Estimating the Value-at-Risk for some stocks at the capital market in Indonesia based on ARMA-FIGARCH models

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Abstract. Value-at-Risk has already become a standard measurement that must be carried out by the financial institution for both internal interest and regulatory. In this paper, the estimation of Value-at-Risk of some stocks with econometric models approach is analyzed. In this research, we assume that the stock return follows the time series model. To do the estimation of mean value we are using ARMA models, while to estimate the variance value we are using FIGARCH models. Furthermore, the mean value estimator and the variance are used to estimate the Value-at-Risk. The result of the analysis shows that from five stock PRUF, BBRI, MPPA, BMRI, and INDF, the Value-at-Risk obtained are 0.01791, 0.06037, 0.02550, 0.06030, and 0.02585 respectively. Since Value-at-Risk represents the maximum risk size of each stock at a 95% level of significance, then it can be taken into consideration in determining the investment policy on stocks.

1. Introduction

There are various financial assets that offer different levels of profit and risk in the capital market. Risks are often associated with variability or dispersion. The asset is said to have no risk if its return does not have a variability. The greater the return variability of an asset, the more the probability of return is different from the expected result [1]. Because investors are facing a risky investment opportunity, investment decisions cannot just consider the expected level of returns, but also the extent of losses that may occur [4]. The commonly used measurement of asset loss risk is the standard variance or deviation. Both measure how far the actual return is different from the average return. Variance measures the average of the quadratic difference between the actual returns and the mean returns. The greater the value of variance, the farther the actual returns is different from the average return. Since variance is a measure of average risk, so it cannot accommodate all risk events. There is an idea of measuring risk by using quintile, which is further known as Value-at-Risk (VaR) [7].

Value-at-Risk measures typically consist of two parameters, namely mean and volatility as well as a certain confidence level percentage [6]. The mean of asset return data is often nonconstant over time, so it is following the time series model, and the mean can be estimated using Autoregressive Moving Average (ARMA) model. Similarly, the volatility of asset return data is often non constant and has a
long-term correlation structure. Characteristics of such volatility can be estimated using Fractionally Integrated Generalized Autoregressive Conditional Heteroscedasticity (FIGARCH) models. We have done the research on Value-at-Risk estimation using time series model approach. Makiel [11], estimates market risk using Value-at-Risk based on ARIMA-GARCH models. Kasman [10], estimates Value-at-Risk for the stock price index in Turkey which concern to the long-term correlation structure in volatility. Balibey and Turkyilmaz [5], conducting Value-at-Risk analysis that concern to the asymmetry and long memory structure. Aloni and Hamida [2], estimates and measures Value-at-Risk performance based on long memory models from GARCH-Class.

According to the previous description, this paper analyzes the estimation of Value-at-Risk of some stocks with econometric models approach. The aim is to estimate Value-at-Risk of some stock return traded on the capital market in Indonesia of which has characteristics that follow ARMA-FIGARCH models. As a case study, stock return data of PRUF, BBRI, MPPA, BMRI, and INDF are analyzed. So that can be used as a consideration for investors who make investments on the five shares.

2. Risk Measurement Model

The intention of this section is to describe the models used in the Value-at-Risk estimation. The models used include stock return, mean model, volatility model, and Value-at-Risk model with its performance measurement method. The discussions begin by following explanation of stock return.

2.1. Stock Return

In this section, the aims are to determine the stock returns. Suppose that the stock price on a day- \( t \) is \( X_t \). To analyze financial data within horizon daily time, return \( r_t \) often given in the form of continuously compound return or log return in following formula:

\[
r_t = \ln \left( \frac{X_t}{X_{t-1}} \right),
\]

with \( t = 1,2,\ldots,T \) where \( T \) is the number of observation data, and it is assumed that \( X_0 = 1 \) [7]. Thus, we used this return for modeling in the following sections.

