Research Journal of Finance and Accounting
ISSN 2222-1697 (Paper) ISSN 2222-2847 (Online)
Vol.7, No.18, 2016

Forecasting Market Risk in ASEAN-5 Indices using Normal and Cornish-Fisher Value at Risk

Bangkit Oetomo[1*] Noer Azam Achsani[1] Bagus Sartono[2]
1. School of Business, Bogor Agricultural University, PO box 16151, Main Padjajaran Avenue - Bogor, Indonesia
2. Department of Statistics, Bogor Agricultural University, PO box 16151, Main Padjajaran Avenue – Bogor, Indonesia

Abstract
The purpose of this paper is to quantify and compare the risk in ASEAN-5 markets consist of Indonesia (IDX), Malaysia (MYX), Singapore (SGX), Thailand (SET), and Philippines (PSE) and design accurate and practical method to measure daily market risk using Value at Risk model. We compare two distribution model namely normal (Normal VaR) and Cornish-Fisher (CFVaR) to modify normal quantile to achieve most precise result. Besides, we employed ARMA-GARCH model to quantify one-day-ahead volatility. This study found that distribution of ARMA residual in all markets show asymetric characteristics with leptokurtic and negative skewness. The ARMA-GARCH (1,1) is powerful forecasting tool in emerging ASEAN but it is less effective in developed ASEAN due to the absence of randomness in ARMA residuals. The Normal VaR is best used in markets with less skewed distribution such as MYX and SGX. However, the CFVaR is rejected in PSE markets due to overestimation of risk. Meanwhile, the CFVaR is best used in IDX and SET markets which indicated by less failures produced by this model in both markets.
Keywords: ARMA-GARCH, normal distribution, modified quantile, value at risk

1. Introduction

The 2008 subprime mortgage crisis fostered Basel Committee of Banking Supervision to impose obligatory risk framework for major financial institutions. One of the key elements in Basel risk framework is value at risk (VaR) which help users to quantify risk and forecast the worst possible return within the time horizon. According to Jorion (2001), VaR summerizes the worst loss of financial instrument over determined time horizon with given confidence level.

The crucial aspects in forecasting market movement is determining volatility and probability models, which these two key elements are captured by VaR model. The model of VaR is emphasis on developing volatility model to forecast risk and probablity distribution to measure the degree of risk. The basic concept of VaR is to measure the worst return under certain level of confidence in certain time interval. The equation for parametric VaR is presented below:

$$\mathrm{VaR}_{t+1} = \sigma_{t+1} \times \alpha(F) \times \sqrt{t} \times M \qquad (1)$$

VaR consist with several components namely t day ahead volatility σ_{t+1}, distribution quantile function α following F type distribution $\alpha(F)$, holding period t, and monetary value M. The level of confidence that generally used in VaR measurement are 1%, 2.5%, 5%, and 10%. The degree of confidence will affect the value of $\alpha(F)$, the smaller the degree of freedom, then the value of

For example, if VaR users determine 95% confidence level with inverse probability of $\alpha \in (0.05)$ then the value of VaR is represents the worst 5% of return, and VaR users confident that 95% of market movement will above this VaR value. The illustration of VaR is easy to understand and straight to the point; if the share price of company A is IDR 1,000 with daily standard deviation σ of IDR 200. If the level of confidence used in this calculation is 1% which means that 99% of market movement will above VaR value and the probability follows Gaussian or normal distribution with probabilty density function of $\alpha(F) = 2.33$, then the VaR:

$$\mathrm{VaR}_{(A)} = \text{IDR } 1{,}000 - (2.33 * \text{Rp } 200) = \text{IDR } 534$$

Users confident that 99% market movement will be above IDR 534, therefore, there are 1% probability that the value of the share would dive under or as low as IDR 534. The simple rule of model validity is; the actual losses (l) exceed forecast rate (L) of VaR_{t+1} is cannot exceed 1% of total observation T, or $\frac{|n|L>l}{T} \leq 1\%$.

The calculation of VaR above is correct if the distribution of return follows normal distribution and volatility is constant throughout the obeservation. However, there are numerous empirical evidence of non normality time series plot behavior in return distribution.

The return of financial markets with high frequency tends to posses non normal distribution. The observation of distribution in emerging and developed countries found that all distribution of random variables posses non normal distribution with non zero mean and skewness, and excess kurtosis in these markets (Angelovska, 2013). The distribution of emerging markets posses further non normal characteristics than developed markets. Similar like previous findings, Al Janabi (2007) founds that emerging markets in the middle east stock markets posses asymetric characteristics. The implication of asymetric distribution is able to weaken the applicability of normal distribution to measure market risk. The studies of performance comparison between normal and non-normal distribution, such as student's-t and generalized hyperbolic distributions, have been carried out by Baciu (2014) found that normal distribution is best used in normal market period where there is only a few extreme negative return value happened in time interval. Meanwhile, the performance of normal distribution in extreme years is insufficient measurement since it was underestimate the risk. In extreme situations, the generalized hyperbolic distributions are producing better result than normal. These findings are consistent with Andersen and Frederiksen (2010), where they compared the performance of normal and extreme market condtions, who found that the returns in the time series sample were both disperse and unevenly distributed, while at the same time being asymmetrically distributed.

The variance of return of financial markets are non-constant and dependent. Therefore, the simple volatility measurement such as standard deviation is no longer accurate prediction of volatility. Fuss, Kaiser, and Adams (2007) use GARCH-type VaR to forecast different value of VaR found that the GARCH-type VaR with the time-varying conditional volatility is able to trace the actual return process more effectively. Volatility modelling under GARCH models consist of several variations to capture different style of volatility. One of most renown GARCH type is Exponential GARCH which capture the asymetric volatility effect. The study compares this two types of GARCH models was conducted by Awartani and Corradi (2005) who found that asymetric GARCH model perform better. However, this study focusing in the probability of worst loss, therefore, only focus on downside risk which model such symetric GARCH is sufficient measurement model to capture downside risk. The GARCH type able to produce dynamic forecasting to address the heteroscedasticity effect in residual series. This capability makes GARCH model is widely used to quantify market volatility.

