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Value-at-risk and Conditional Value-at-risk Assessment and Accuracy Compliance in Dynamic of Malaysian Industries

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Abstract: Risk management becomes increasingly crucial for financial institutions in competitive market today. Value-at-risk (VaR) and Conditional Value-at-risk (CVaR) methods have taken important places in risk management field as recognized by Basel Committee on Banking Supervision (BCBS, 2012). While VaR measures the maximum loss in a given confidence level and period, CVaR gauges the amount of loss exceeding VaR in a given confidence level. This study attempts to describe and compare VaR and CVaR methods within Malaysian industries using both parametric and non-parametric approaches. Moreover, researcher measures the accuracy of predicted VaR and CVaR by applying "Backtesting" technique. To this regards, results revealed that VaR always tends to underestimate the risk, while CVaR models tend to overestimate the risk in most of the cases. The results also indicated Technology industry with the highest risk, while Consumer Product industry had the lowest one. All in all, the choice of picking the right risk model is highly depend on the preference of institutions in Malaysia.

Key words: Backtesting, conditional value-at-risk, risk analysis, value-at-risk

INTRODUCTION

Risk management is one of the most critical issues in various institutions. Risk management is defined as a technique to measure, monitor or even control financial situation of an organization. Among all types of risk management, market risk has been stressed by many researchers as by the authors of this paper. Market risk is the risk related to losses and arises from adverse movement in market prices of financial assets. The main approach to market risk is Value-at-Risk (VaR) measurement, which can be developed to various scales of complexity. VaR measures the highest loss that could happen over a specified period of time and confidence level (Jorion, 2000).

VaR has been very widespread among risk practitioners due to its comprehensibility and interpretability mechanism. Conditional Value-at-Risk (CVaR), however, assesses the likelihood of specific loss that could exceed the VaR in a given confidence level. It is also known as Expected Tail Loss (ETL), Expected Shortfall or tail VaR. From May 2012, Basel committee follows up an announcement regarding market risk and use of CVaR in market risk assessment (BCBS, 2012).

Pritsker (1997) stated that in order to increase effectiveness of market risk models, they must be fairly accurate. As VaR estimates the highest loss over a specified period of time and confidence level, it can also be overestimated or underestimated with inaccurate or appropriate method. On the other hand, it is believed CVaR as superior method compare to VaR due to its coherency in risk estimation (Acerbi *et al*., 2001; Altay and Kucukozmen, 2006). In general, only few studies concerned VaR approaches, or CVaR in Malaysian industries (Chin, 2008; Lim *et al*., 2006). The notion of using various types of parametric and nonparametric models of VaR and CVaR is still an open debate among researcher in Malaysian industries.

To this context, this study attempts to present VaR and CVaR measurements within Malaysian industry setting and to contrast VaR and CVaR measurements among diverse range of industries in specific period of time. The study also investigates the attributes of Malaysian industries and the benchmarks (Kuala Lumpur Composite Index, KLCI) as well as testing the accuracy of predicted VaR and CVaR models. With the objective of evaluating the accuracy of the VaR and CVaR measurements, the related models have to be backtested as well.

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LITERATURE REVIEW

Value at risk (VaR): A comprehensive definition was described by Jorion (2000) as; VaR estimates the maximum worst loss could happen in a given period of time and confidence level. Initially, Basel Committee specified a basic model to calculate VaR, yet the model had some inadequacies and critics (Taleb and Jorion, 1997). Therefore, Basel Committee allowed institutions to implement internal models to access their VaRs by using backtesting in order to evaluate the accuracy of their models. In addition to its popularity, VaR has its drawbacks as a tool for risk estimation. Some are obvious such as model risk, which is the risk associated with improper assumptions about selected model or implementation risk. In another words, it is the risk associated with how to implement the model. These risks are not just for VaR but to all types of risks. Another severe drawback is called non-sub-additively through which sum of individual risks does not increase the aggregate risk.

Conditional value at risk (CVaR): Initially, the term CVaR was introduced by Rockafellar and Uryasev (2000). CVaR measures the amount of loss may happen in tail events, whereas VaR tells nothing about the magnitude of loss that may occur beyond the threshold. Therefore, the CVaR of a specific portfolio is equal or larger than the VaR of that portfolio. CVaR emerged when VaR failed to measure the amount of loss in the condition that VaR exceeded. Pflug (2000) argued CVaR as a coherent risk metric regards to the theory of coherent risk measures formulated by Artzner *et al*. (1999). Alexander (2009) defined CVaR as the value of losses if the losses happen in the excess of VaR. For instance, if VaR is calculated at 95% confidence level, Historical Simulation CVaR is the excess losses in remaining 5% and it could be calculated using the average of those 5% worst losses (Allen and Powell, 2007). Next section describes the accuracy of VaR and CVaR.

