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Asset Allocation in Indonesian Stocks Using Portfolio Robust

Abdurakhman

Department of Mathematics, Gadjah Mada University, Yogyakarta, Indonesia

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Abstract The mean-variance portfolio has several weaknesses. It does not accommodate the uncertainty of parameters, tends to be sensitive to the changes of parameter input, and tends to be unreliable on extreme observations. Moreover, it cannot accommodate the changes in investor preferences regarding the evidence of abnormal and asymmetric asset return distribution. To overcome these three weaknesses, we can use the robust mean-variance portfolio that is based on the uncertainty of parameters. However, the robust mean-variance portfolio has not included skewness in its optimization. Therefore, here in this paper, we use the robust mean-variance-skewness portfolio which includes skewness in its optimization. So it can be used for the condition where the data return is skewed asymmetric and contains extreme values. An empirical study of robust mean-variance and robust mean-variance-skewness portfolios has been conducted on four banking stocks in Indonesia, i.e AGRS.JK, BTPN.JK, BBNI.JK, and BBCA.JK. The data used in this study is the daily closing price of the company's stock price for the period January 2, 2020 – January 2, 2022 (489 days) obtained from Yahoo! Finance. From the results of the data analysis, it can be concluded that the variance still plays an important role in determining the weight of the allocation of a portfolio. Meanwhile, the large value of skewness leads to the allocation of the same weight for each stock in a portfolio.

Keywords Portfolio, Robust, Mean, Variance, Skewness

1. Introduction

Investors can form a portfolio to reduce the risk of investment [1]. The Mean-Variance (MV) portfolio was introduced by Markowitz in 1952. In the MV portfolio, investors only consider the mean and variance [2]. The MV portfolio uses the mean return and its variance to obtain the smallest variance [1]. However, this MV portfolio has several weaknesses. The first weakness, the standard assumption in the mean MV is the deterministic input, i.e., expected return and variance assumed as the true value [2]. The second weakness is sensitivity to parameter input changes, where small changes in the MV method input parameters could cause considerable changes in portfolio composition. The third weakness is unreliable in extreme observations [3]. Related to this, the MV approach tends to show its limitations, especially in the period when the financial return behaves in the most extreme way [5]. The fourth weakness is the change in investor preferences related to the existence of any evidence about the distribution of assets return that is not normal and asymmetric. Thus, investor preferences are increasing. Not only consider the maximum mean and minimum variance, but also skewness, where investors prefer positive skewness because the chances of extreme negative return are lower [4]. So investors want to maximize positive skewness.

There are several methods that can be used to overcome the weaknesses of MV methods such as the robust mean-variance, robust mean-CVaR, and Mean-Variance-Skewness (MVS) methods. Robust optimization has been developed to address issues related to the uncertain condition, therefore, sometimes called uncertain optimization [6]. Furthermore, the robust model has been adapted in portfolio optimization to address the sensitivity of the MV portfolio to its input. Optimization of the robust portfolio represents all available information about the input of unknown parameters in the form of an uncertainty set containing possible values for this parameter. This method optimizes the portfolio for the worst-case parameter input. This method is considered strong even to the input parameter changes to the worst. This method is also intended to address cases where parameter estimators are unreliable [7] and the data return contains extreme values (outliers). Of the several methods already mentioned, researchers are interested in the robust MV method because it overcomes most of the weaknesses of the MV method. In addition, the use of estimators for return and variance is not complicated.

However, the robust MV optimization method has not included the element of skewness in its optimization. Whereas it has been said before that the preferences of investors tend to change after much evidence of the discovery that the return of financial assets tends to be asymmetric. Therefore, we apply a robust MVS optimization method which can be used for conditions where data return contains extreme values (outlier) and skewness.

In this paper, we want to compare the performance of Robust MV and robust MVS portfolio, on the return assets containing outlier and skewness.

2. Robust Portfolio Optimization

2.1. Robust Mean-variance (RMV) Portfolio

Keep in mind that the optimization of the RMV portfolio here is the result of modifications from previous research [7]. According to Ben-Tal and Nemirovski [8], robust optimization methods form an optimal portfolio by creating a set of uncertainties for parameters. The set of uncertainties is ensured to contain all possible parameters. Given a problem with uncertain input, then the optimization problem can be formulated as a question: How to determine the value of a variable that can optimize the objective function for the worst case? Therefore, robust optimization establishes an optimal portfolio under the worst case scenario [6]. For this RMV portfolio, the worst condition is the minimum expected portfolio return and maximum portfolio variance (risk).