However, there is no simple answer what best approach and models used in calculating VaR. According to Manganelli and Engle (2001), there are three general approaches used to design distribution model of VaR calculation namely parametric, semi parametric, and non parametric approach. The non parametric model such as Historical Simulation is the most popular method used by institutional banks to measure VaR (Perignon & Smith, 2006). Despite its practicality, this approach posses substantial drawbacks such as its constant volatility model and assumption that return series are independent. Models used in HS cannot answer market phenomenon where there is volatility clustering and serial correlation. However, generating model to present accurate VaR measurement is a complex task for practitioners. For example, the time interval used as a foundation to build conditional volatility model is might be different from time to time due to changing pattern movement. Consequently, the time interval taken to develop conditional volatility model has to represent the movement in the near future. The VaR only can forecast risk in normal market movement. Besides, the semi parametric model such as Extreme Value Theory (EVT) focusing on extreme deviation from the median of probability distributions. This model is associated with extreme catastrophic events that occur rarely. Therefore, this EVT model is suitable for special cases such as market crash (Li et. al. , 2011).

This study is focus on measuring risk in ASEAN-5 markets which has diversified economic profile that generally devided by two catagories; emerging and developed markets. Emerging ASEAN markets which consist of Indonesia (IDX), Malaysia (MYX), Phillippines (PSE), and Thailand (SET), and developed market which consist of Singapore (SGX). Emerging ASEAN markets have been listed among worldwide top performers with substantial growth for the past decade. However, several global instability issues increase the surge of hot money in these emerging countries that contribute to severe volatility for the last couple of years. Empirical study found that emerging markets have similar characteristics; high volatility due to inconsistent government regulation, exchange rate devaluation, dan political risk (Bekaert, Erb, Harvey, & Viskanta, 1998). Anggarwal et al. (1999) found that emerging markets posses fat-tailed volatility distribution and difficult to model.

On the other hand, emerging markets sustain tremendous improvement in macroeconomics and regulatory institution management after 1997 Asia crisis. Meanwhile, several developed markets experience economics hurdle characterized by overlaverage debt and severe fiscal deficit in recent years (Muromcew & Renfrew, 2013). Furthermore, financial crisis created more impact on developed markets (Costa et. al, 2014). Furthermore, ASEAN markets have dynamic characteristic which signed by the members' endeavour to strengthen economic cooperation between markets through ASEAN Economic Comunity (AEC). One of the main objectives of AEC is to achieve financial integration that possesses liberalization of capital movement and to strengthen economic cooperation among ASEAN markets. Financial integration agenda will open further opportunity for all investors to invest in diverse ASEAN markets. Therefore, it is important to study the risk profile in this region to map the diverse risk level in each market. The ASEAN-5 markets include in this study are based on the composite index points. In modern portfolio theory, financial manager eliminate risk by diverse its asset alocation in assets that have low covariance. However, asset diversification is not able to eliminate systematic risk that affect all assets in the market.

There are several past studies that applied normal and quantile modification to find the best-fit model in each market. Andersen and Frederiksen (2010) found that distribution of return in financial markets is asymetric which makes normal distribution is no longer sufficient model to measure VaR accurately. There are several studies compare non normal and normal distribution found that normal distribution is the best model to measure VaR (Akin & Orhan, 2011; Aktas & Sjostrand, 2011). Aktas and Sjostrand (2011) applied Cornish-Fisher Expansion as alternative to subtitute normal distribution weakness in measure extreme deviation by modify normal quantile according to skewness coefficient as modification operator.

1.1 Study Objectives

This paper objective is to develop accurate and practical methods in measuring risk by using VaR parametric approach which consist of two main components; (i) conditional volatility model and (ii) distribution assumption. The volatility model used in this paper need to have an ability in forecast dynamic change of variance movement. One of the most used model to comply with volatility phenomenon is ARMA-GARCH model. This paper employed time series autoregressive moving average (ARMA) and conditional volatility model; generalized autoregressive conditional heteroscedasticity (GARCH), as forecasting tools of one-day-ahead VaR. Conditional volatility models that proposed by Engle (1982) and Bollerslev (1986) has effective performance in predicting serial volatility in stock exchange (Siddikee & Begum, 2016). This study focus on developing practical approach on developing accurate VaR approach that able to be implemented by risk managers. This study employe parametric model under normal distribution assumption. However, to comply with the assymetric distribution, this study employed quantile modification model.

2. Literature Review and Methodologies

The VaR methodology has been used by market practitioners to interpret and quantify market risk they are facing in the future depends by the designated probability rate or confidence level. Jorion (2001) defines VaR as a method to conclude the worst loss over assigned holding period at certain level of confidence. For example, using a probability of α percent and a holding period of t days, an entity's VaR is the loss that is expected to be exceeded with a probability of only α percent during next t days holding period. Typical values for the probability or confidence level (α) are 1, 2.5, and 5 percent, while common holding periods (t) are 1,2, and 10 days, and 1 month (Pearson & Linsmeier, 1996). Therefore, the objectives of VaR is to quantify worst return possible based on level of confidence and time interval applied by the user, and to provide quantitative guideline for planning of capital requirements in case of potential worst loss occurred (see; Jorion, 2001; Pearson & Linsmeier, 1996; for detail of VaR concept and application). The variance-covariance approach using conditional distribution to forecast risk in left tail of distribution to measure the worst return. However, the probability density fuction of the normal quantile might not represent the real distribution of data that contain skewness and kurtosis. The relationship between volatility and distribution fuction is shown in equation 2.

$$\mathrm{VaR}_{\alpha,t} = \mu_t + \sqrt{\sigma^2_{t+h}}\,[-q_\alpha(F)] \qquad (2)$$

The VaR method consist of several key components namely mean (μ_t), volatility (σ) on the day h (σ_{t+h}), probability density function (pdf) based on the quantile (q) of designated confidence level α (q_α) at probability assumption F (q_α(F)). The intrepretation of VaR is straight forward; by using α of 95% with $\alpha \in 5\%$ means that 95% of market return value will be located above the worst 5%, the VaR will represent the worst 5% of daily market return. The main concept of the model is; the probability of real loss (L) exceeded predicted worst loss or VaR (l) cannot be exceeded 1-α, or in ineferential statistics desicribed

$$\mathrm{VaR}_\alpha = \inf\{\alpha \in F(L > l) \leq 1 - \alpha\} \qquad (3)$$

There are two concentrations of VaR method under parametric approach; developing volatility model and choosing statistical distribution assumption to fit the data characteristics to measure and forecast risk accurately. There are several volatility approaches that widely used such as standard deviation and GARCH types model.

