Value-at-Risk and Modified Value-at-Risk under Asset Liability by Using Time Series Approach

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Abstract

Proper risk measurement can be useful in determining investment decision choices in the financial asset market. There are several models for measuring risk, including Value-at-Risk (VaR) and Modified Value-at-Risk (MVaR). Which of the two risk measures are more appropriately applied to analyze multiple stock prices, depending on the behavior pattern of each return of the financial assets analyzed. This paper aims to choose a more appropriate risk measurement model, if the return of financial assets has a certain behavior pattern. It is assumed that the return of financial assets follows the asset-liability model. Similarly, it is assumed that the return data on financial assets follows the time series pattern. In this paper, we formulate VaR and MVaR risk measurement models under liability assets. Furthermore, an analysis of the comparison between VaR and MVaR is carried out under the asset-liability model, using a time series approach. The evaluation of the performance of a risk measure has been done using the Lopez II approach. The results of the analysis show that some stocks are more suitable to be measured by VaR, and others are more suitable to be measured based on MVaR. So, to choose a more appropriate risk measure, it depends on the behavior pattern of stock returns.

Keywords:
Asset Return, Time Seies, Value-at-Risk, Modified Value-at-Risk, Lopez-II

1. Introduction

Several types of risks in financial markets, including credit risk, operational risk, and market risk, are the three main categories of financial risk. Value-at-Risk (VaR) is mainly related to market risk, but this concept can also be applied to other types of risks (Khindanova and Rachev 2005, Holto 2002). VaR can be defined as the maximum loss of financial position, along the time period and certain probabilities given (Dowd 2002, Froot et al. 2007). VaR is a measure of the level of risk of investment losses. VaR is an attempt to identify what causes of risk and what policies are effective in reducing risk (Dowd 2002). To take policy in the future, policy makers (regulators) always look carefully at VaR as a policy-making tool. VaR is a measure of the volatility of an asset. The standard method assumes that the return of an asset is normally distributed, so VaR only involves two parameters of the average and standard deviation (Sukono 2011).

But in practice not all asset returns are normally distributed, there are several asset returns that have a non-normal distribution. Therefore, VaR is deemed necessary for adjustments. The size of the adjusted VaR is called Modified Value-at-Risk (MVaR). The MVaR measurement method will involve four parameters, namely average, standard deviation, skewness, and kurtosis (Sukono 2011). MVaR was developed using the Cornish-Fisher extension approach. The Cornish-Fisher extension is used to determine the percentile of an abnormal distribution distribution. The Cornish-Fisher extension is intended to give a factor of adjustment to the percentages estimated from the non-normality distribution, and the adjustments given from normality are "small". Therefore, Cornish-Fisher's expansion can be used to estimate VaR when Profit / Loss (P / L) has a non-normality distribution (Dowd 2002, Khindanova and Rachev 2005).

There are several investments in an asset accompanied by liabilities that must be paid by an investor. Therefore, the return that will be obtained by an investor is a surplus return, which is the difference between asset returns and liability returns (Gersner et al. 2008, Imaduddin 2010, El-Ansary 2017). Surplus return can be analyzed using the asset-liability model. Both asset returns and liability returns are often time series data, so analysis needs to be done using the time series models. In the time series model approach, to estimate the average can be done using an autoregressive integrated moving average (ARMA) model, while estimating volatility (variance) can be done using a generalized approach to autoregressive conditional heteroscedastic (GARCH) (Johansson and Sowa 2013, Tsay 2005, Baltac 2015). This paper aims to analyze the comparison between VaR and MVaR under the liability asset model, when an asset return and return liability are assumed to be time series data. For the comparison measure used Quadratic Probability Score statistics approach to the Lopez II model. As an illustration, some data on asset prices are traded on the Indonesia Stock Exchange.

2. Mathematical Model

Some mathematical models used in this analysis, according to the stages of analysis include: determining asset-liability returns, estimating the average model and volatility of asset returns, determining average, variance, skewness, and kurtosis surplus returns, determining VaR and MVaR, then testing VaR and MVaR performance.