2.2. Mean Model

The aim of this section is to discuss the mean model in time series data. Suppose that \( r_t \) is a log return stock at time \( t \), generally, the Autoregressive Moving Average model, ARMA(\( p,q \)), can be expressed by the following equation [13], [14]:

\[
r_t = \phi_0 + \sum_{i=1}^{p} \phi_i r_{t-i} + \sum_{j=1}^{q} \theta_j a_{t-j}.
\]

Where \( \{a_t\} \) is a residual sequence assumed to be normal white noise distribution with mean 0 and variance \( \sigma_a^2 \). A non-negative integer \( p \) and \( q \) are the order of ARMA. AR and MA model are the special cases of ARIMA(\( p,q \)) model. Using back-shift operator, model (2) can be written as:

\[
(1 - \phi_1 B - \ldots - \phi_p B^p) r_t = \phi_0 + (1 - \theta_1 B - \ldots - \theta_q B^q) a_t.
\]

Polynomial \( 1 - \phi_1 B - \ldots - \phi_p B^p \) is from AR model and polynomial \( 1 - \theta_1 B - \ldots - \theta_q B^q \) is from MA model. If the solution of characteristic equations is absolutely less than 1, then the ARMA model is stationary weak. In this case, the non-conditional mean of the model is \( E(r_t) = \phi_0 / (1 - \phi_1 - \ldots - \phi_p) \) [13].

Mean Modeling Steps. Broadly speaking, according to Tsay [14], the steps of modeling the mean models are as follows: (i) Identification of the model, determining order value of \( p \) and \( q \) by autocorrelation function (ACF) and partial autocorrelation function (PACF) plot. (ii) Parameter
Estimation can be done by least squares method or maximum likelihood. (iii) Diagnostic test by white noise test and non-correlation serially against residual $a_t$. (iv) Forecasting, if the model is suitable it can be used for prediction done recursively [7], [15].

2.3 Volatility Model

The aims of this section are to discuss the volatility model of time series data. Engle in 1982 proposed the autoregressive conditional heteroscedasticity (ARCH) model. In ARCH model, the following conditional variance is an autoregressive process. ARCH($p$) model assumes that log return $r_1, r_2,...$ described by the process [8], [14]:

$$r_t = \mu_t + a_t, \quad a_t = \sigma_t \varepsilon_t, \quad \text{and} \quad \sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 + \varepsilon_t,$$

where $\mu_t$ is the expectation of $r_t$, $\sigma_t^2$ is the variance of $r_t$, $\varepsilon_t$ is the random residual shock with mean 0 and variance 1. The general assumption are that $\{\varepsilon_t\} \sim iid N(0,1)$, $\alpha_0$ and $\alpha_i$ are constant, $\alpha_0 > 0$, and $\alpha_i \geq 0$, $i = 1, ..., p$.

Testing of ARCH Effect. The test that widely used for the detection of ARCH effect is the Lagrange Multiplier (LM) test, which was introduced by Engle in 1982. Refer to the equation (4), test for the ARCH($p$) effect is based on the null hypothesis $H_0: \alpha_0 = \alpha_1 = ... = \alpha_p = 0$ against alternative hypothesis $H_1: \exists \alpha_0 \neq \alpha_1 \neq ... \neq \alpha_p \neq 0$ [7], [14].

Statistical LM test. This hypothesis shows that it is asymptotically equivalent to the statistical test $T \times R^2$, where $T$ is the sample size and $R^2$ is calculated from regression [13]:

$$\hat{\varepsilon}_t^2 = \hat{a}_0 + \hat{a}_1 \hat{\varepsilon}_{t-1}^2 + ... + \hat{a}_p \hat{\varepsilon}_{t-p}^2 + \nu_t.$$

Under the null hypothesis, there is no ARCH effect, LM and statistical test $T \times R^2$ asymptotically $\chi^2(p)$ distributed. As an alternative to the LM test form, by asymptotically equivalent can used the portmanteau test, as the Ljung and Box statistical test for $\varepsilon_t^2$ [14].

GARCH Model. GARCH model was introduced by Bollerslev in 1986, is a common form or generalizations of ARCH models. In general, GARCH $(p, q)$ models can be written as follows [2]:

$$a_t = \sigma_t \varepsilon_t, \quad \sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \varepsilon_t.$$

Based on equations (4) and (5), the conditional expectation and variance of $\varepsilon_t$ is:

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

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

Compared to ARCH model, GARCH model is considered to provide simpler results because it uses less parameter [2], [14].