The choice of distribution assumption will impact the VaR result dramatically due to the goodness of fit the assumed probability distribution with the actual probability distribution of data. The failure in choosing the best fit model will cause the overestimate or underestimate the VaR forecast value that in turn will lower the validity of VaR model. There are several studies to compare the performance of normal and non normal distribution have found that non normal distribution such as generalized hyperbolic and student's-t distribution types outperform normal distribution (Baciu, 2014; Liu, Cheng, & Tzou, 2009; Yudong, 2015). However, the performance of normal distribution is not always been inferior compares with non normal distribution. Empircal evidence of this phenomenon is well captured by Orhan and Akin (2011) who found that normal distribution is outperform Student's-t distribution model.

The concentration of VaR is located at the left distribution tail which represent the probability distribution of worst possible return. The distribution of possible profit and losses on return data can be represented by the probability density function (pdf) that describes the relative likelihood for random variable to take on a given value. The basic distribution model is normal distribution with pdf function of αz in equation 4.

$$\alpha_z = \frac{1}{\sqrt{2\pi\sigma}} e^{-\left(\frac{(r-\mu)^2}{2\sigma}\right)} \qquad (4)$$

Using normal distribution with α 0.95 then the value of α_z at $\alpha \in 5\%$ is 1.645. This normal α_z value is often regarded as unsufficient risk measure due to inability to capture the extreme negative deviation of the data. In order to understand the the differences between assumed distribution and actual distribution, this research observe the four distribution moments consist of; mean (μ), deviation (σ), skewness (γ), and kurtosis (δ). The $\gamma \neq 0$ indicates that there is asymetric effect on the distribution of random variable about its mean. The negative γ indicate that there is a fat left distribution tail. In this case, the value of α_z migh be not represent the density of random variables at this tail. The moment coefficient of skewness is represented in equation 5.

$$\gamma = E\left[\frac{(r-\mu)^3}{\sigma}\right] = \frac{\mu_3}{\sigma_3} = \frac{E[(r-\mu)^3]}{(E[(r-\mu)^2])^{3/2}} \qquad (5)$$

Where μ_3 is the third central moment and E is the expectation operator. The normality of distribution is not single handedly determined by the γ but also with its fourth moment about the mean δ. The normal distribution has $\delta = 3$, therefore $\delta \neq 3$ indicates non normal distribution shape where $\delta > 3$ is leptokurtic distribution which has tails that produces more outliers than the normal distribution (further reading e.g Kim & White, 2003). The moment coefficient of kurtosis is represented in equation 6.

$$\delta = E\left[\frac{(r-\mu)^4}{\sigma}\right] = \frac{\mu_4}{\sigma_4} = \frac{E[(r-\mu)^4]}{(E[(r-\mu)^2])^2} \qquad (6)$$

There are considerable numbers of studies have found that stock market returns both in emerging and developed markets posses non normal distribution with fat tails and high peaks. However, the emerging markets have more higher kurtosis and more negative skewness than developed markets (Rikumahu, 2014; Aparicio & Estrada, 1997). Normal distribution shortcomings in measure the the extreme deviation is due to the limitation of its pdf in representing the density of random variables outside of the distribution tail. One of the methods to overcome the shortcoming of normal distribution is by modifying the value of quantile pdf function based on the third and fourth moments of the actual distribution. The Cornish Fisher Expansion (CF) model has been used in previous study such as Aktas and Sjostrand (2011) and Favre and Galeano (2002) to overcome the limitation of standard distribution by modify the value of pdf quantile $q\alpha_z$ to $CFq\alpha_z$. The value of $CFq\alpha_z$ will be higher than $q\alpha_z$ if the actual distribution has $-\gamma$. Therefore the value of CFVaR will be greater than Normal VaR if the distribution has negative skewness, this method is to overcome the extreme deviation that cannot be observed trhough normal distribution. The CF model is represented by equation 7.

$$CFq\alpha_z = q\alpha_z - \left[(q\alpha_z{}^2 - 1)\frac{\gamma}{6}\right] + \left[(q\alpha_z{}^3 - 3q\alpha_z)\frac{\delta}{24}\right] - \left[(2q\alpha_z{}^3 - 5q\alpha_z)\frac{\gamma^2}{36}\right] \qquad (7)$$

Performance comparison of VaR calculation under normal and CF distribution need to be taken to find the most accurate distribution model in measuring risk. Aktas and Sjostrand (2011) has found that CF distribution or CFVaR is overestimate the risk and normal VaR has better performance. There diverse results among VaR users under various models make the result of normal and non normal distribution need to backtested to determine which models turned out the best.

The objective of time series modelling is to find the combination of two parameters namely autoregressive (AR) and moving average (MA) to best mimic the pattern of return series x_t based on serial correlation of historical series at lag p and q. The AR (p) model with p lag as parameter.

$$x_t = \delta + \emptyset_1 x_{t-1} + \emptyset_2 x_{t-2} + \cdots + \emptyset_p x_{t-p} + \varepsilon_t \qquad (8)$$

Residual ε_t is the white noise or unknown factor that cannot be observed through AR model. The MA assume there is a serial correlation between ε_t and ε_{t-q}. The MA(q) model with q lag parameter.

$$x_t = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} \qquad (9)$$

This study combines model $x_t = \delta + \emptyset_1 x_{t-p} + \varepsilon_t$ and $x_t = \varepsilon_t + \theta_1 \varepsilon_{t-q}$ to form ARMA (p,q) model. The common used ARMA (1,1) model is a linear fuction of correlation between one-day historical return x_{t-1} and residual ε_{t-1}.

$$x_t = \delta + \emptyset_1 x_{t-1} + \varepsilon_t - \theta_1 \varepsilon_{t-1} \qquad (10)$$