Accuracy of VaR and CVaR: The performance of VaR and CVaR models should be evaluated because the reliability of every estimated model is based on its accuracy. Financial institutions must perform their accuracy evaluations regularly to confirm the reliability of estimated risk. The pressure of inside and outside parties (e.g., investors, regulators, senior managers, etc.) also require institutions for the accuracy assessment of their risk models (Blanco and Oks, 2004). Among different models of validation, "Backtesting" model is very popular among practitioners. Jorion (2000) defined backtesting as a statistical model, which compares the actual losses of an entity with estimated ones. In other words, backtesting compares the predicted VaR or CVaR with the actual returns and reveals the number of times that related risk model failed to predict accurately.

Basel Committee also accentuated the importance of daily backtesting in evaluating the performance of the risk model (BCBS, 2012). A recent study by Nieppola (2009) found that VaR models underestimated the risk. Samanta and Nath (2003) also argued that although conventional methods of VaR underestimate the risk, Historical Simulation VaR is a reliable model in risk estimation. White (2009) appraised the accuracy and validity of VaR models, through which the result revealed the underestimation of risk due to non-normal distribution in bank's asset class. The results of study by Yoon and Kang (2007) also confirmed the risk underestimation even with normal distribution assumption by VaR approach. They found that VaR has a better performance in 95% confidence level.

RESEARCH METHODOLOGY

Empirical data: Bursa Malaysia is a name given to Malaysian stock exchange, which previously was known as Kuala Lumpur Stock Exchange (KLSE) (Bursa Malaysia, 2012). The Kuala Lumpur Composite Index (KLCI) is a capital weighted stock market index and it was changed to the Financial Times Stock Exchange (FTSE, 2012) Bursa Malaysia KLCI. FTSE Bursa Malaysia KLCI is considered as the key benchmark index for Malaysian equity market and consists of 30 companies with 162.08 billion USD market capitalizations (FTSE, 2012). The Bursa Malaysia Index Series comprises of industrial indices such as Construction, Consumer Product, Finance, Industrial Product, Mining, Plantation, Property, Technology and Trading/Services. Mining industry consists of only one company and therefore; in order to have a meaningful conclusion, this industry is excluded from this study. KLCI is used as the benchmark index for this study. There are eight industries with the benchmark considered as sample data. Although Basel Committee requires 250 day data, to have more detailed and precise VaR and CVaR, daily prices for a period of 10 years (2002-2012) is collected for purpose of this study.

VaR calculation: VaR is a loss which one is pretty confident will not go further over a period of time and confidence level. Thus, VaR consists of two underlying arguments; (1) The risk horizon referred as h that is the period of time, (2) The confidence level so-called $(1-\alpha)$ or significance level i.e., α. In order to have a better generalizability, the study chooses 95% confidence level and one-day risk horizon (Pearson, 2002). Besides, 99% confidence level is used in some sections for comparison purpose. Geometric return is also applied in order to calculate VaR (Morgan, 1996). Geometric return is the logarithm of today's price over the price for a day before:

$$R_t = \ln\left(\frac{p_t}{p_{t-1}}\right) \tag{1}$$

where, R_t is the return in time t, p_t is prices for today and p_{t-1} is the price of a day before. Several techniques can be used in order to calculate VaR of an entity. They are commonly classified into three classes; Variance-Covariance approach, Historical Simulation approach and Monte Carlo Simulation approach.

Variance-covariance approach: In this approach, VaR is the proportion of standard deviation as an entity. Four models have been used in order to compute VaR. Beside the Normal Linear VaR, three methods from Autoregressive Conditional Heteroskedasticity (ARCH) family are applied namely; ARCH VaR, Generalized ARCH (GARCH) VaR and Exponential GARCH (EGARCH) VaR.

Normal linear VaR: The most popular and simplest method to calculate VaR is the Normal Linear VaR. Only two parameters are required; the standard deviation and the mean:

$$\sigma_h = \sqrt{\frac{\sum_{i=1}^{n}(R_i - \bar{R})^2}{n-1}} \tag{2}$$

This model is based on assumption that the returns are normally distributed. Over h-day risk horizon and significance level of α, Normal Linear VaR Formulate as follows:

$$VaR_{h,\alpha} = -\mu_h + \phi^{-1}(1-\alpha)\,\sigma_h \tag{3}$$

where, μ_h is the mean of returns; ϕ is standard normal distribution function and σ_h is the standard deviation of returns.