2.1 Determine Return

Suppose P_t the price or value of an asset at the time t ($t = 1,...,T$ and T the amount of observation data), and r_t asset-liability return at the time t. The amount of return on assets can be determined by equation (Tsay 2005):

$$r_t = \ln P_t - \ln P_{t-1} \tag{1}$$

Return data r_t then used in estimating the average model as follows.

2.2 Estimate the Average Model

Suppose r_t log *return* stock at the time t, in general the model *autoregressive moving average*, ARMA(p,q), can be expressed in the equation as follows (Tsay 2005):

$$r_t = \phi_0 + \sum_{i=1}^{p} \phi_i r_{t-i} + \varepsilon_t - \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \tag{2}$$

which $\{\varepsilon_t\}$ is assumed to be a distribution of normal white noise with zero averages and variance σ_ε^2. A non-negative integer p and q are ARMA order. The AR model and MA model are special cases of the ARMA (p, q) model. By using a back-shift operator, the model (2) can be written as

$$(1-\phi_1 B - \ldots - \phi_p B^p)r_t = \phi_0 + (1-\theta_1 B - \ldots - \theta_q B^q)\varepsilon_t \tag{3}$$

Polynomial $1-\phi_1 B - \ldots - \phi_p B^p$ from the AR model and polynomial $1-\theta_1 B - \ldots - \theta_q B^q$ from the MA. If all solutions to the characteristic equation are absolutely smaller 1, then the stationary ARMA model is weak. this case, the unconditional average of the model is $E(r_t) = \phi_0 / (1-\phi_1 - \ldots - \phi_p)$ (Tsay 2005).

Average Modeling Stages. According to Tsay (2005), the average modeling stage is as follows: (i) Identification of the model, determining the order value and using the plot ACF (autocorrelation function) and PACF (partial autocorrelation function). (ii) Parameter estimation, can be done by the least squares method or maximum likelihood. (iii) Diagnostic tests, with white noise tests and serial correlations against residuals. And (iv) Prediction, if the model is suitable, then it can be used for perediction recursion.

2.3 Estimate Volatility

The estimation of the volatility model is done using GARCH models. The GARCH model, introduced by Bollerslev in 1986 is a general form or generalization of the ARCH model. In general, the GARCH (p, q) model can be written as follows (Shi-lie Deng 2004, Johansson adn Sowa 2013)

$$\varepsilon_t = \sigma_t u_t,\ \ \sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + u_t \tag{4}$$

Based on equation (4), the conditional expectation and variance of ε_t are:

$$E(\varepsilon_t | F_{t-1}) = 0 \tag{5}$$

$$Var(\varepsilon_t | F_{t-1}) = E(\varepsilon_t^2 | F_{t-1}) = \sigma_t^2 \tag{6}$$

Compared to ARCH, the GARCH model is considered able to provide simpler results because it uses fewer parameters (Tsay 2005).

Stages of Volatility Modeling. In general, according to Tsay (2005), the stages of volatility modeling are as follows: (i) Estimated average models with time series models (for example: ARMA models). (ii) Use residuals from the average model to test ARCH effects. (iii) If there is an ARCH effect, estimate the volatility model, and form a combined estimate of the average model and the volatility model. (iv) Perform a diagnostic test to test the suitability of the model. (v) If the model is suitable, use it for predictions done recursively.

2.4 Aset Liability Model

Modeling surplus asset returns is briefly described as follows. Suppose A_t assets are at time *t*, L_t liabilities at time *t*, and S_t surplus at time *t*. At the initial time *t* = 0, the initial surplus is given by:

$$S_0 = A_0 - L_0 .$$

Surplus obtained after one period are:

$$S_1 = A_1 - L_1 = A_0[1 + r_{A.1}] - L_0[1 + r_{L.1}],$$

so on, so that an increase in surplus over time can be expressed as (Imaduddin 2010, Sukono 2011):

$$S_t - S_{t-1} = A_{t-1} r_{A.t} - L_{t-1} r_{L.t} .$$

Suppose $r_{S.t}$ surplus return at time t stated as:

$$r_{S.t} = \frac{S_t - S_{t-1}}{A_{t-1}} = \frac{A_{t-1} r_{A.t}}{A_{t-1}} - \frac{L_{t-1} r_{L.t}}{A_{t-1}} = r_{A.t} - \frac{1}{f_{t-1}} r_{L.t} , \tag{7}$$

with $f_{t-1} = \dfrac{L_{t-1}}{A_{t-1}}$.