In order to develop the best fit model, the random variables must meet fundamental requirement of stationarity and invertability where $\sum \emptyset_1 + \cdots + \emptyset_p < 1$ and $\sum \theta_1 + \cdots + \theta_q < 1$. Otherwise, the first level difference $\Delta P = x_t - x_{t-1}$ need to be taken. However, the ARMA model has limitation in construct variance σ_t^2 model due to its inability to forecast value that greatly scattered from the mean. This deficiency causes ARMA model produces white noise ε_t. Engle (1982) proposed Autoregrresive Conditional Heteroscedasticity (ARCH) to capture unconstant and dependent ε_t. In ARCH model, the variance series is the function of past squared unexpected return ε_{t-p}^2.

$$\sigma_t^2 = \xi + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \cdots \ldots + \alpha_t \varepsilon_{t-p}^2 \qquad (11)$$

The main focus of conditional variance model is to generate dynamic volatility model that able to forecast volatility clustering, such caractheristic that connot be observed through ordinary volatility measurement such as strandard deviation. Bollerslev (1986) revised the ARCH model and introduced Generalized Autoregressive Conditional Heteroscedasticity (GARCH (p,q)) model to account ε_{t-p}^2 and past variance at lag q σ_{t-q}^2 as linear function of conditional variance σ_t^2. The most basic GARCH (1,1) model:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \qquad (12)$$

Where volatility σ_t is squared root of variance or $\sigma_t = \sqrt{\sigma_t^2}$.

2.1 Backtest Method

Kupiec (1995) proposed a method to determine model validity by measure wether the failure rate is consistent with determined level of confidence, or so called Likelihood Ration of Proportion of Failure (LRPoF). The backtest model is represented in equation 1.12.

$$LR_{PoF} = -2\ln\left(\frac{(1-p)^{T-x}p^{x}}{\left[1-\left(\frac{x}{T}\right)\right]^{T-x}\left(\frac{x}{T}\right)^{x}}\right) \qquad (13)$$

Where T is number of observations, x is number of failures, p is level of confidence, and x/T is the rate of failure. Based on statistical concept, the rate of failure suppose to be $x/T \leq 1-p$. The hipotethical determination is used by compare LRPoF with $\chi 2$ 5%, where we can reject model if $LR_{PoF} > 3.841$.

3. Empirical Findings

We employed wide range data set started from 5 January 2009 to 19 January 2016 consist of more 1700 daily index value for each market. There are diverse movements in this time frame with bullish periods started from 2009 to 2013 and with volatile conditions with several market shocks in 2013 to 2014, finally in 2014 to 2016 markets are suffered from bearish periods. Emerging ASEANs consist of IDX, PSE, and SET tend to move in the same direction. Meanwhile, MYX -most advanced economy among emerging ASEANs- tend to move independently than other emerging ASEAN. On the other hand, random movement can be indentified in SGX market. Daily indices value are retrieved from google finance and yahoo finance. For further model estimates and analysis, this study using daily return data that calculated through geometric mean return r_t:

$$r_t = \ln\frac{P_t}{P_{t-1}} \qquad (14)$$

Based on visualized time series plot using Minitab, return data in all indices indicate stationerity where the mean is constant throughout the time frame. Besides, there is an indication for heteroscedasticity in all markets where volatility is clustered in certain period. We employed Augmented Dickey Fuller (ADF) test to determine wether a variable follows a unit-root process that containing trend and seasonality. In non stationer process, the data need to be differenced $\Delta P = P_t - P_{t-1}$. The null hypthesis is that the variable contains unit root, and the alternative is that the variable was generated by a stationarity process. The sample data is stationer if the value of t statistics is less than its critical value at $\alpha = 5\%$. All of indices follow stationarity patterns since the t statistics is way smaller than its critical value. There are significant t statistics value difference between emerging and developed ASEAN. For example, the t statistics for SGX is -39.36769 and its critical value is -2.862997. Meanwhile, the t statistics fro PSE is -25.73030 and its critical value is -2.864225. The gap between the critical value and t statistics in SGX is more significant than PSE index.

Table 1. Statistics descriptive analysis for ASEAN-5 markets using return series

Descriptive	IDX	MYX	SGX	PSE	SET
M	0.000663	0.000328	0.000180	0.000683	0.000559
γ	-0.373102	-0.116264	0.146064	-0584896	-0.327190
δ	7.379549	5.340007	7.251387	7.001425	5.881459
Jarque-Bera	1412.860	400.4426	1326.409	1240.484	633.3627
ADF test	-25.85633	-36.50749	-39.38769	-25.73030	-26.69522

Note: The mean μ, skewness γ, and kurtosis δ value are retreived from histogram analysis using return series. This analysis is only to describe data characteristics in ASEAN markets. The γ and δ coefficient from residual series are used to modify quantile density value.

Time series ARMA model can be developed after all the data have showed stationarity behavior. This study developed best ARMA model through validation and selection criterias such as; (i) significance level of parameter value, (ii) least error value, and (iii) significance level of p value Ljung-Box statistics. The first step to develop the best ARMA model is to identifiy the serial correlation from autocorrelation function (ACF) and partial autocorrelation (PACF) that available is statistics software. The ACF and PACH are used to visualize the significant correlation ρ_i between price at lag i x_{t-i} to current price x_t, or $\rho_i = Corr(x_t, x_{t-i})$. This procedures need to be taken due to construct the best model with highest autocorrelation function and produce least error. The significant model must have $p \leq 0.05$ at all of its parameters, otherwise the model is not qulify for the first test and need to be re-modelled.

Table 2. Parameter measurement for ARMA modelling to determine the significant lag

Indices / Model Parameters	IDX SARIMA $(2,2)^6$	MYX SARIMA $(2,1)^6$	SGX SARIMA $(2,3)^{12}$	PSE SARIMA $(2,2)^5$	SET SARIMA $(2,2)^5$
δ	0.0005641	0.00012877	**0.001083	0.0005253	0.003688
$\emptyset_2$	-0.6791	0.1477	-0.9384	-0.5267	-0.8152
θ_1	n.a	-0.8584	n.a	n.a	n.a
θ_2	-0.5984	n.a	n.a	-0.4079	-0.8514
θ_3	n.a	n.a	-0.0922	n.a	n.a
Residual SS	0.255804	0.0653624	0.161627	0.209102	0.232542
Residual MS	0.000150	0.0000378	0.000093	0.000123	0.000134
P value lag 12	0.061	0.358	0.100	0.065	0.287
P value lag 24	0.415	0.604	0.066	0.153	0.322
P value lag 36	0.050	0.271	**0.005	0.336	0.380
P value lag 48	0.110	0.163	**0.000	0.224	0.597

Note: Not available (n.a) indicate there is no significant lag for particular parameter in each model. The parameter validation is done through observation of P statistics value, sum of square and mean square residuals, and Ljung Box p value statistics. The ** sign rejection for P value lag 36 and 48 in SGX market, this sign indicates that the residual from ARMA modelling is not following white noise or non random process. This issue will influence the ability of GARCH model in developing sufficient modelling.

