inadequate tail probability; [2] to reduce the volatility asymmetric effect and [3] to eliminate the non-negativity constraints of a less 'efficient' model. However, other types of ARCH-based models can also be utilized if conditions like leverage effect and jump-dynamics are assumed.

As a summary, VaR can be applied with the intention to produce a better risk decomposition report. A reason for it is that the method can be used to highlight 'hot spots' (the top-ranking) investment or the biggest sources of risk under multiple sectors of economy. Not only VaR complements financial risk management decision-making in related sectors such as setting up capital requirements, it also assist in choosing among alternative portfolios or to position the trading limits thereby permitting investors to achieve the highest return per unit of risk.

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