FIGARCH Model. FIGARCH model empirically is a volatility long memory in the financial market [14]. To demonstrate the properties of long memory of volatility in the financial markets, Baille, Bollerslev & Mikkelsen in 1996, expand the IGARCH model by replacing the first difference operator $(1 - B)$ to fractional difference operator $(1 - B)^d$ with $0 < d < 1$. The FIGARCH($p,d,q$) model is expanded as follows [12], [15]:

$$\phi(B)(1 - B)^d \varepsilon_t^2 = \omega + (1 - \beta(B)) \nu_t; \quad \varepsilon_t = \varepsilon_t^2 - \sigma_t^2.$$
It is obvious that FIGARCH model is GARCH and IGARCH special models in the case \( d = 0 \) or \( d = 1 \). Generally, the formula of FIGARCH\((p,d,q)\) model variance is:

\[
\sigma_t^2 = \alpha (1 - \beta(1))^{-1} + (1 - \beta(1))^{-1} (1 - \phi(B)(1 - B)^d) \varepsilon_t^2.
\]

where \((1 - B)^d\) can be shown by the expansion of Maclaurin series:

\[
(1 - B)^d = \sum_{k=0}^{\infty} \frac{\Gamma(k - d)}{\Gamma(k + 1)} \frac{B^k}{B^{k-d}}.
\]

\[
\Gamma(k - d) / \Gamma(k + 1) \approx k^{-d-1} \quad \text{if} \quad k \quad \text{is large, then the above coefficients in the infinite polynomials are hyperbolic decreased [3], [9].}
\]

**Volatility Modeling Steps.** In general, according to Tsay [14], the steps of volatility modeling are as follows: (i) Estimate the mean model by time series model (for example ARMA model). (ii) Use the residual of the mean model to test the ARCH effect. (iii) If there is an ARCH effect, estimate the volatility model, and construct the combined estimation form the mean model and volatility model. (iv) Conduct diagnostic tests to observe the suitability of the model. (v) If the model is fit, use to predict by recursive prediction [13], [15].

2.4 Value-at-Risk Model

In this section, the aim is to discuss the Value-at-Risk as a measure of risk. Suppose that the portfolio depends only on one risk factor. The standard method assumes that the distribution of assets return is univariate normally distributed, has two parameters: mean \( \mu \), and standard deviation \( \sigma \). The Value-at-Risk estimation issue is how to determine the \((1 - \alpha)\% \) percentile of the standard normal distribution \( z_{1-\alpha} \) [7], [14]:

\[
1 - \alpha = \int_{-\infty}^{\Phi(z)} f(r)dr = \int_{-\infty}^{\Phi(z)} \Phi(z)dz = N(z_{1-\alpha}) , \text{ with the quantile } q = z_{1-\alpha} - \mu ,
\]

where \( \Phi(z) \) is the density function of standard normal distribution, \( N(z) \) is a normal cumulative distribution function, \( R \) is a random variable of stock returns with mean \( r \), \( f(r) \) is a density function of normal distribution for log returns with a mean \( \mu \) and standard deviation \( \sigma \), and \( \xi \) is the smallest log return if given the level of confidence is \( \alpha \). The estimate Value-at-Risk (VaR) is performed by the formula:

\[
VaR = -S_0 \times \xi = -S_0 (z_{1-\alpha} - \mu_t ) ,
\]

where \( S_0 \) is the initial investment, and the minus sign (-) state the losses [7].

**Back Test Model.** To measure the performance of VaR which has been estimated, can be perform by using the back test method. Suppose that \( r_t \) is a profit or loss incurred over a period of time \( t \), and \( VaR_t \) is a prediction of VaR in time \( t \). Lopez in 1998 introduced the size-adjusted frequency model approach as:

\[
C_t = \begin{cases} 
1 + (r_t - VaR_t)^2 ; & r_t > VaR_t \\
0; & r_t \leq VaR_t 
\end{cases}.
\]

A performance of VaR is said to be good if the following Quadratic Probability Score (QPS) function:

\[
QPS = \frac{2}{n} \sum_{i=1}^{n} (C_t - p)^2 ,
\]

has a small value near to zero. Where \( p \) is a probability or a confidence level [7].
3. Results and Discussion

This section is intended to perform the data processing and the discussion, which includes: analyzed data, estimating the mean model, estimating the volatility model, predicting one period ahead, estimating Value-at-Risk, and discussion. It starts with a discussion of the data being analyzed, as follows.