The significant and the best time series process is determined by three main catagories which consist of; (i) significant p value at each parameter where the p value must be less than 0.05, (ii) the least residual SS and MS, and (iii) significant Ljung-Box statistics value where the value must be larger than 0.05 (for further reading please read Mabrouk, 2016; Baciu, 2014; Milos, 2011).

The result of time series modelling in emerging ASEAN are not vary significantly. The δ** at SGX is not valid because of its p statistics value 0.469 exceed 0.05 critical value. The SGX Ljung Box statistics p value at lag 36** and 48** are not significant indicate the residual from ARMA model is not random. The interpretation of PSE ARMA model can be expressed as follow; return from two days earlier x_{t-2} has negative autocorrelation of $\emptyset_2$ -0.5267 with future return x_{t+1}. However the MA assume that the residuals from AR model are dependent. Therefore, the residuals from two days earlier $\theta_2$has autocorrelation with future return x_{t+1}. The Ljung Box p value for all of emerging markets are ≥ 0.05, indicating that all residuals are random. Residual randomness result is different for SGX where the p value ≤ 0.05. Note that the Ljung Box p value is no longer valid at lag 36 and 48 indicate that the residual of SGX ARMA is not random. This issue will affect residual modelling under ARCH/GARCH method which assume serial correlation.

The residual or error produced by ARMA model is used for further conditional volatility modelling using ARCH/GARCH method. Residual analysis need to be taken before we enter to modelling process. The objectives of residual analysis is to determine data characteristics including; (i) normality test and (ii) heteroscedasticity test.

Normality test revealed the form of actual distribution. The random variables using residual data display non normal characteristics with substantial kurtosis and negative skewness. This empirical evidence shows that all ASEAN markets contain fat tail and posses non normal distribution. The negative skewness indicates that residuals more distributed to the left tail rather than the right. The normal density function might not captured the fat tail due to limitation of density value. Consequently, these findings encourage the adoption of more sophisticated distribution method to capture the extreme deviation.

Table 3. Normality and heteroscedasticity test of residual ASEAN-5 markets

Indeks	Mean (μ)	Median	Skewness (γ)	Kurtosis (δ)	Jarque-Bera	ARCH-LM F statistics
IDX	0.0000196	0.000533	-0.446067	7.370762	1417.84	0.0000
MYX	0.0000209	0.000201	-0.103800	5.336817	396.73	0.0000
SGX	0.0000743	0.000338	-0.049655	6.027423	664.43	0.0000
PSE	-0.000419	0.000042	-0.669887	7.204894	1380.37	0.0000
SET	0.0000014	0.000194	-0.269568	5.868199	614.31	0.0000

Note: The ARCH-LM test indicates the presence of heteroscedasticity effects on all market. Distributions with skewness closer to zero and kurtosis close to three are closer to normal distribution characteristics.

Emerging ASEAN markets posses more asymetric distribution compared with developed ASEAN. The PSE index is the most skewed and IDX has the highest kurtosis. This two distribution moments namely skewness and kurtosis will impact the quantile modification. This study employed heteroscedasticity test using ARCH LM method to determine if the variables have non constant variance prosess. The null hypothesis used in this test is variables are homoscedastic or constant variance. If the value of F statistics ≤ 0.05 then reject null hypothesis and determine that variables is experiencing non constant volatility. We can conclude that all the variables posses non constant variance based on ARCH-LM test results. Therefore, more sophisticated dynamic variance model such as ARCH/GARCH need to be employed in order to construct best variance forecasting model. We determine the best model according to several criterias such as; (i) p statistics ≤ 0.05 in every parameter, (ii) smallest AIC and SIC, and (iii) have 0.95-0.99 persistency $\alpha + \beta$ value.

Table 4. Result of GARCH modelling for each parameters and validations

Indices	IDX	MYX	SGX	PSE	SET
Model	GARCH (1,1)	GARCH (1,1)	GARCH (0,1)	GARCH (1,1)	GARCH (1,1)
ξ	3.77E-06	1.45E-06	1.50E-07	7.33E-06	2.95E-06
α	0.114625	0.103186	-	0.158953	0.123881
β	0.863536	0.858397	0.996854	0.790584	0.859353
SIC	-6.175247	-7.481758	-6.625584	-6.276149	-6.265389
AIC	-6.143409	-7.506987	-6.653861	-6.301583	-6.303215
$\alpha + \beta$	0.978466	0.961583	0.996854	0.949537	0.983234

Note: The models above are choosen based on comparison of several modes with significant parameters. However, the models are choosen with lowest SIC and AIC values and has high persistency.

The ARCH-GARCH modelling proccess is using residual variables retrieved from the best fit ARMA models. The GARCH (1,1) model is sufficient measurement in all emerging ASEAN. However, ARCH-GARCH model failed to model the residual from SARMA $(3,2)^{12}$ SGX model. The Ljung Box p value indicates non random process at SARMA $(3,2)^{12}$ residual variables. Therefore, the the variance equation loosing its ARCH effect. The model of ASEAN-5 markets can be expressed as follow:

Table 5. Expression of conditional variance model for ASEAN-5 Indices

Indices	Model	Variance Model
IDX	GARCH (1,1)	$\sigma_t^2 = 0.0000370 + 0.108980\varepsilon_{t-1}^2 + 0.869486\sigma_{t-1}^2$
MYX	GARCH (1,1)	$\sigma_t^2 = 0.0000145 + 0.103186\varepsilon_{t-1}^2 + 0.858397\sigma_{t-1}^2$
SGX	GARCH (0,1)	$\sigma_t^2 = 0.0000015 + 0.996854\sigma_{t-1}^2$
PSE	GARCH (1,1)	$\sigma_t^2 = 0.0000733 + 0.158953\varepsilon_{t-1}^2 + 0.790584\sigma_{t-1}^2$
SET	GARCH (1,1)	$\sigma_t^2 = 0.00000295 + 0.123881\varepsilon_{t-1}^2 + 0.859353\sigma_{t-1}^2$

As presented in table 5, the SGX variance model cannot capture its ε_{t-1}^2 which retreieved from error ε_t of SARIMA $(2,3)^{12}$ model. Before we enter to VaR calculation, quantile modification based on skewness and kurtosis using Cornish Fisher method need to be conducted. This paper use 95% confidence level to measure risk in all ASEAN-5 indices with normal quantile density function $\alpha_z = 1.645$. The CFVaR will use modified α_z to α_{CF} according to skewness γ and kurtosis δ.