Based on equation (7) the average of surplus returns can be determined by the formula:

$$\mu_{S.t} = E[r_{S.t}] = \mu_{A.t} - \frac{1}{f_{t-1}}\mu_{L.t}. \tag{8}$$

Where $\mu_{S.t}$, $\mu_{A.t}$ and $\mu_{L.t}$ respectively are the averages of surplus return-assets, assets, and liabilities at the time t. Also based on equation (7), the surplus variance can be determined by the formula:

$$\sigma^2_{S.t} = \sigma^2_{A.t} - \frac{2}{f_{t-1}}\sigma_{AL.t} + \frac{1}{f^2_{t-1}}\sigma^2_{L.t}. \tag{9}$$

where $\sigma^2_{S.t}$, $\sigma^2_{A.t}$ dan $\sigma^2_{L.t}$ successive variances of surplus return-assets, assets, and liabilities at the time t. While $\sigma_{AL.t}$ covariance between asset returns and liability returns at time t (Sukono 2011)

2.5 VaR and MVaR Modeling

Suppose VaR_t stated *Value-at-Risk* at the time t. If given μ_t average and σ_t standard deviation, then VaR_t expressed as:

$$VaR_t = -W_0\{\mu_t + z_\alpha \sigma_t).$$

Where W_0 initial funds invested, and z_α percentile of a standard normal distribution with a level of significance α (Khindanova and Rachev 2005). Using average and surplus return variances in the equation (8) and (9), VaR_t under the asset model can be presented as:

$$VaR_{S.t} = -W_0\{(\mu_{A.t} - \frac{1}{f_{t-1}}\mu_{L.t}) + z_\alpha(\sigma^2_{A.t} - \frac{2}{f_{t-1}}\sigma_{AL.t} + \frac{1}{f^2_{t-1}}\sigma^2_{L.t})^{\frac{1}{2}}\}. \tag{10}$$

Furthermore, the MVaR model is formulated, but beforehand it is necessary to first formulate the skewness and kurtosis models of surplus returns. Using equation (7), skewness is:

$$\varsigma_{s.t} = \frac{E[(r_{S.t} - \mu_{S.t})^3]}{\sigma^{3/2}_{S.t}} = \frac{E[\{(r_{A.t} - \mu_{A.t}) - \frac{1}{f_{t-1}}(r_{L.t} - \mu_{L.t})\}^3]}{(\sigma^2_{A.t} - \frac{1}{ft-1}\sigma_{AL.t} + \frac{1}{f^2_{t-1}}\sigma^2_{L.t})^{3/2}}$$

Suppose $D_{A.t} = r_{A.t} - \mu_{A.t}$ and $D_{L.t} = r_{L.t} - \mu_t$, therefore the Skewness equation becomes

$$\varsigma_{s.t} = \frac{E[(D_{A.t} + \frac{1}{f_{t-1}}D_{L.t})^3]}{(\sigma^2_{A.t} - \frac{1}{f_{t-1}}\sigma_{A.L.t} + \frac{1}{f^2_{t-1}}\sigma^2_{L.t})^{3/2}}$$

$$\varsigma_{s.t} = \frac{\sum_{t=1}^{T}[D^3_{A.t} - \frac{3}{f_{t-1}}D^2_{A.t}D_{L.t} + \frac{3}{f^2_{t-1}}D_{A.t}D^2_{L.t} - \frac{1}{f^3_{t-1}}D^3_{L.t}]}{T(\sigma^2_{A.t} - \frac{1}{f_{t-1}}\sigma_{A.L.t} + \frac{1}{f^2_{t-1}}\sigma^2_{L.t})^{3/2}} \tag{11}$$

Where T the amount of data observed.