ARCH family: ARCH model was introduced by Engle (1982) as a way to solve the problem of financial data clustering. ARCH family assumes that the variance of the dependent variable is a function of past values of the dependent variable and independent variables. In order to model the time series related to an ARCH process, one should specify two distinguishable equations; conditional mean and conditional variance. For conditional mean equation usually AR(k) is used (Angelidis *et al.*, 2004):

$$y_t = c_0 + \sum_{i=1}^{k} c_i y_{t-1} + \varepsilon_t \tag{4}$$

where, y_t is the return at time t; c is constant and ε_t is the error term or return residuals. Conditional Variance equations for each model of ARCH family are as follows:

ARCH (q): Engle (1982) showed that the conditional variance is a linear function of squared return residuals. The parameters α_0 and α_i must be larger than zero, so conditional variance will be positive:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \tag{5}$$

GARCH (p,q): Bollerslev (1986) introduced the GARCH model. The parameters α_0 and α_i must be larger than zero and the summation of these parameter is equal or less than one. Conditional variance equation for GARCH (p,q) is equal to:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{6}$$

EGARCH (p,q): Nelson (1991) proposed the EGARCH in order to capture the asymmetric effects of data. EGARCH (p,q) is equal to:

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{q}\left(\alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right) + \sum_{j=1}^{p} \beta_j \ln(\sigma_{t-j}^2) \tag{7}$$

It should be noted that the most frequently applied factors in academic literatures is selected for this study. According to McNeil *et al.* (2005), using the lower order lags are better due to parsimony reasons. Thus, this study is restricted to ARCH (1), GARCH (1,1) and EGARCH (1,1) with the asymmetric order of 1.

Historical simulation approach: The basic assumption of this approach is that future events have already happened in the past and all simulated returns are equal to returns in the future risk horizon. According to Van den Goorbergh and Vlaar (1999), if one chooses a sample size of t, Historical Simulation VaR is equal to the p_{th} percentile of selected sample:

$$V\alpha R_t = -R_t^p \tag{8}$$

R_t^p is the p_{th} percentile of sample t. For instance, the 95% 1 day Historical Simulation VaR of an entity with 100 trading days is equal to 5th worst loss return of that entity.

Monte carlo simulation approach: Normally distribution of returns is the assumption of Monte Carlo Simulation. However, this approach is far more flexible than the Normal Linear and many assumptions in distribution can be adapted. In order to compute VaR, one should simulate a large number of independent standard normal variables and use standard deviation to get a list of simulated returns. In Monte Carlo Simulation, the returns are equal to:

$$\ln\left(\frac{R_t}{R_{t-1}}\right)=z_t\sigma \tag{9}$$

where, z_t is the normal distribution function with random probability of between 0 to 1 and σ is the standard deviation of an entity. Pseudo Random Number Generator (PRNG) is used in order to generate a set of random number between 0 and 1. A number of 10,000 simulations is generated by multiplying with standard deviation. Similar to Historical Simulation VaR, Monte Carlo Simulation VaR is a p_{th} percentile of simulated returns.

CVaR calculation: CVaR defined as an amount of loss exceeds VaR. Over h-day risk horizon and significance level of α, a parametric approach or Normal Linear CVaR is equal to (Alexander, 2009):

$$CVaR_{h,\alpha} = -\mu_h+\alpha^{-1}\varphi\,(\phi^{-1}(\alpha))\sigma_h \tag{10}$$

where, φ referred the standard normal density and ϕ distribution function. Thus, $\phi^{-1}(\alpha)$ is the α quantile and $\varphi(\phi^{-1}(\alpha))$ represents the highest amount of standard normal density. In order to calculate nonparametric CVaR or Historical CVaR, the following formula can be used (Alexander, 2009):

$$CVaR_{h,\alpha} = -E(X_h|X_h<-VaR_{h,\alpha}) \tag{11}$$

In other words, CVaR using Historical approach can be obtained by averaging all returns which are lower than negative Historical Simulation VaR.