In this paper, the set of uncertainties is presented in the form of confidential intervals so that the lower and upper limits are formed for the following two parameters:

$$\mu_i^L \le \mu_i \le \mu_i^U, \quad i = 1,2,\dots,n$$
$$\sigma_{ij}^L \le \sigma_{ij} \le \sigma_{ij}^U, \quad i,j = 1,2,\dots,n \qquad (1)$$

with n is the number of assets in the portfolio.

In determining the set of uncertainties, we can use two methods proposed by Tütüncü and Koenig [7]: bootstrap, moving average, and moving window. We use the bootstrap block method with length $l = N^{1/3}$, and the process is given as follows:

1. Given $\mathbf{R} = (\mathbf{r}_{it})$ the matrix return of all assets $(i = 1,\dots,n)$ or period time to $t = 1,\dots,N$, determine the length of the bootstrap block $l = N^{1/3}$. The division of this block is done overlapping.
2. Do resampling by taking as many $N\,/\,l$ blocks with returns.
3. Calculate the estimation of mean vector and the covariance matrix. In this case, mean return estimator for i-th stock is searched using

$$\widehat{\mu_i} = \frac{1}{N}\sum_{t=1}^{N} r_{it} \qquad (3)$$

While estimator for covariance of the return of i,j-th stock is searched using

$$\widehat{\sigma_{ij}} = \frac{1}{N-1}\sum_{t=1}^{N}(r_{it} - \widehat{\mu_i})(r_{jt} - \widehat{\mu_j}) \qquad (4)$$

with r_{it} return of the i-th stock in period t..

4. Repeat steps 2 and 3 1000 times.
5. Sort the values obtained in step 4 from the smallest to the largest.
6. Create a set of uncertainty 95% bootstrap for $\boldsymbol{\mu}$ and $\sum$ by removing some 2.5% each top and bottom observations.
7. Determine μ_i^L as the smallest return value obtained from the previous step, and μ_i^U as the largest mean return value.
8. In the same way, we also can determine σ_{ij}^L and σ_{ij}^U.

Based on [6], the notations in equation (1) above can be changed by giving $\mu_i^0 = (\mu_i^L + \mu_i^U)/2$, $\beta_i = (\mu_i^U - \mu_i^L)/2$, $\sigma_{ij}^0 = (\sigma_{ij}^L + \sigma_{ij}^U)/2$ and $\delta_{ij} = (\sigma_{ij}^U - \sigma_{ij}^L)/2$ and can be expressed as

$$U_{\boldsymbol{\mu}} = \{\boldsymbol{\mu}: \mu_i^0 - \beta_i \le \mu_i \le \mu_i^0 + \beta_i, \beta_i \ge 0\}$$
$$U_{\Sigma} = \{\textstyle\sum: \sigma_{ij}^0 - \delta_{ij} \le \sigma_{ij} \le \sigma_{ij}^0 + \delta_{ij}, \delta_{ij} \ge 0\} \qquad (2)$$

After determining the set of uncertainties, then we conduct the RMV optimization. The purpose of the investor is to maximize the mean and minimize the variance assuming all funds are invested. Mathematically, it can be written as

maximize $\boldsymbol{R}_{port} = \boldsymbol{\mu}^T\mathbf{w}$

minimize $\boldsymbol{\sigma}_{port}^2 = \mathbf{w}^T\sum\mathbf{w}$

with constrain

$$\mathbf{1}_n^T\mathbf{w} = 1 \qquad (3)$$

Robust optimization works in the worst case scenario. The worst condition for expected return is when the value is minimum. Since it is assumed that shortsell is not allowed, its value is

$$\min_{\mu}[\boldsymbol{\mu}^T\mathbf{w}] = \min_{\mu}\sum_i \mu_i w_i = [(\boldsymbol{\mu}^0)^T\mathbf{w} - \boldsymbol{\beta}^T|\mathbf{w}|] = [(\boldsymbol{\mu}^L)^T\mathbf{w}] \quad (4)$$