While the kurtosis model is as:

$$\kappa_{s.t} = \frac{E[(r_{S.t}-\mu_{S.t})^4]}{\sigma_{S.t}^{4/2}} = \frac{E[\{(r_{A.t}-\mu_{A.t})-\frac{1}{f_{t-1}}(r_{L.t}-\mu_{L.t})\}^4]}{(\sigma_{A.t}^2-\frac{1}{ft-1}\sigma_{A.L.t}+\frac{1}{f_{t-1}^2}\sigma_{L.t}^2)^2}$$

Suppose $D_{A.t} = r_{A.t} - \mu_{A.t}$ dan $D_{L.t} = r_{L.t} - \mu_t$, therefore the Skewness equation becomes

$$\kappa_{s.t} = \frac{E[(D_{A.t}+\frac{1}{f_{t-1}}D_{L.t})^4]}{(\sigma_{A.t}^2-\frac{1}{f_{t-1}}\sigma_{A.L.t}+\frac{1}{f_{t-1}^2}\sigma_{L.t}^2)^2}$$

$$\kappa_{S.t} = \frac{\sum_{t=1}^{T}[D_{A.t}^4-\frac{3}{f_{t-1}}D_{A.t}^3D_{L.t}+\frac{6}{f_{t-1}^2}D_{A.t}^2D_{L.t}^2-\frac{3}{f_{t-1}^3}Dt_{L.ij}^3+\frac{1}{f_{t-1}^4}D_{L.t}^4]}{T(\sigma_{A.t}^2-\frac{1}{f_{t-1}}\sigma_{A.L.t}+\frac{1}{f_{t-1}^2}\sigma_{L.t}^2)^2} \qquad (12)$$

Where T the amount of data observed.

Modified Value-at-Risk (*MVaR*) is

$$MVaR = -W_0\left\{\mu+\left(z_\alpha+\frac{1}{6}(z_\alpha^2-1)S+\frac{1}{24}(z_\alpha^3-3z_\alpha)K-\frac{1}{36}(2z_\alpha^3-5z_\alpha)S^3\right)\sigma\right\}$$

where μ average, σ standard deviation, S *skewness*, K *kurtosis*, dan z_α standard normal distribution percentile with a level of significance α (Dowd 2002).

When equations (8), (9), (11) and (12) are substituted into the MVaR equation will be obtained, the MVaR model is under the asset-liability model, as follows:

$$MVaR_{S.t} = -W_0\left\{\mu_{A.t}-\frac{1}{f_{t-1}}\mu_{L.t}+\left(z_\alpha+\frac{1}{6}(z_\alpha^2-1)\times\right.\right.$$

$$\left(\frac{\sum_{t=1}^{T}[D_{A.t}^3-\frac{3}{f_{t-1}}D_{A.t}^2D_{L.t}+\frac{3}{f_{t-1}^2}D_{A.t}D_{L.t}^2-\frac{1}{f_{t-1}^3}D_{L.t}^3]}{T(\sigma_{A.t}^2-\frac{1}{f_{t-1}}\sigma_{A.L.t}+\frac{1}{f_{t-1}^2}\sigma_{L.t}^2)^{3/2}}\right)+\frac{1}{24}(z_\alpha^3-3z_\alpha)\times$$

$$\left(\frac{\sum_{t=1}^{T}[D_{A.t}^4-\frac{3}{f_{t-1}}D_{A.t}^3D_{L.t}+\frac{6}{f_{t-1}^2}D_{A.t}^2D_{L.t}^2-\frac{3}{f_{t-1}^3}D_{A.t}D_{L.t}^3+\frac{1}{f_{t-1}^4}D_{L.t}^4]}{T(\sigma_{A.t}^2-\frac{1}{f_{t-1}}\sigma_{A.L.t}+\frac{1}{f_{t-1}^2}\sigma_{L.t}^2)^2}\right)$$