Backtesting process: This section demonstrates an advanced method of VaR and CVaR validation based on evaluations of selected model action in the past. The basic assumption of backtesting models is that the loss distribution follows a Bernoulli process. A Bernoulli variable could take only one form of two possible values, which are 1 as "success" and 0 as "failure". In this study, success represents the time that VaR exceeds the return in specific day. The following indicator function illustrates the process (Alexander, 2009):

$$I_{\alpha,t} = \begin{cases} 1, \text{if } Y_t < -VaR_{1,\alpha,t} \\ 0, \text{ if } Y_t \geq -VaR_{1,\alpha,t} \end{cases} \tag{12}$$

where, Y_t is the return of day t and the VaR prediction is made for the same day. If the estimated VaR model is a correct model and the loss distribution follows the Bernoulli process, therefore the sum of successes divided by total observation should be α:

$$P\,(I_{\alpha,t} = 1) = \alpha \tag{13}$$

Imagine $X_{n,\alpha}$ is a number of violations which considered as "success." Hence the expected number of "success" with n observation will be nα:

$$E\,(X_{n,\alpha}) = n\alpha \tag{14}$$

Therefore the standard deviation is:

$$SD\,(X_{n,\alpha}) = n\alpha(1-\alpha) \tag{15}$$

Due to sampling error, there are fewer possibilities to gain the exact number of expected violation. Consider n as a very large number, the distribution of cumulative violations ($X_{n,\alpha}$) tend to be normal. Thus, the 1-θ confidence interval can be defined as:

$$\left(n\alpha + z_\theta\sqrt{n\alpha(1-\alpha)},\ na - z_\theta\sqrt{n\alpha(1-\alpha)}\right) \tag{16}$$

For the purpose of this study the significance level (θ) of 0.05 is chosen. Under the null hypothesis the model is accepted (H_0: $X_{n,\alpha}$ = nα). The null hypothesis is accepted if the cumulative number of violations falls within confidence interval.

DATA ANALYSIS

Descriptive statistics and normality test: In Table 1, all the details for descriptive statistics are presented along with the normality test using Jarque Bera model.

All industries show positive average return except Technology with negative 0.05%. KLCI average return is equal to the weighted average returns of all industries meaning that the benchmark is pretty well representing the Malaysian industries. Lowest standard deviation is accorded to Consumer Product with 0.62% and the

Table 1: Descriptive statistics and normality test results

Industry name	Mean (%)	Median (%)	SD (%)	Skewness	Kurtosis	Jarque-Bera	Prob. (%)
Consumer product	0.04	0.02	0.62	-0.65	8.54	3516	0.00
Construction	0.01	0.00	1.28	-1.19	20.63	34411	0.00
Finance	0.04	0.02	0.94	-0.37	8.52	3377	0.00
Industrial product	0.02	0.00	0.82	-0.79	11.14	7472	0.00
Plantations	0.06	0.02	1.15	-0.36	17.40	22598	0.00
Properties	0.02	0.00	1.07	-0.60	11.12	7324	0.00
Technology	-0.05	0.00	1.29	0.30	6.87	1664	0.00
Trade and services	0.02	0.00	0.83	-0.80	14.19	13890	0.00
KLCI (Benchmark)	0.03	0.02	0.80	-0.94	15.21	16600	0.00

Table 2: VaR and CVaR of Malaysian industries

Industry	SD (%)	Normal linear VaR* (%)	Historical simulation VaR (%)	Monte carlo simulation VaR (%)	ARCH VaR (%)	GARCH VaR (%)	EGARCH VaR (%)	Normal linear CVaR (%)	Historical simulation CVaR (%)
Consumer product	0.62	0.98	0.94	1.01	1.01	0.97	0.97	1.23	1.47
Construction	1.28	2.09	1.83	2.06	2.06	1.96	1.93	2.63	3.04
Finance	0.94	1.50	1.38	1.51	1.52	1.46	1.45	1.90	2.20
Industrial product	0.82	1.33	1.26	1.36	1.32	1.28	1.27	1.68	2.03
Plantations	1.15	1.83	1.56	1.87	1.84	1.69	1.68	2.31	2.79
Properties	1.07	1.73	1.50	1.73	1.70	1.64	1.63	2.18	2.58
Technology	1.29	2.17	2.08	2.10	2.10	2.06	2.04	2.70	3.01
Trade and services	0.83	1.34	1.30	1.32	1.35	1.31	1.29	1.68	1.93
Weighted average	0.89	1.43	1.34	1.43	1.44	1.38	1.37	1.80	2.10
KLCI (Benchmark)	0.80	1.29	1.23	1.31	1.30	1.24	1.23	1.62	1.90

*95% confidence level and 1 day risk horizon

highest is Technology with 1.29% that is much higher than the benchmark. Longer left tail is confirmed for all industries; the benchmark as the skewness is negative, except for Technology, which has a long tail to the right by its positive skewness. It should be noted that a normal distribution has a skewness of zero and a kurtosis of 3 (Hair *et al*., 1998). Skewness is referred to the fact that distribution is off-centered.