Table 6. Modification of normal quantile density function using Cornish Fisher expansion

Indices	IDX	MYX	PSE	SET	SGX
γ	-0.446067	-0.1038	-0.66989	-0.26957	-0.04966
δ	7.370762	5.338817	7.204894	5.868199	6.027423
μ	0.0000196	0.0000209	-0.000419	0.0000014	0.0000743
Jarque-Bera	1417.84	396.73	1380.37	614.31	664.43
α_z	1.645	1.645	1.645	1.645	1.645
α_{CF}	1.680018353	1.6271853	1.742298	1.662487	1.598071

The value of α_{CF} in emerging markets such as IDX, SET, and PSE are substantially greater than α_z due to presence of significant γ and δ in these markets. The value of α_{CF} is getting smaller than α_z due to closer value of γ to zero. Note that the normal distribution has $\gamma = 0$ and $\delta = 3$, then quantile modification has no effect if the distribution moments exactly normal. However, the distribution of SGX is closer to normal with excess δ and slightly negative γ. Despite the distribution moments of SGX are not much different to normal distribution, excess kurtosis with slightly negative γ make α_{CF} has lower value than α_z.

We divided two different VaR calculations using nomal VaR (Normal VaR) and Cornish Fisher VaR (CFVaR). The Normal VaR and CFVaR volatility model are using same ARCH-GARCH result. Therefore, the main difference is located at its quantile value. We employed three different holding period; 1 day, 5 days, and 10 days. The result of Normal VaR and CFVaR is presented below:

Table 7. Result of VaR calculation using normal distribution and Cornish Fisher expansion

Indices	Volatility	Normal VaR			CFVaR		
	σ_{t+1}	1	5	10	1	5	10
IDX	0. 01001310	-1.647%	-3.683%	-5.209%	-1.695%	-3.791%	-5.361%
MYX	0.006632932	-1.091%	-2.440%	-3.450%	-1.098%	-2.456%	-3.473%
SGX	0.006948003	-1.143%	-2.556%	-3.614%	-1.147%	-2.564%	-3.626%
PSE	0.01576613	-2.707%	-6.053%	-8.560%	-2.856%	-6.386%	-9.031%
SET	0.01342949	-2.209%	-4.940%	-6.986%	-2.248%	-5.027%	-7.109%

Note: The backtest model need to be taken to measure model validity and accuracy of prediction. This process only to measure the one-day-ahead VaR or daily VaR.

From the result shows in table 7, market with highest risk is PSE followed by SET, IDX, SGX and MYX. Quantile modification VaR produces greater risk in market with substantial negative skewness such as IDX, PSE and SET. The quantile modification using Cornish Fisher adapt with actual distribution contains with skewness and kurtosis, therefore the value of of its quantile value is change due to its asymetric factor to capture the excess deviation than normal.

For markets which their skewness are closer to zero, such as MYX and SGX, the value of quantile fuction is smaller than normal. This issue makes CFVaR method calculates lower risk in these markets. Despite the skewness do not differ greatly from normal distribution, this market distributions still posses excess kurtosis. The effect of excess kurtosis draw the tail shorter due to distribution of residuals converge around the mean.

All of the models are tested to forecast daily market movement using its own data. The result can be seen on graph (xx) for daily forecast result of Normal VaR and CFVaR. The SGX ARCH-GARCH model lost its dynamic ability due to absence of ARCH factors in the model. The SGX ARMA-GARCH model is dependent only to one random variable which is historical one day variance σ_{t-1}^2.

The ARCH-GARCH models perform remarkably in forecasting dynamic volatility in emerging ASEAN. The GARCH (1,1) is sufficient model to produce reliable volatility forecasting in these markets. However, there are failures of prediction in several incidents that produce extreme deviation. These failures are not able to be forecasted due to limited quantile value and immidiate shock that cannot be observed by GARCH model. The table below summerizes the total expected and actual failures at 5% confidence level.

Table 8. The expected failure with 5% significant level and the actual failures proportions

Index	T	Failures		
		Expected (5%)	Normal VaR	CFVaR
IDX	1710	86	5.146%	5.029%
MYX	1730	87	5.029%	5.145%
SGX	1738	87	5.351%	5.639%
PSE	1701	85	4.292%	3.704%
SET	1731	87	5.488%	5.430%

Note. The Normal VaR and CFVaR failures rate is retrieved from total failures of each model devided by total observation. The expected failures are the 5% fraction from total observation.

The implication of quantile modification is obviously created higher failure rate at SGX and MYX due to lower density function than normal. The performance of Normal VaR is better than CFVaR in this markets. Figure 1 to 4 visualizing the result of GARCH model performance in forecast the one-day-ahead VaR.

Contrary with what we found on the MYX and SGX, the performance of CFVaR is outperform Normal VaR in IDX, PSE, and SET in terms of numbers of failures. Failures are due to several market shocks factors such as the implication of external and internal factors. The most prominent global shocks such as Europe credit default, currency devaluation, and US interest rate hike are among external factors that create market shocks in ASEAN-5 markets. Besides, the internal factors such as political unrest also created market downward risk.