For the worst risk is when the maximum value for shortsell is not allowed, that is

$$\max_{\Sigma}[\mathbf{w}^T\Sigma\mathbf{w}] = \max_{\Sigma}\sum_{i,j}\sigma_{ij}w_iw_j$$

$$[\mathbf{w}^T\Sigma^{\mathbf{0}}\mathbf{w} + |\mathbf{w}^T|\boldsymbol{\delta}|\mathbf{w}|] = [\mathbf{w}^T\Sigma^{\boldsymbol{U}}\mathbf{w}] \quad (5)$$

Robust optimization problems work in the worst- case conditions. This optimization problem can be viewed as a multi objective problem because it has several goals. One of the solution to solve it is with scalarization [1] by giving coefficient $s \geq 0$ and $t > 0$.

$$\max_{\mathbf{w}}\left[s[(\boldsymbol{\mu}^L)^T\mathbf{w}] - t[\mathbf{w}^T\Sigma^{\boldsymbol{U}}\mathbf{w}]\right]$$

with constrains $\mathbf{1}^T\mathbf{w} = \mathbf{1}$

$$0 \leq w_i \leq 1 \quad (6)$$

In the classical MV method, it can be viewed as a multi objective problem by providing small s values and large t values, as well as for RMV method. To simplify the RMV optimization computing software is used R solnl function on the NlcOptim package by converting maximize $f(\mathbf{w})$ to minimize $-f(\mathbf{w})$.

2.2. Robust Mean-variance-skewness (RMVS)

Previously it has been mentioned the importance of considering skewness in portfolio optimization. Investors tend to be interested in returns that have positive skewness because it decreases the likelihood of a very extreme return below [4]. Thus, the investor prefers has the goal of maximizing the positive skewness value in portfolio optimization. The idea of this optimization method is similar to the idea of RMV optimization. However, there are additional parameters included in the objective function, i.e. skewness. To calculate skewness portfolio, a coskewness matrix is required which contains coskewness between asset returns. Defined coskewness as

$$\sigma_{ijk} = E\left[(r_i - \mu_i)(r_j - \mu_j)(r_k - \mu_k)\right] = E(r_ir_jr_k) - \mu_i\sigma_{jk} - \mu_j\sigma_{ik} - \mu_k\sigma_{ij} - \mu_i\mu_j\mu_k \quad (7)$$

where
r_i: the realized return of the stock i (random variable)
μ_i: mean (expected return) of stock i

Suppose there are n assets in the portfolio. The coskewness matrix (M_3) is a $n \times n^2$ matrix with entry σ_{ijk}. More clearly, it can be written by

$$\boldsymbol{M}_3 = \begin{bmatrix} \sigma_{111} & \cdots & \sigma_{1n1} & \vdots & \ldots & \vdots & \sigma_{11n} & \cdots & \sigma_{1nn} \\ \vdots & \ddots & \vdots & \vdots & \ldots & \vdots & \vdots & \ddots & \vdots \\ \sigma_{n11} & \cdots & \sigma_{nn1} & \vdots & \ldots & \vdots & \sigma_{n1n} & \cdots & \sigma_{nnn} \end{bmatrix} \quad (8)$$

Further skewness portfolio (s_{port}) is defined as the third moment around the average that is:

$$\boldsymbol{s}_{port} = E(R_p - E(R_p))^3 = \mathbf{w}^T\boldsymbol{M}_3(\mathbf{w}\otimes\mathbf{w}) \quad (9)$$

where $\otimes$ is Kronecker product and $\mathbf{w}_i$ are the entries in $\mathbf{w}$ that represent weights for the stock i that we are looking for.

Investors want to maximize positive skewness, so for this RMVS portfolio, the uncertainty is presented in the form of intervals for three parameters, namely mean, covariance, and coskewness. So that formed the lower limit and upper limit for the three parameters as follows:

$$\mu_i^L \leq \mu_i \leq \mu_i^U, \qquad i = 1,2,\ldots,n$$

$$\sigma_{ij}^L \leq \sigma_{ij} \leq \sigma_{ij}^U, \qquad i,j = 1,2,\ldots,n$$

$$\sigma_{ijk}^L \leq \sigma_{ijk} \leq \sigma_{ijk}^U, \qquad i,j,k = 1,2,\ldots,n \quad (10)$$