From Table 1, kurtosis for all industries and the benchmark indicate leptokurtosis compared to the normal distribution. McNeil and Frey (2000) believed that the distribution of returns habitually tends to have leptokurtic. Construction industry shows the highest kurtosis compare to others with 20.63 and Technology has the lowest amount of kurtosis with 6.87, which is still higher than the normal kurtosis of 3. Prices in Technology sector appear to be substantially less volatile compare to other industries with lesser kurtosis than the others. The standard deviation for Technology has the highest volatility. This may lead to a conclusion that a simple estimation of standard deviation may be a poor reflection of volatility.

The results of Jarque Bera test indicated that null hypotheses are rejected where the p-values are less than 0.05%., meaning that all data returns are not normally distributed. However, many studies proved that the assumption of normality is not necessary for large sample size. Diehr and Lumley (2002) showed that linear models do not need any assumption of normality in adequately large sample size. In this study, the sample for each industry and the benchmark is 2610 elements, which is far more than the aforementioned assumptions.

VaR and CVaR assessment: To assess VaR and CVaR, first the Augmented Dickey-Fuller (ADF) test were conducted to examine the stationarity of time-series returns for eight Malaysian industries and KLCI. The results revealed no unit root in time-series of returns (stationary) in Malaysian industries and the benchmark. Six models of VaR are applied namely; Linear Normal VaR, Historical Simulation VaR, Monte Carlo Simulation VaR, ARCH VaR, GARCH VaR and EGARCH. CVaR also calculated using only Normal Linear CVaR and Historical Simulation CVaR. Table 2 shows the VaR and CVaR test results. Ten years data (2002-2010) and models are calculated using daily returns with 95% confidence level.

All models of VaR and Normal Linear CVaR ranked Technology industry with the highest risk followed by Construction industry. Historical Simulation CVaR categorized Construction as number one risky industry with a slight difference to Technology sector in second place. The reason is due to a very high volatility of Technology and Construction industries with 1.29 and 1.28%, respectively. This finding is also found by Allen and Powell (2007) study through which Technology sector carried the highest risk in Australia. Properties and Plantation industries were in third and fourth places rated by the models.

Table 3: Number of violations in backtesting

Industry	NL VaR	HS VaR	MCS VaR	ARCH VaR	GARCH VaR	EGARCH VaR	NL CVaR	HS CVaR
Consumer product	**121**	**131**	106	**108**	**121**	**122**	67	42
Construction	102	**131**	103	102	**115**	**117**	62	45
Finance	**111**	**131**	**108**	107	**121**	**123**	66	48
Industrial product	**116**	**131**	**112**	**119**	**128**	**129**	69	41
Plantations	**107**	**131**	98	104	**118**	**120**	64	41
Properties	101	**131**	**101**	105	**114**	**114**	66	43
Technology	**121**	**131**	**128**	**127**	**132**	**132**	65	44
Trade and services	**118**	**131**	**125**	**112**	**128**	**132**	66	38
KLCI (Benchmark)	**114**	**131**	**112**	**118**	**129**	**131**	67	42
Confidence interval	[108.72, 152.37]							

*Bold values represents accepted models

Lowest risk was accorded to Consumer Product industry and confirmed by all models. The results tended to locate Industrial Product and Trade and Services industries in 6th and seventh places. Finance industry was close to the weighted average of all industries and it situated in the 5th order. Generally, the weighted average of VaRs and CVaRs of industries tended to have higher risks compare to KLCI. The spectrum of risky models was ranked from 1 to 8 as one was the riskiest model and eight was the least risky one. Normal Linear VaR highly correlated to samples' standard deviation. For each industry with high standard deviation, this model tends to show relatively higher risk. For instance, Technology and Construction industries were experiencing high amount of standard deviation with 1.29 and 1.28%, respectively. Therefore, their Normal Linear VaR took third place in the spectrum of risky models for related industry. Consumer Product with low standard deviation placed as 7th place in the spectrum.