$$\left.\left.-\frac{1}{36}(2z_\alpha^3-5z_\alpha)\times\left(\frac{\sum_{t=1}^{T}[D_{A.t}^3-\frac{3}{f_{t-1}}D_{A.t}^2D_{L.t}+\frac{3}{f_{t-1}^2}D_{A.t}D_{L.t}^2-\frac{1}{f_{t-1}^3}D_{L.t}^3]}{T(\sigma_{A.t}^2-\frac{1}{f_{t-1}}\sigma_{A.L.t}+\frac{1}{f_{t-1}^2}\sigma_{L.t}^2)^{3/2}}\right)^3\right)\right\}$$

$$\left.\times (\sigma_{A.t}^{2} - \frac{1}{f_{t-1}} \sigma_{A.L.t} + \frac{1}{f_{t-1}^{2}} \sigma_{L.t}^{2})^{1/2} \right\} \qquad (13)$$

Equation (13) is a *Modified Value-at-Risk* a single asset under the asset-liability model, which is formulated.

2.6 VaR and MVaR Performance Measurement Models

To see the performance of VaR that has been estimated, it can be done using the Back Test method. If r_t declare profits or losses that occur throughout the period of time t, and VaR_t is a prediction of VaR at the time t, then Lopez in 1998 introduced a model of the size-adjusted frequency approach as [1]:

$$C_t = \begin{cases} 1 + (r_t - VaR_t)^2; & r_t > VaR_t \\ 0; & r_t \le VaR_t \end{cases} \qquad (14)$$

A VaR performance is said to be good if the Quadratic Probability Score (QPS) function is given as

$$QPS = (2/n) \sum_{i=1}^{n} (C_t - p)^2 \qquad (15)$$

A measure of risk is said to have a good performance if it has a small to zero. Where is the probability or level of confidence (Dowd 2002).

3. Numerical Illustration

The data in this illustration is downloaded from: http: //www.finance.go.id//. Data includes 6 shares, for the period of January 2, 2010 to June 4, 2013. Stock data includes: INDF, DEWA, AALI, LSIP, ASII, and TURB. While data about the liabilities of each share are taken as imitation data. Both asset price data and the price of liabilities are determined by each return, using equation (1). The data for each return is then used to estimate the average model and estimate the volatility model.

The estimation of the average model is done using equation (2), with the stages of the estimation process as explained in section 2.2. While the estimation of the volatility model is done using equation (4), with the stages of the estimation process as explained in section 2.3. Based on the results of the estimation of time series models in outline, and also predictions of one period ahead for the mean and variance given in Table-1 as follows:

Tabel 1: Prediction of Mean Values and Time Series Variances

Asset	**Time Series Model**	**Prob (*F*)**	**Mean ($\hat{\mu}_t$)**	**Variance ($\hat{\sigma}_t^2$)**
A_1	ARMA(1,1)-GARCH(1,1)	0.000000	0.004501	0.000215
A_2	ARMA(2,1)-GARCH(2,2)	0.000021	0.002873	0.000421
A_3	ARMA(1,1)-ARCH(1)-M	0.000000	0.001580	0.000135
A_4	ARMA(1,2)-GARCH(1,1)	0.000034	0.002693	0.000135
A_5	AR(2)-GARCH(1,1)-M	0.000000	0.009728	0.000118
A_6	ARMA(2,2)-GARCH(1,2)	0.000042	0.001510	0.000303
L	ARMA(1,1)-GARCH(1,1)	0.000003	0.006211	0.000729

Using the average value estimator $\hat{\mu}_t$ and variance estimator $\hat{\sigma}_t^2$, it is used to determine the average value of surplus returns using equation (8), and determine the value of surplus return variance using equation (9). Whereas skewness and kurtosis values of surplus returns are determined using equations (11) and (12). The results of the calculations are given in Table-2.