Where n is the number of assets in the portfolio. As mentioned earlier, the set of uncertainties is determined by referring to the bootstrap block process with the following steps:

1. Given $\mathbf{R} = (\mathbf{r}_{it})$ the matrix return of all assets $(i = 1,\ldots,n)$ or period time to $t = 1,\ldots,N$, determine the length of the bootstrap block $l = N^{1/3}$. The division of this block is done overlapping.
2. Do resampling by taking as many N / l blocks with returns.
3. Calculate the estimation of mean vector and the covariance matrix. In this case, mean return estimator for i-th stock and estimator for covariance of the return of i-th stock j-th stock is searched using (1), and the estimator for coskewness return of the i-th stock, j-th stock and k-stock are sought by

$$\widehat{\sigma_{ijk}} = \left\{\frac{1}{N}\sum_{t=1}^{N} r_{it}r_{jt}r_{kt}\right\} - \widehat{\mu_i}\widehat{\sigma_{jk}} - \widehat{\mu_j}\widehat{\sigma_{ik}} - \widehat{\mu_k}\widehat{\sigma_{ij}} - \widehat{\mu_i}\widehat{\mu_j}\widehat{\mu_k} \quad (11)$$

   with r_{it} return of i-th stock in period t.
4. Repeat steps 2 and 3 1000 times.
5. Sort the values obtained in step 4 from the smallest to the largest.
6. Create a set of uncertainty 95% bootstrap for $\boldsymbol{\mu}$ and Σ by removing some 2.5% top and bottom observations.
7. Determine μ_i^L as the smallest return value obtained from the previous step, and μ_i^U as the largest mean return value. In the same way, it can be determined also, σ_{ij}^L, σ_{ij}^U, σ_{ijk}^L and σ_{ijk}^U.

The notation in (10) can be changed by giving $\mu_i^0 = (\mu_i^L + \mu_i^U)/2$, $\beta_i = (\mu_i^U - \mu_i^L)/2$, $\sigma_{ij}^0 = (\sigma_{ij}^L + \sigma_{ij}^U)/2$, $\delta_{ij} = (\sigma_{ij}^U - \sigma_{ij}^L)/2$, $\sigma_{ijk}^0 = (\sigma_{ijk}^L + \sigma_{ijk}^U)/2$, $\gamma_{ijk} = (\sigma_{ijk}^U - \sigma_{ijk}^L)/2$, and we have that

$$U_{\boldsymbol{\mu}} = \{\boldsymbol{\mu}: \mu_i^0 - \beta_i \leq \mu_i \leq \mu_i^0 + \beta_i, \beta_i \geq 0\}$$

$$U_{\Sigma} = \{\Sigma: \sigma_{ij}^0 - \delta_{ij} \leq \sigma_{ij} \leq \sigma_{ij}^0 + \delta_{ij}, \delta_{ij} \geq 0\}$$

$$U_{\mathbf{M_3}} = \{\mathbf{M}_3: \sigma_{ijk}^0 - \gamma_{ijk} \leq \sigma_{ijk} \leq \sigma_{ijk}^0 + \gamma_{ijk}, \gamma_{ijk} \geq 0\} \quad (12)$$

After we determined the set of uncertainties, we did the RMVS optimization. The investor's goal is to maximize the mean and minimize variance, or mathematically:

maximize $\boldsymbol{R}_{port} = \boldsymbol{\mu}^T\mathbf{w}$

minimize $\boldsymbol{\sigma}^2_{port} = \mathbf{w}^T\sum\mathbf{w}$

maximize $\boldsymbol{s}_{port} = \mathbf{w}^T\mathbf{M_3}(\mathbf{w} \otimes \mathbf{w})$

with constrain

$$\mathbf{1}_n^T\mathbf{w} = 1 \quad (13)$$

The worst condition for expected return is when the minimum value and the worst risk is when the maximum value as in RMV, i.e equations (11) and (13), while for worst skewness is when its value is minimum

$$\min_{\mathbf{M_3}}[\mathbf{w}^T\mathbf{M_3}\mathbf{w} \otimes \mathbf{w}] = \min_{\mathbf{M_3}} \sum_{i,j,k} \sigma_{ijk}\, w_i w_j w_k =$$

$$\left[\mathbf{w}^T\mathbf{M_3}^{\mathbf{0}}\mathbf{w} \otimes \mathbf{w} - |\mathbf{w}^T|\boldsymbol{\gamma}|\mathbf{w}| \otimes |\mathbf{w}|\right] \quad (14)$$