Historical Simulation VaR considered as the least risky model compare to other models. This model showed the least amount of risk for six out of eight industries. This is the reason why most of the banks tend to use Historical Simulation VaR in determining their capital requirements. Monte Carlo Simulation VaR is based on the idea that returns are a function of standard deviation. This idea happened in all industries spectrums when the model located in third to fifth places. The result of ARCH VaR showed a higher risk, almost similar to Monte Carlo Simulation VaR. ARCH VaR located in third to 5th place of the spectrum for each industry. GARCH VaR indicated higher risk in compare to EGARCH VaR as mostly placed in 6th order of the spectrum. EGARCH VaR regarded as the 2nd least risky model.

CVaR is recognized as a conservative and risk-averse technique to VaR (Alexander and Baptista, 2004). As CVaR gauges the loss exceeding the VaR, it must always exceed VaR (Alexander, 2009). The results of this study supported this argument as CVaR estimated the highest risk for each industry. Historical Simulation CVaR observed as the most conservative model by obtaining the first place for all industries' spectrum. To this end, Normal Linear CVaR grabbed the second place of the spectrum.

Backtesting VaR and CVaR models: Backtesting examines the performance of predicted VaR and CVaR on the past returns. The confidence level chosen for this study is 95% for all models. Thus, the expected number of losses exceeds VaR or CVaR (number of violations) is approximately 5% of observed days. If the number of violations is more than 5%, the respective model would underestimate the risk. On the other hand, if the number of violation is less than 5%, the respective model is too conservative or so-called overestimated the risk. Table 3 demonstrates the number of violations for all models in industries and the benchmark. The expected number of violation was 131.5 (Eq. 14) and the confidence interval (Eq. 16) shows the domain of acceptance. Thus, any violation result that falls outside of the confidence interval [108.72, 152.37] considered as a failed estimation. As it could be expected, executing backtesting on CVaR leads to failed estimations. All results for CVaR either Normal Linear or Historical Simulation showed overestimation of the risk as the numbers of violations were much lower than the confidence interval down threshold that is so conservative.

The highest number of violations in Normal Linear CVaR would not above 69. This figure for Historical Simulation CVaR was only 48. Monte Carlo simulation VaR and ARCH VaR failed in backtesting by overestimating the risk in four different samples. The failed results for ARCH VaR were much closer to lower bound. Normal Linear VaR failed to show the accurate risk measure in two industries with 102 and 101 number of violations. It is not surprising that Historical Simulation VaR performed equally in all samples as it calculated the percentile of 5% returns. Hence, the number of violations would be the exact 5% of observed days. This is why practitioners use rolling window approach in backtesting. The following section demonstrates the backtesting procedure using rolling window.

Table 4: Backtesting results for different normal linear VaR period

Industry/window length	Normal linear VaR 95% 1000	500	250	100	Normal linear VaR 99% 1000	500	250	100
Consumer product	**87**	**97**	**94**	**94**	40	43	38	42
Construction	**77**	**75**	**73**	**91**	35	38	38	34
Finance	**78**	**78**	**80**	**88**	35	39	37	43
Industrial product	**85**	**80**	**81**	**88**	43	47	41	46
Plantations	105	**94**	**83**	**79**	51	45	39	38
Properties	**83**	**76**	**75**	**87**	36	34	37	41
Technology	**88**	**88**	**84**	**88**	44	40	37	39
Trade and services	**78**	**84**	**85**	**90**	33	43	38	43
KLCI (Benchmark)	**80**	**83**	**84**	94	32	48	43	47
Confidence interval	[63.36, 97.63]				[5.81, 27.38]			

*Bold values represent accepted models

Table 5: Backtesting results for different HS VaR periods

Industry/window length	Historical simulation VaR 95% 1000	500	250	100	Historical simulation VaR 99% 1000	500	250	100
Consumer product	**97**	**89**	**85**	**87**	**24**	**22**	**21**	**20**
Construction	**92**	100	**95**	**93**	**24**	**23**	**24**	**26**
Finance	**95**	**93**	**97**	**92**	**19**	**21**	**21**	29
Industrial product	101	**95**	**89**	**87**	**25**	**27**	**24**	**27**
Plantations	121	**111**	**95**	99	**24**	28	33	**22**
Properties	109	**94**	**89**	**87**	**21**	**20**	**23**	**25**
Technology	**93**	**86**	**87**	**88**	**24**	**20**	**21**	**21**
Trade and services	**91**	**92**	**93**	**89**	**17**	**27**	**23**	**25**
KLCI (Benchmark)	103	**95**	**88**	**93**	**16**	**27**	**24**	28
Confidence interval	[63.36, 97.63]				[5.81, 27.38]			