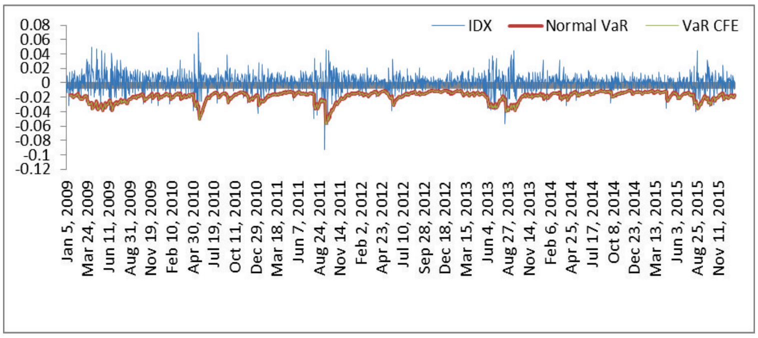

Figure 1.Visualization of VaR_{t+1} in IDX Using Normal VaR and CFVaR

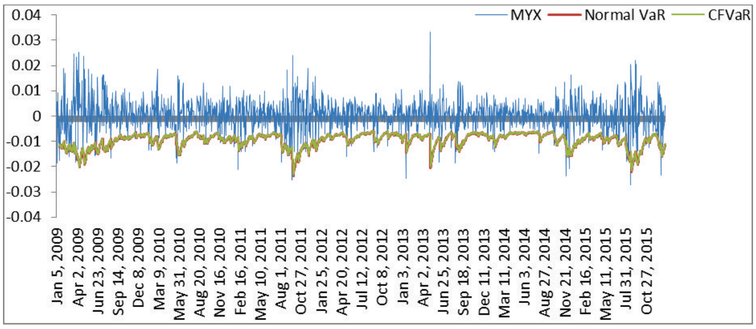

Figure 2. Visualization of VaRt+1 in MYX Using Normal VaR and CFVaR

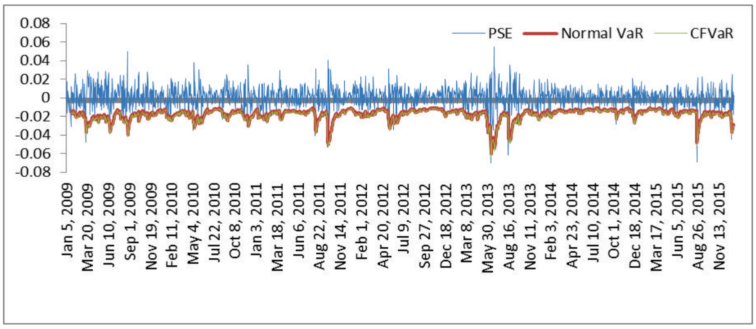

Figure 3. Visualization of VaRt+1 in PSE Using Normal VaR and CFVaR

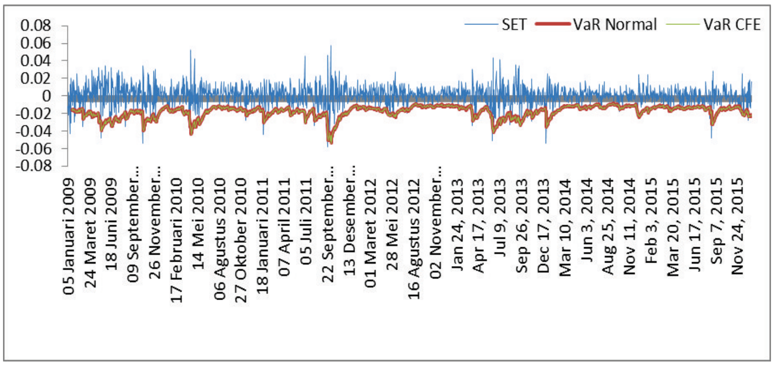

Figure 4. Visualization of VaRt+1 in SET Using Normal VaR and CFVaR

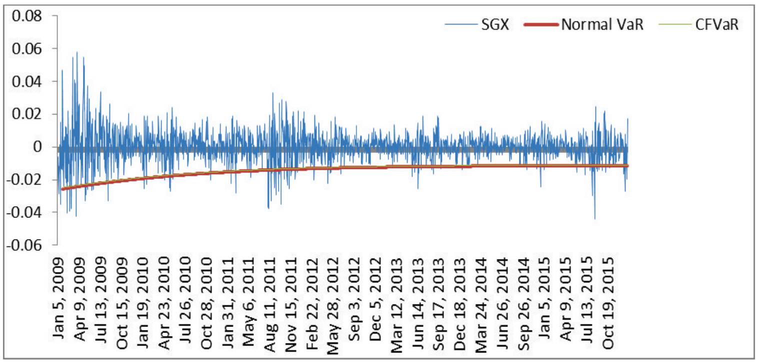

Figure 5. Visualization of VaRt+1 in SGX Using Normal VaR and CFVaR

Note: Figure 5 shows that there is no dynamic ability in GARCH (0,1) model due to the absence of squared residual variable which derived from SARIMA residual

This empirical evidence shows that ARCH-GARCH models are unable to forecast an immidiate shocks. Furthermore, the risk factors created extreme deviation that cannot be observed using Normal or Cornish Fisher distribution.

The failure rate indicates models performance but it is not a sufficient measurement to determine model validity. Kupiec backtest measures the accuracy of models to forecast daily risk accrording to significance level. This study use likelihood ratio proportion of failures (LR_{PoF}) test to determine the best model to measure a 5% quantile of distribution.

Table 9. Kupiec backtest result of Normal VaR and CFVaR

Index	Normal VaR	CFVaR
IDX	0.076246495	0.003072203
MYX	0.003036751	0.075372921
SGX	0.44107602	1.435842262
PSE	1.883771149	6.586339293**
SET	0.842870752	0.657432613

Note. (**) is indicate rejection of this model in particular market.

Table 9 shows that VaR under normal disribution is successful in assesing risk in ASEAN-5 markets. There is no rejection for Normal VaR in all markes with 5% significance level. Therefore, the normal assumption is still valid risk measurement in this markets. The CFVaR model is rejected in measuring PSE market due to overestimation of the risk. Quantile modification under Cornish Fisher creates high quantile density value that is not fit with the actual distribution. Therefore, the quantile modification is not neccessarily suitable for all form of asymetric distribution.