Since we assume that short sell is not allowed, the worst skewness in (14) is when its value

$$\left[\mathbf{w}^T\mathbf{M_3}^{L}\mathbf{w} \otimes \mathbf{w}\right] \quad (15)$$

Robust optimization problems work in the worst- case conditions. This optimization problem has many purposes, so it is called multi- objective problem. To solve it, one of them is by scalarization [1] by giving the weight coefficient $s, u \geq 0$ and $t > 0$.

$$\max_{\mathbf{w}} \begin{bmatrix} s[(\boldsymbol{\mu}^{\mathrm{L}})^T\mathbf{w}] - t[\mathbf{w}^T\sum^U\mathbf{w}] \\ +u[\mathbf{w}^T\mathbf{M_3}^{L}\mathbf{w} \otimes \mathbf{w}] \end{bmatrix}$$

with constrains $\mathbf{1}^T\mathbf{w} = \mathbf{1}$

$$0 \leq w_i \leq 1 \quad (16)$$

To simplify the RMVS optimization computing, we used solnl function on the NlcOptim package in R by converting maximize $f(\mathbf{w})$) to minimize $-f(\mathbf{w})$.

3. Empirical Study

In this section, a case study will be conducted to compare the portfolio performance of RMV and RMVS. The first step is downloading the stock price data and calculating the return value (log return). In this research, the application of these two models are done on the price data of four banking stocks in Indonesia namely PT. Bank Agris Tbk (AGRS.JK), PT. Bank Tabungan Pensiunan Nasional Tbk (BTPN.JK), PT. Bank Negara Indonesia (Persero) Tbk (BBNI.JK), and PT. Bank Central Asia Tbk (BBCA.JK). Data that are used in the form of daily closing price data for the period of January 2, 2020 – January 2, 2022 (489 days) earned from Yahoo! Finance. Figure 1 below are plots of stock price movements.

The time series plot of return data for the four stocks shows a significant trend. This indicates that the four selected stocks are in good performance. This data is then used to calculate the return value (log return) (there are 489 data returns) and following calculated the mean, variance, risk (standard deviation), and skewness of return of each stock and the result are given in Table 1.