3.1. Data Analyzed

This section purposed in giving the explanation about the analyzed data. The data analyzed here include stock data of PRUF, BBRI, MPPA, BMRI, and INDF, from the period of January 2013 to April 2016. The data is accessed through the website http://www.finance.go.id/. The rate of return (return) of each stock data are specified using equation (1), and then used for modeling the mean and variance below.

3.2. Estimating the Average Model

In this section the aims is to estimate the mean model of the return data following the time series pattern. Return data that has been determined based on the equation (1), then used to estimate the mean model using statistical software Eviews-8. We did the estimation by the following steps. First, the stock return data is tested stationarity by using Augmented Dickey Fuller (ADF) statistic. The test results, indicating that the data return of the five stocks analyzed all have been stationary. Second, we performed the identification and estimation of the mean model. We do the identification through the sample autocorrelation function (ACF) and partial autocorrelation function (PACF). Based on the pattern of ACF and PACF each return of five stocks, determined tentative model. Further, an estimate is made according to the tentative model, concerning the equation (2). Based on the estimation result, the return data from five stocks follow the following models: ARMA (0,1), ARMA (1,1), ARMA (2.0), ARMA (1,1) and ARMA (2,0) is best. Third, the results of estimators of these models are tested for verification and diagnosis. Verification and diagnostic test performed using correlogram residuals data and Ljung-Box hypotheses test. The test results showed that residuals of these models are white noise. Normality test results for each residual $a_i$ shows normal distribution. So there is no need find other alternative models. The residual data of the five stock returns were analyzed, then it is used for the following volatility modeling.

3.3. Estimating the Volatility Model

In this section, the aim is to estimate the volatility models of return data that follows the time series pattern. The steps description are as follows.

Identification of long memory effects; in the volatility models, the residual data of the mean model on the return of five stocks are analyzed. Before the estimation of the volatility models, it is necessary to detect the effect of long memory by referring to equations (8), (9), and (10).

For this purpose, we do the fractional differentiation of $d$ towards residual data of mean model. The parameter $\hat{d}$ is estimated using GPH method (Geweke Potter and Huddak). This process is performed using the R software, and in Table 1 are the results. To assure that the pattern of long memory exists, the hypothesis $H_0: \hat{d}_i = 0$ is done against $H_1: \hat{d}_i \neq 0$, $i = 1, ..., 5$. Based on the calculation, statistics are obtained $z_i$, while for the level of significance $\alpha = 0.05$. From the table of standard normal distribution, we obtained the values of $z_{0.05/2} = -1.96$ and $z_{1-0.05/2} = 1.96$. Since $z_1$, $z_2$, $z_4$ and $z_5$ are greater than $z_{1-0.05/2}$, can be concluded that the test results are significant, means that data of stock return of PRUF, BBRI, BMRI, and INDF have a long memory effect. The confident interval is within $-0.5 < d < 0.5$. In the other hand, MPPA stock return rate has no long memory effect because that interval exceeded $-0.5 < d < 0.5$. Next step, the fractionally differentiated data $\hat{d}_i$ is used to estimate the mean and variance models.
Table 1. The results of identification of long memory effects

| Stocks | \( \hat{d}_i \) | SE(\( \hat{d}_i \)) | Interval of Confidence | \( z_i \) | Long Memory Effects |
|--------|---------------|----------------|-----------------------|--------|---------------------|
| PRFU   | -0.096        | 0.1345         | -0.317< \( \hat{d}_1 \)<0.125 | 5.87   | Significant         |
| BBRI   | -0.064        | 0.1331         | -0.283< \( \hat{d}_2 \)<0.155 | 2.48   | Significant         |
| MPPA   | 0.043         | 0.3453         | -0.525< \( \hat{d}_3 \)<0.611 | 3.12   | Not Significant     |
| BMRI   | 0.132         | 0.1152         | -0.058< \( \hat{d}_4 \)<0.322 | 3.62   | Significant         |
| INDF   | 0.238         | 0.1343         | -0.017< \( \hat{d}_5 \)<0.459 | 3.54   | Significant         |

**Estimation of Volatility Models:** firstly, the detection of autoregressive conditional heteroscedasticity (ARCH) element against residual \( a_t \) for each stock returns, using ARCH-LM method by using Eviews-8 software. The obtained results of \( \chi^2 \) (obs*R-Square) of each stock return of PRUF, BBRI, MPPA, BMRI, and INDF are respectively 112.8209; 52.8883; 9.1234; 17.7026 and 9.12340 with probability of each is 0.0000 or less than 5%, means that those have ARCH element.