*Bold values represent accepted models

Rolling windows backtesting: From section above, results of backtesting indicated successful estimation of accurate risk measures for all models of VaR. In this part, Normal Linear 1 day VaR is examined using rolling windows method in different length of windows and two confidence levels of 95 and 99%. In rolling windows method, the estimation sample is rolled over all data, yet the duration of the window is held unchanged. Using this method helps better judgment on accuracy of subjected models. There are one thousands of out-sample data (from 31st of October 2005) picked for the largest window. The number of observations was 1610 for all windows. Confidence intervals for both confidence levels were calculated using Eq. 16.

Normal linear VaR: From Table 4, Normal Linear VaR was completely successful at 95% confidence level. Only in Plantation industry, this model failed to estimate the risk accurately by showing the 105 number of violations outside the confidence interval. Normal Linear VaR is not a proper model for those companies who need high confidence level in their risk prediction. It can be seen that the model underestimated the risk at 99% confidence level using all windows length.

Historical simulation VaR: Historical Simulation VaR is the most popular VaR model performed admissible in both confidence levels. Table 5 shows the backtesting results of Historical Simulation VaR.

Confidence interval at 95 and 99% were between [63.36, 97.63] and [5.81, 27.38], respectively. At 95% confidence level, no failed results found within 250 days window length. However, using 1000 days window, the study received four failed results by underestimating the risk. 1000 days window was suitable for 99% confidence level since no failed result observed. Historical Simulation VaR proved its flexibility at both confidence levels.

ARCH family VaR: In order to get more precise backtesting results among ARCH family, the rolling window backtesting of 1 day VaR was performed in this section. Both 95 and 99% confidence levels were used to realize the difference. Since ARCH family assumes the variance of a specific day as a function of previous day, the number of observations would be same as the number of sample data. Confidence interval at 95 and 99% were between [108.67, 152.32] and [13.01, 39.19], respectively.

From Table 6 using 95% confidence level, GARCH performed better by only one failed result within Plantation industry. ARCH and EGARCH models failed to

Table 6: Backtesting results for ARCH family in 95 and 99%

	95% Confidence level			99% Confidence level		
Industry/window length	ARCH VaR	GARCH VaR	EGARCH VaR	ARCH VaR	GARCH VaR	EGARCH VaR
Consumer product	**109**	**133**	**124**	43	43	43
Construction	106	**112**	106	46	45	**38**
Finance	**106**	**111**	**109**	45	**35**	**37**
Industrial product	**115**	**118**	**113**	46	49	45
Plantations	97	97	95	44	**36**	**33**
Properties	**103**	**117**	**116**	44	42	**39**
Technology	**132**	**122**	**126**	**38**	46	42
Trade and services	**117**	**120**	**120**	50	49	46
KLCI (Benchmark)	**112**	**120**	**118**	43	42	44
Confidence interval	[108.67, 152.32]			[13.01, 39.19]		

*Bold values represents the accepted models

Table 7: Backtesting results for different NL CVaR periods

	Normal linear CVaR 95%				Normal linear CVaR 99%			
Industry/window length	1000	500	250	100	1000	500	250	100
Consumer product	52	54	56	60	30	29	**24**	30
Construction	46	45	46	47	**27**	30	**23**	**27**
Finance	43	45	49	57	**26**	28	29	33
Industrial product	58	59	54	60	32	35	36	35
Plantations	63	55	54	46	32	33	31	**27**
Properties	46	48	45	57	28	**26**	**26**	28
Technology	57	53	52	57	31	**27**	**27**	**27**
Trade and services	40	53	52	53	**25**	29	**27**	28
KLCI (Benchmark)	47	55	57	60	**26**	31	31	30
Confidence interval	[63.36, 97.63]				[5.81, 27.38]			

*Bold values represents the accepted models

Table 8: Backtesting results for different HS CVaR periods

	Historical simulation CVaR 95%				Historical simulation CVaR 99%			
Industry/window length	1000	500	250	100	1000	500	250	100
Consumer product	35	38	32	41	**10**	**9**	**8**	0
Construction	34	34	35	42	**7**	**11**	**9**	0
Finance	30	31	32	42	**9**	**11**	**11**	0
Industrial product	38	41	35	47	**10**	**11**	**7**	0
Plantations	47	44	44	40	**11**	**14**	**14**	0
Properties	31	32	31	46	**8**	**11**	**8**	0
Technology	40	32	28	36	**7**	**9**	**6**	0
Trade and services	29	36	34	45	**9**	**11**	**9**	0
KLCI (Benchmark)	32	41	35	43	**10**	**12**	**11**	0
Confidence interval	[63.36, 97.63]				[5.81, 27.38]			