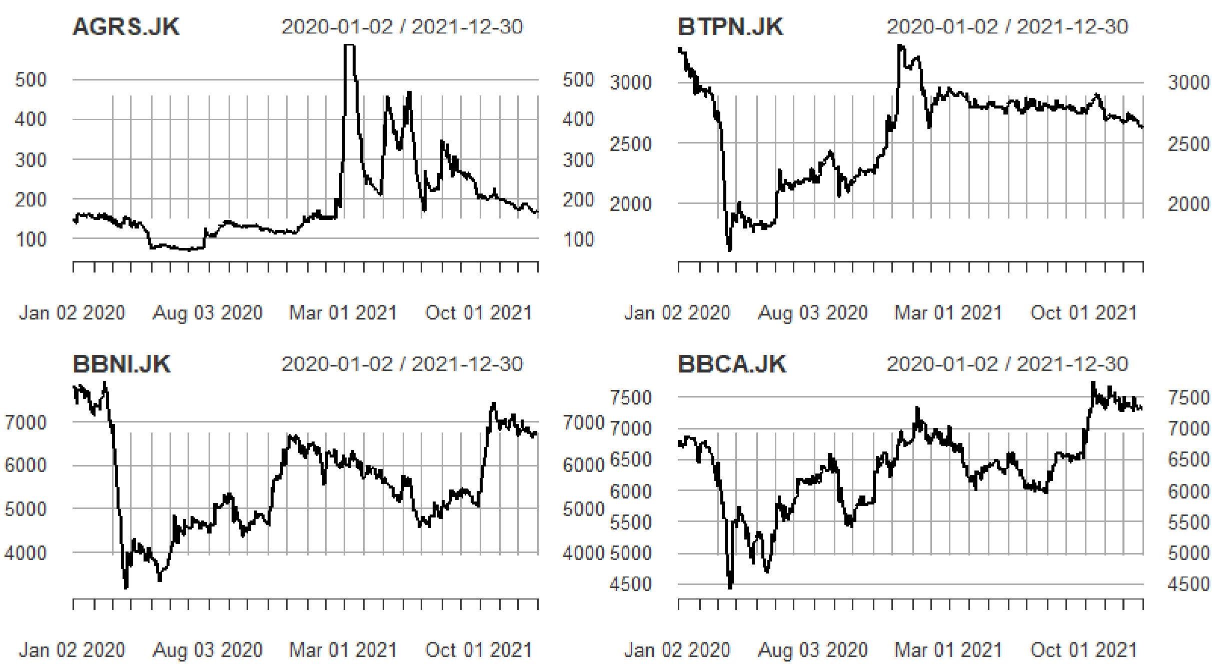

Figure 1. Plot of Stock Price Movements

Table 1. Mean, Variance, Risk (Standard Deviation) and Skewness

No	Stock	Mean	Variance	Risk	*Skewness*
1	AGRS.JK	0,0024451831	0,0039794000	0,06308249	1,5538602
2	BTPN.JK	0,0015017319	0,0005900869	0,02429170	4,0380596
3	BBNI.JK	0,0010681430	0,0003484720	0,01866740	0,5620039
4	BBCA.JK	0,0009649463	0,0001258058	0,01121632	0,3108030

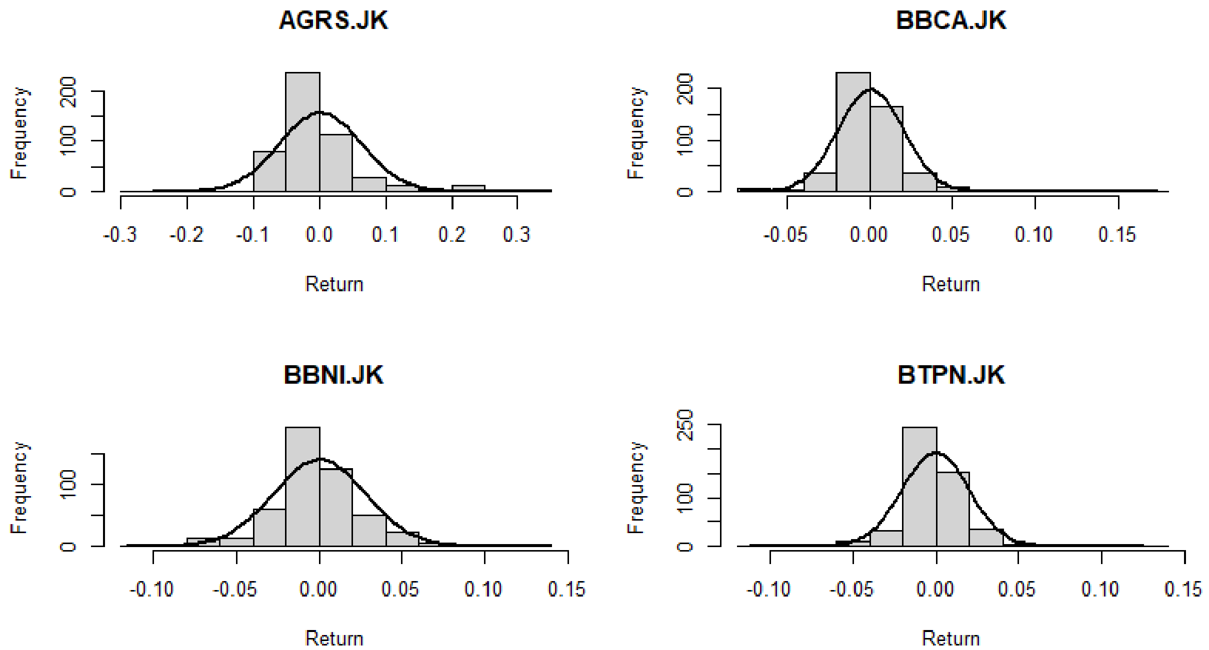

Figure 2. Arithmetic Stock Return Histogram Approached by Normal Curve

Table 2. Test Significance of Skewness Return Each Stock

No	Stock	*Skewness* ($\hat{\tau}$)	$\|S\|$	Critical Value	Conclusion
1	AGRS.JK	1,5538602	10,251487652	> 1,96	Sig
2	BTPN.JK	4,0380596	26,640825298	> 1,96	Sig
3	BBNI.JK	0,5620039	3,7077827471	> 1,96	Sig
4	BBCA.JK	0,3108030	2,0505017868	> 1,96	Sig

The selection of the four stocks is based on the mean value and the variance of the stock's return so that no one stock is more dominant than the other. The positive meaning and skewness are also to be considered. From Figure 2, we have the histogram arithmetic return of each stock with normal curve approximation corresponding to mean and variance of each stock return.