Secondly, the identification and estimation of the volatility models. Here, we use the models of generalized autoregressive conditional heteroscedasticity (GARCH) refer to the equation (5). Based on the squared residuals correlogram \( \sigma_t^2 \), that is the ACF and PACF, we select each possible tentative volatility model. We estimate volatility model of each stock return simultaneously with its mean model. Resulted that the best model obtained respectively as follows:

- **PRUF** follows ARMA(0, 1)-FIGARCH(1, \( \hat{d}_1 \_1 \)) model which is formulated as:
  \[
  \eta_t = a_t - 0.070448 \ a_{t-1} ; \\
  \sigma_t^2 = 0.00000674 + 0.072812 \sigma_{t-1}^2 + 0.897956 \sigma_{t-1}^2 + \epsilon_t ;
  \]

- **BBRI** follows ARMA(1, 1)-FIGARCH(1, \( \hat{d}_2 \_1 \))-M model which is formulated as:
  \[
  \eta_t = -0.359453 \ a_{t-1} + 0.465529 \ a_{t-1} + 0.676944 \sigma_{t-1}^2 + a_t ; \\
  \sigma_t^2 = 0.0000196 + 0.054776 \sigma_{t-1}^2 + 0.915829 \sigma_{t-1}^2 + \epsilon_t ;
  \]

- **MPPA** follows ARMA(2, 0)-GARCH(1,1) model which is formulated as:
  \[
  \eta_t = -0.15440 \ a_{t-1} - 0.126754 \ a_{t-2} + a_t ; \\
  \sigma_t^2 = 0.0000774 + 0.177777 \sigma_{t-1}^2 + 0.488259 \sigma_{t-1}^2 + \epsilon_t ;
  \]

- **BMRI** follows ARMA(1,1)-FIGARCH(1, \( \hat{d}_4 \_1 \))-M model which is formulated as:
  \[
  \eta_t = -0.646429 \ a_{t-1} + 0.700476 \ a_{t-1} + 3.105569 \sigma_{t-1}^2 + a_t ; \\
  \sigma_t^2 = 0.0000212 + 0.056086 \sigma_{t-1}^2 + 0.912034 \sigma_{t-1}^2 + \epsilon_t ;
  \]

- **INDF** follows ARMA(2, 0)-FIGARCH(1, \( \hat{d}_5 \_1 \)) model which is formulated as:
  \[
  \eta_t = -0.013454 \ a_{t-1} - 0.004895 \ a_{t-2} + a_t ; \\
  \sigma_t^2 = 0.0000753 - 0.254042 \sigma_{t-1}^2 + 0.033608 \sigma_{t-1}^2 + 0.545633 \sigma_{t-1}^2 + \epsilon_t ;
  \]

Based on ARCH-LM test, residual \( \epsilon_t \) of volatility models of stocks PRUF, BBRI, MPPA, BMRI, and INDF, there is no element of ARCH, and also have white noise. This mean model and volatility, then used to predict the value of \( \mu_t = \hat{\eta}_t (1) \) and \( \sigma_t^2 = \sigma_t^2 (1) \) one step ahead.
3.4. The Prediction of Mean and Volatility.

In this section, the aims is to predict the mean values and volatility of stock returns for one-period ahead. By using the mean models and volatility of the stock returns of PRUF, BBRI, MPPA, BMRI, and INDF mentioned previously, we calculate the values of \( \hat{\mu}_i = \hat{r}_i(1) \) and \( \hat{\sigma}_i^2 = \sigma_i^2(1) \) recursively. The results are given in columns \( \hat{\mu}_i \) and \( \hat{\sigma}_i^2 \) in Table 2.