Tabel 2: Average, Variance, Skewness, and Kurtosis under Asset Liabilities

Surplus	**Average** ($\mu_{S.i}$)	**Variance** ($\sigma^2_{S.i}$)	**Skewness** ($\varsigma_{S.i}$)	**Kurtosis** ($\kappa_{S.i}$)
S1	0.000450	0.04638	0.160	2.910
S2	0.002873	0.06487	0.868	5.041
S3	0.001581	0.03680	-0.030	5.880
S4	0.000269	0.03675	-0.600	9.150
S5	0.000972	0.03429	0.070	5.050
S6	0.001511	0.05504	1.193	11.032

Next, using the values of the parameters given in Table-2, the amount of VaR and MVaR is determined. Calculation of VaR and MVaR is done by referring to equations (10) and (13). Furthermore, the risk size performance testing is carried out using QPS which refers to equations (14) and (15). The results of these calculations are given in Table-3.

Taking into account the calculation of VaR and MVaR along with the QPS values, as given in Table-3, it appears that the illustrated data analyzed have some surplus returns, the risk is better measured using VaR and some better measured using MVaR. This can be used as a reference, that the selection of risk measures needs to pay attention to the characteristics of the return assets analyzed.

Tabel 3: VaR and MVaR calculations along with QPS

Surplus	$VaR_{S.t}$	QPS_{VaR}		$MVaR_{S.t}$	QPS_{MVaR}
S1	0.075845	0.0535		0.082417	0.0064
S2	0.086922	0.0768		0.078534	0.0089
S3	0.093442	0.0042		0.087542	0.0833
S4	0.088428	0.0852		0.098562	0.0037
S5	0.054909	0.0003		0.055879	0.0067
S6	0.059430	0.0963		0.075622	0.0064

4. Conclusion

In this paper, we have analyzed the comparison between measures of VaR risk and MVaR under liability assets with an average approach and non-constant volatility. In this paper a risk measurement model for VaR and MVaR has been formulated under liability assets. Based on illustrated data analysis, that there are several surplus returns, the risk is better measured using VaR and some are better measured using MVaR.

Acknowledgements
Acknowledgments are conveyed to the Rector, Director of Directorate of Research, Community Involvement and Innovation, and the Dean of Faculty of Mathematics and Natural Sciences, Universitas Padjadjaran, with whomthe Internal Grant Program of Universitas Padjadjaran was made possible to fund this research.The grant is a means of enhancing research and publication activities for researchers at Universitas Padjadjaran.

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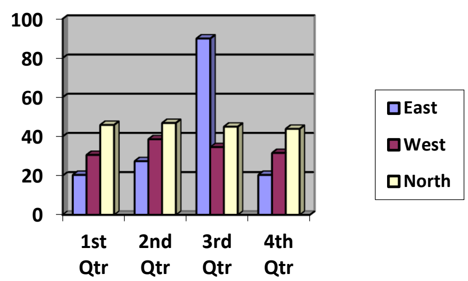

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- Title of table should be sentence case with center justification and 10 font size
- All table numbers must be mentioned in the body of the paper.
- One space between texts and table, table and title of the table and title of the table and texts.

Table 1. Name of the table

Equations

- Equation numbering is optional.

Acknowledgements

- Add acknowledgement if needed

References (12 font)

- References title – 12 font with bold and left justification
- References texts – 10 font
- No numbering should be used for reference title
- Last name and year should be used for any reference citation. Last name and year should be used for single author and double authors. For more than two authors, last name of the first author and "et al." with year should be used. For examples: Reimer (2009), (Reimer 2009), Reimer and Ali (2009), (Reimer and Ali 2009), Reimer et al. (2009) and (Reimer et al. 2009). Number is not allowed in the reference citation.
- All references must be cited in the paper.
- Journal and conference names should in in italic.
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- All lines after the first line of references list should be indented one-fourth (1/4) inch from the left margin. This is called hanging indentation. .
- Last name and first initial should be should in the reference formatting like below examples.

Chang, T., Wysk, R., and Wang, H., *Computer-Aided Manufacturing*, 3rd Edition, Prentice Hall, New Jersey, 2006.

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Biography / Biographies (for single author – biography and multiple authors- biographies) – 12 font bold

- Include bio of each author at the end of the paper

- Limited to 200 words

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