*Bold values represents the accepted models

show the accurate results in Construction and Plantation industries. Perhaps, conducting ARCH family at 99% confidence level may not be a good idea since most of the results tend to display underestimation of risk. ARCH model was successful in only one industry when GARCH model gained two successful results at 99% confidence level. EGARCH showed a better performance compare to its relatives by having four accepted results at 99% confidence interval. Totally, ARCH family results indicated a greater performance at 95% confidence level and GARCH was the best model with the lowest failed results.

Normal linear CVaR: The results of the normal backtesting revealed that both models of CVaR failed in accurate risk measurement. The reason may rely on conservative nature of CVaR in prediction of risk. From Table 7, results of all rolling windows failed to fall between the confidence interval at 95% confidence level. The interesting result was 14 out of 36 backtesting results fall within the interval at 99% confidence level. Moreover, most of the rejected results were very close to the confidence interval with underestimating the risk. More than half of the results in the 250 days window are accepted by backtesting that is considered as the best window among all. 1000 day rolling window also revealed tolerable outcome by generating four accepted results out of nine.

Historical simulation CVaR: The results in Table 8 showed that Historical Simulation CVaR was far more conservative than Normal Linear CVaR.

Historical Simulation CVaR failed in all window lengths at 95% confidence level and the number of violation were very fewer than the related confidence interval. Since CVaR is a conservative model, it shows a better performance at the higher confidence level. The backtesting results illustrated that Historical Simulation CvaR was thoroughly appropriate for 250, 500 and 1000 days windows with no failed result. It is expected that 100 days window failed to establish successful results since the CVaR picks 1% of the 100 days window which is the lowest return of the basket. Therefore, it shows a really high CVaR in every trial. Overall, the CVaR performs well with the more out-sample data.

CONCLUSION

According to results, different VaR and CVaR models ranked Technology as the highest risk industry among all other ones. The reason is that Technology industry always presents a rapid growth compare to other industries. The competitive nature of Technology sector along with its continuous innovation makes it highly volatile and risky. The next risky industry was Construction as another growing sector. Industries involve with individuals' basic needs are expected to be less volatile and risky in comparison to others. For instance, Consumer Product was the least risky industry dealing with consumers' necessities. Industrial Product and Trade and Services industries revealed low risk among Malaysian industries as well.

As CVaR identifies the loss beyond VaR, it would show higher risk compare to VaR models. Historical Simulation CVaR and Normal Linear CVaR presented the highest risk for industries under investigation. Historical Simulation VaR represented the lowest risk for all industries and was a favorable risk model for banks. The reason is to reserve lowest possible capital requirements by the model. Among ARCH family models, ARCH VaR depicted highest risk, while EGARCH VaR showed the lowest. EGARCH VaR revealed to be the lowest risk model in Technology and Trade & Services industries.

In this study, estimating the accuracy of different risk models using four rolling windows and two confidence levels resulted remarkable outcomes. Although the risk models have their own advantages, the choice of picking the right model highly depend on the preference of institutions. For instance, for those institutions requiring high confidence level, CVaR models would be a better measurement of risk as well as Normal Linear CVaR and Historical Simulation CVaR. Indeed, Historical Simulation CvaR performs better in rolling window higher than 250 days. As such Normal Linear CVaR could be a proper substitution when an institute needs 100 day rolling window with a high confidence level. On the other hand, institutions required lower confidence level, Normal Linear VaR and ARCH family would be suitable measurement of risk.

Further, VaR models always tend to underestimate the risk. For instance, Normal Linear VaR underestimated the risk in all rolling windows for Malaysian industries. In other cases VaR models tend to stay in upper bound of the confidence interval. CVaR models, however, tend to overestimate the risk in most of the cases. As a result, the models failed to fall in the confidence interval at 95% confidence level and stayed in lower bound of confidence level. These results may lead to a conclusion that VaR cannot show the maximum amount of loss could happen in let's say 5% worst cases; while it indicates the maximum amount of loss may occur in 95% best cases. To this end, VaR model can be perceived as "best of worst cases scenario" and thus, may result in underestimating the possible losses related to specific confidence level.

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