The test of skewness uses α=5% significance level. It is done by comparing the value of $|S| = \left|\frac{\hat{\tau}}{SE(\hat{\tau})}\right| = \left|\frac{b_1}{SEb_1}\right|$ against the value of 1.96. Where $b_1 = \frac{m_3}{m_2^{\frac{3}{2}}}\left(\frac{N-1}{N}\right)^{\frac{3}{2}}$ is a skewness estimator with $m_r = \sum_i \frac{(x_i-\mu)^r}{N}$. We compute the estimator standard error skewness using the formula $SEb_1 = \sqrt{\frac{6(N-2)}{(N+1)(N+3)}}\left(\frac{N-1}{N}\right)^{\frac{3}{2}}$ and for N = 489, we have $SEb_1 = 0{,}1515741181$. Furthermore, we can test the significance of skewness for our data return as shown in Table 2 and give that all data have significance skewness.

Next we have the boxplot for each return stock to see the presence of outlier. Based on Figure 3, it appears that the stock return data AGRS.JK, BTPN.JK, BBNI.JK, or BBCA.JK contain outliers. In addition, it can be seen also that most outlier values are greater than the upper limit.

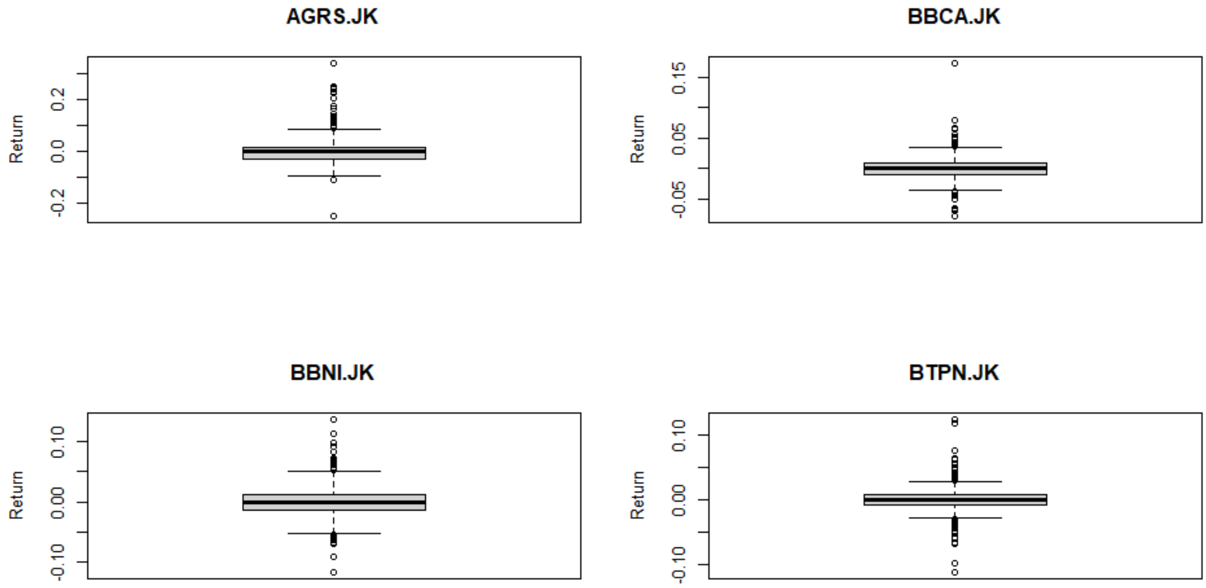

Figure 3. Boxplot for stock's arithmetic return

Table 3. Optimal weight and trading simulation

Stock	RMV ($s = 0,1$ $t = 100$)	RMVSm ($s = 0,1$ $t = 0,01$ $u = 0,01$)	RMVSv ($s = 0,1$ $t = 10$ $u = 0,1$)	RMVSs ($s = 0,1$ $t = 0,1$ $u = 10$)
AGRS.JK	0,6659873%	24,92661%	0%	24,83612%
BTPN.JK	10,7507686%	25,01915%	10,092810%	24,86266%
BBNI.JK	10,2574478%	25,01579%	9,815387%	25,05980%
BBCA.JK	78,3257963%	25,03844%	80,091803%	25,24143%
Total	100%	100%	100%	100%
Return Portfolio *(%)*	**0,1043098**	**0,1494034**	**0,1029252**	**0,14919**
Risk (%)	**0,9793078**	**1,742325**	**0,9905721**	**1,737139**
Sharpe Ratio	**0,01054061**	**0,01131868**	**0,01034139**	**0,01131937**
Profit - Loss				
day-1	-418.620,6	-15.668.255	0	-15.611.175
day-2	3.668.134,3	-16.399.890	4.343.915	-16.287.638
day-3	-8.304.328	-30.678.457	-7.517.585	-30.555.889
day-4	6.457.184,9	-17.140.042	7.201.941	-17.060.544
day-5	16.872.456,8	10.831.935	16.879.126	10.775.864

The third step is performing the bootstrap block method to obtain parameter values. In this section, we compute the values of $\mu_i^L, \mu_i^U, \sigma_{ij}^L, \sigma_{ij}^U, \sigma_{ijk}^L, \sigma_{ijk}^U$ by applying the bootstrap block method as mentioned before. For 489 data, the width of block $l = \sqrt[3]{489} \approx 8$ so that there are 61 blocks. Sampling bootstrap is done 1000 times iteration. It is assumed shortsell not be allowed, then only the matrices $\boldsymbol{\mu}^L, \sum^{\boldsymbol{U}}$, and $\mathbf{M_3}^{\boldsymbol{L}}$ are formed. The fourth step, forming RMV and RMVS portfolio and making trading simulation for five