4. Concluding Remarks

This paper objectives are to create accurate and practical model to measure downside market risk in ASEAN-5 indices that consist of emerging and developed markets. This study employed parametric VaR approach to design best forecasting model using 95% significance level, or to forecast 5% probability of worst lost in daily market return. The distribution assumptions taken in this study are normal and modified normal density function using Cornish Fisher expansion. In other hand, this study assumed that variance is dependent and heteroscedastic which make conservative volatility measurement such as standard deviation is no longer a sufficient model to use. Therefore, this study employed ARCH-GARCH model to forecast daily downside risk. There are several key findings that need to be centered in this study:

a. The residual of ARMA model, which essential for ARCH-GARCH modelling, show randomness in all market except for SGX. The non random residual process makes ARCH effect cannot be modelled in the GARCH model. The GARCH SGX model solely rely on past variance to predict one-day-ahead volatility. This issue impact the performance of ARCH-GARCH which has lost its dynamic ability in predicting variance movements. Therefore, the ARMA-GARCH model is incompatible to be used for SGX index which catagorized as developed market.
b. Modification of quantile density function is not neccessarily effective to apply in all asymetric distributions. The SGX and MYX distributions have slight negative skewness and excess kurtosis which make the modified quantile density has lower value than normal density. As a result, the performance of CFVaR is worse compare with Normal VaR in these markets. Moreover, the CFVaR model is not a suitable model in PSE since it is overestimated the risk. The distribution characteristics of PSE is distinct compare with other markets. The negative mean value and extreme kurtosis indicate that the frequency of returns are concentrate nearby the mean.
c. Contrary with most empirical findings, this study found that normal distribution is sufficient risk measurement for ASEAN-5 markets. The normal quantile density function is able to capture the deviation. However, the extreme market shocks due to external and internal factors cannot be measured using distribution assumption used in this study.

References

Aktas, O., & Sjostrand, M. (2011, September 7). Cornish-Fisher Expansion and Value-at-Risk method in application to risk management of large poertfolios. Retrieved May 19, 2016, from School of Information Science, Computer and Electrical Engineering Halmstad University: http://www.diva-portal.se/smash/get/diva2:442078/FULLTEXT01.pdf

Al Janabi, M. A. (2007). A value at risk approach to measuring equity trading risk exposure in emerging stock markets. Asian Academy of Management Journal of Accounting and Finance, Vol.3, No.1, 1-19.

Andersen, T. T., & Frederiksen, T. C. (2010, August). Modelling value-at-risk under normal and extreme market conditions. Retrieved June 03, 2016, from Copenhagen Business School Institute of Finance: studenttheses.cbs.dk/.../troels_thostrup_andersen_og_thomas_chr._frederiksen.pdf?...

Angelovska, J. (2013). Managing market risk with VaR. Management, 81-96.

Anggarwal, R., Inclan, C., & Leal, R. (1999). Volatility in emerging markets. Journal of Financial and Quantitative Analysis, 33-55.

Aparicio, F., & Estrada, J. (1997, April). Empirica Distributions of Stock Returns: Scandinavian Securities Markets, 1990-95. Retrieved May 19, 2016, from IESE Department of Business, and Statistics and

Econometrics: http://web.iese.edu/jestrada/PDF/Research/Others/DSRSSM.pdf

Awartani, B., & Corradi, V. (2005). Predicting the volatility of the S&P-500 stock via GARCH models" the role of asymmetries. International Journa of Forecasting, Vol. 21, 167-183.

Baciu, O. A. (2014). Value-at-risk estimation on Bucharest stock exchange. Journal of Applied Quantitative Method Vol. 9 No. 4, 40-50.

Favre, L., & Galeano, J. A. (2002). Mean-modified Value-at-Risk optimization with hedge funds. Journal of Alternative Investments, 21-25.

Fuss, R., Kaiser, D. G., & Adams, Z. (2007). Value at risk, GARCH modelling and the forecasting of hedge fund return volatility. Journal of Derivatives & Hedge Funds Vol. 13, 2-25.

Jorion, P. (2001). Value at RIsk The New Benchmark For Managing Financial Risk 2nd ed. New York: Donnelley & Sons Company.

Kim, T. H., & White, H. (2003). On More Robust Estimation of Skewness and Kurtosis: Simulation and Application to the S&P 500 Index. Retrieved May 19, 2016, from Department of Economics, UCSD: http://escholarship.org/uc/item/7b52v07p#page-1

Li, H., Fan, X., Li, Y., Zhou, Y., Jin, Z., & Liu, Z. (2011, February 21). Approaches to VaR. Retrieved May 2016, 19, from Stanford University: https://web.stanford.edu/class/msande444/2012/MS&E444_2012_Group2a.pdf

Liu, H. C., Cheng, Y. J., & Tzou, Y. P. (2009). Value at Risk based risk management on exchange traded fund: the Taiwanese experience. Banks and Banks Systems.

Mabrouk, S. (2016). Forecasting Financial Assets Volatility Using Integrated GARCH-Type Models: International Evidence. Journal of Finance and Economics, 4(2): 54-62.

Manganelli, S., & Engle, R. F. (2001). Value at Risk Models in Finance. European Central Bank.

Milos, E. (2011). Using the Value at Risk Mehod in Estimation of Investment Risk in the Metallurgical Sector Companies. eFinanse, 7(1): 37-50.

Orhan, M., & Akin, A. (2011). Performance of VaR in Assessing Risk: Evidence form the Istanbul Stock Exchange. Journal of Economic and Social Research Vol. 13(1), 57-73.

Pearson, N. D., & Linsmeier, T. J. (1996, January). Casualty Actuarial Society. Retrieved May 2016, from Risk Measurement: An introduction to Value at Risk: https://www.casact.org/education/specsem/99frmgt/pearson2.pdf

Perignon, C., & Smith, D. (2006). The level and quality of Value-at-Risk disclosure by commercial banks. Simon Fraser University.

Rikumahu, B. (2014). Pemodelan Distribusi Tingkat Imbal Hasil Indeks Harga di Tujuh Bursa Asia. Jurnal Manajemen Indonesia, 1-15.

Siddikee, M. N., & Begum, N. N. (2016). Volatility of Dhaka Stock Exchange. International Journal of Economics and Finance Vol. 8 No. 5, 220-229.