| Stock   | \( \hat{\mu}_i \) | \( \hat{\sigma}_i^2 \) | VaR\(_i\) | QPS | \( \hat{\mu}_i / \text{VaR}_i \) |
|---------|--------------------|-------------------|---------|-----|-----------------|
| PRUF    | 0.000112           | 0.00012           | 0.01791 | 0.016368 | 0.006254        |
| BBRI    | 0.001840           | 0.00143           | 0.06037 | 0.005721 | 0.030481        |
| MPPA    | 0.000511           | 0.00025           | 0.02550 | 0.042813 | 0.020040        |
| BMRI    | 0.002980           | 0.00148           | 0.06030 | 0.008252 | 0.049416        |
| INDF    | 0.000158           | 0.00025           | 0.02585 | 0.013623 | 0.006112        |

3.5. The Calculation of Value-at-Risk

This section aims to calculate Value-at-Risk of the stock returns analyzed. The estimator of mean value \( \hat{\mu}_i \) \( (i = 1, \ldots, 5) \) and volatility (variance) \( \hat{\sigma}_i^2 \) \( (i = 1, \ldots, 5) \) from Table 2 are used to calculate the Value-at-Risk. If we determine a 95% confidence level, it is obtained in a standard normal distribution table that \( z_{0.05} = -1.645 \), and by assuming initial investment is \( S_0 = 1 \) unit, then we do the Value-at-Risk calculation by using equation (12). Value-at-Risk calculation results are given in Table 2, column VaR\(_i\).

Furthermore, the estimator of Value-at-Risk performance needs to be evaluated. If the probability is determined to be \( p = 0.05 \), then using equations (13) and (14), the values of performance indicators of Value-at-Risk are obtained as given in columns QPS in Table 2. By notice to the QPS values in Table 2, it appears that the values are relatively small and tend to be close to zero. This shows that the performance of Value-at-Risk is good. This means that the measurement of risk using Value-at-Risk based on the ARMA-FIGARCH model is good to be used on the five stock returns analyzed.

3.6. Discussion

In this section aims to hold a discussion of the results of analysis of stock return data are analyzed. By taking into account the estimator of the ratio values between the mean and Value-at-Risk in Table 2, the column \( \hat{\mu}_i / \text{VaR}_i \) the values vary from the largest to the smallest. The largest ratio value is for BMRI stock return that is 0.049416, it illustrates that by investing stocks to BMRI will provide a relatively large expected return compared to the risk value faced. The second largest ratio value is for stock return of BBRI of 0.030481, and the third largest value ratio is for stock return of MPPA of 0.020040. While the smallest ratio value is for INDF stock return of 0.006112, it illustrates that by investing in INDF stock will give relatively small expected return compared to risk value encountered. The second smallest ratio value is for PRUF share return of 0.006254.

These values of ratio are very useful for investors, in deciding of which stock the investors will invest. If investors choose three out of five shares to invest, then the priority order of choice is on stocks of BMRI, BBRI, and MPPA. However, if in the stock selection the investor merely sees large profit, then the priority of choice to invest funds is the stocks of BMRI, BBRI, and MPPA. Meanwhile, if the investors in the stock selection simply see a small risk, then the priority of
choice is the stocks of PRUF, INDF, and MPPA. So this analysis of risk investment using Value-at-Risk is useful for investors to assist in the selection of stocks as a means of investment.

4. Conclusions

In this paper, we have analyzed of Value-at-Risk estimation using economics time series approach. The data analyzed is the return of five shares, namely: PRUF, BBRI, MPPA, BMRI, and INDF. Based on the previous analysis, we draw the following conclusions. Return of the five stocks analyzed, respectively follows the models: ARMA(0, 1)-FIGARCH(1, \( \hat{\alpha}_1 \),1), ARMA(1, 1)-FIGARCH(1, \( \hat{\alpha}_2 \),1)-M, ARMA(2, 0)-GARCH(1,1), ARMA(1,1)-FIGARCH(1, \( \hat{\alpha}_4 \), 1)-M, and ARMA(2, 0)-FITGARCH(1, \( \hat{\alpha}_5 \), 1). Value-at-Risk of the return of five stocks that have been analyzed, respectively are as follows: 0.01791, 0.06037, 0.02550, 0.06030, and 0.02585. Based on the values of QPS that relatively small and close to zero, indicating that the measurement of risk using Value-at-Risk at five stocks analyzed was have a good performance. This research certainly very useful in making decisions for investors in selection of stocks as a means of investment.

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