days. In this section we will establish an optimal portfolio with RMV and RMVS methods with various priorities, then continued with a five-day portfolio simulation date. Firstly, it is determined the value for $,t,u$, which are the coefficients of the mean, variance, and skewness, respectively. The following Table 3 shows the results of stock weighting and optimal portfolio simulation, then comparison between these two models with various priorities. The expected return, risk, and profitability of RMV and RMVS methods of various priorities have been tested. The expected return of the largest portfolio of all methods is the return of the RMVS priority portfolio method of maximizing the return (RMVSm (s = 0.1 t = 0.01 u = 0.01)) i.e. 0.1494034%, this corresponds to the priority of the method. The smallest portfolio risk of the entire portfolio risk method of RMV method (s = 0.1 t = 100) is 0.9793078%, but this value is not much different from the risk of the RMVS priority method portfolio minimizing variance (RMVSv (s = 0.1 t = 10 u = 0.1)) that is 0.9905721%. This is because both methods have the same priority of minimizing risk. While the highest sharpe ratio was obtained on the RMVS portfolio priorities maximizing skewness (RMVSs (s = 0.1 t = 0.1 u = 10)) that is 0.01131937. This value is not much different from the sharpe ratio RMVS priority portfolio maximizing the return (RMVSm (s = 0.1 t = 0.01 u = 0.01)) that is 0.01131868.

During the simulations carried out for five days, it was concluded that the greatest advantage was obtained when using the RMVSv method portfolio (s = 0.1 t = 10 u = 0.1), and selling all shares of the portfolio at day 5. The profit gained is Rp. 16,879,126.00 relative to total investment fund of Rp 1 Billion. While the greatest loss is obtained if using RMVS priority portfolio maximizes return (RMVSm (s = 0.1 t = 0.01 u = 0.01)) Rp. 30.678.457,00. We can see that, RMVS priority portfolio maximizes skewness (RMVSs (s = 0.1 t = 0.1 u = 10)) tend to provide better performance than other portfolios.

4. Conclusion

From the discussion, case study, and portfolio simulation of robust mean variance and mean variance skewness above, we can conclude that the role of variance is still dominant in determining the percentage weight of a portfolio. If investors take into account the risk of a portfolio, then the greatest weight occurs in stocks with the smallest risk. Furthermore, when investors consider the skewness of return data, the allocation of portfolio weights tends to be evenly distributed among each stock.

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