

## Value-at-Risk Analysis in Risk Measurement and Formation of Optimal Portfolio in Banking Share

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### INDEXING

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Historical Simulation;  
Optimal Portfolio;  
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#### Kata kunci:

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### ABSTRACT

This study analyzes Value at Risk (VaR) in estimating investment risk in banking stocks and forming an optimal portfolio using the Mean-VaR method based on the Markowitz approach. Many studies showed that market data were often abnormal and made the assumption of normality considered irrelevant. This background of research on VaR used the historical simulation method, which is a method that moves away from the concept of normality. In addition, the crisis due to the COVID-19 pandemic has caused difficulties for the market to predict. The period used in this study was during a normal market and a crisis (the COVID-19 pandemic). VaR was calculated with a holding period (t) of one week and a confidence level of 95%. Based on the backtesting test, the historical simulation method is accepted as accurate in estimating the VaR value in normal and crisis periods. The optimal portfolios formed based on the mean-VaR are Portfolio-1 (normal period) and Portfolio-2 (crisis period). The composition of Portfolio-1 is BBRI, BBKA, BNLI, BTPN, and BNBA with the optimal proportion of each share sequentially of (18.35%), (23.90%), (11.39%), (18.63 %), and (27.73%). The VaR value of Portfolio-1 was -0.0107, while the composition of Portfolio-2 was BNII and BNBA with optimal proportions of each share (22.71%) and (77.29%). The VaR value of Portfolio-2 was -0.0354. Investors can use the results of this study as a reference in making investment decisions that focus on downside risk.

### ABSTRAK

Penelitian ini menganalisis Value at Risk (VaR) dalam mengestimasi risiko investasi pada saham perbankan dan membentuk portofolio optimal dengan menggunakan metode Mean-VaR berdasarkan pendekatan Markowitz. Banyak penelitian menunjukkan bahwa data pasar seringkali tidak normal dan membuat asumsi normalitas dianggap tidak relevan. Latar belakang penelitian VaR ini menggunakan metode historical simulation yang merupakan metode yang menjauhi konsep normalitas. Selain itu, krisis akibat pandemi COVID-19 menyebabkan pasar kesulitan untuk memprediksi. Periode yang digunakan dalam penelitian ini adalah pada saat pasar normal dan masa krisis (pandemi COVID-19). VaR dihitung dengan holding period (t) satu minggu dan tingkat kepercayaan 95%. Berdasarkan pengujian backtesting, metode simulasi historis diterima akurat dalam mengestimasi nilai VaR pada periode normal dan krisis. Portofolio optimal yang terbentuk berdasarkan mean-VaR adalah Portofolio-1 (periode normal) dan Portofolio-2 (periode krisis). Komposisi Portofolio-1 adalah BBRI, BBKA, BNLI, BTPN, dan BNBA dengan proporsi optimal masing-masing saham secara berurutan (18,35%), (23,90%), (11,39%), (18,63 %), dan (27,73%). Nilai VaR Portofolio-1 adalah -0,0107, sedangkan komposisi Portofolio-2 adalah BNII dan BNBA dengan proporsi optimal masing-masing saham (22,71%) dan (77,29%). Nilai VaR Portofolio-2 adalah -0,0354. Investor dapat menggunakan hasil penelitian ini sebagai acuan dalam mengambil keputusan investasi yang berfokus pada downside risk.

### Article History

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## INTRODUCTION

Since the introduction of RiskMetrics™ in 1994 by J.P. Morgan, Value at Risk (VaR) has begun to be adopted as a model for measuring risk exposure. Measuring market risk has become an important issue (Mostafa et al., 2017). Value at Risk (VaR) is a risk measurement that is currently widely accepted and is considered a standard method in measuring risk (Zulfikar, 2016). Value at Risk (VaR) has been designed and adopted by financial institutions

as a standard tool for reporting risk. The advantage of Value at Risk (VaR) is that it can summarize exposure in some money or percentage that can be easily interpreted and understood (Mostafa et al., 2017). According to the theoretical concept by Jorion (1996), Value at Risk (VaR) is a risk measurement that estimates the maximum loss of investment along with a specific time horizon target at a certain level of confidence in normal market conditions. Value at Risk (VaR) measures the maximum loss that may occur in the following 1-day, 1-week ahead, and so on according to the desired period.

Thanh et al. (2018) explained that VaR could be through three primary methods, the variance-covariance method (parametric), the Monte Carlo simulation method (semiparametric), and the historical simulation method (non-parametric). The parametric approach is based on the assumption that returns are normally distributed. In contrast, the non-parametric system is based on historic data and does not require the normality of the data.

In actual market reality, financial data is often not normally distributed. Hull (2015) explained that the standard distribution assumption does not describe the distribution of losses because it has a fat tail (abnormality) nature. Thanh et al. (2018) showed that the return on the stock market is not normally distributed. The historical simulation approach helps to solve the data normality problem. The use of historical data in this method eliminates the need to make assumptions about the distribution of underlying assets (Mostafa et al., 2017). Christoffersen (2012) explained that a historical simulation method is an approach that does not assume a normal data distribution but is based on the assumption that the distribution of possible changes in market factors during the following period is identical to the distribution observed in the previous period. Historical simulations are computationally easy and are capable of summarizing many types of exposures. Wikström (2016) mentioned that historical simulation is the easiest method to implement. This situation makes measuring risk through this method easy to communicate to top-level managers.

In their investment decisions, investors are fundamental in understanding the trade-off returns and risks according to their references (Bodie et al., 2019). Investors who make decisions based on fundamental analysis tend to choose to avoid trouble (risk-averse) (Zulfikar, 2016:159). The Markowitz model in Modern Portfolio Theory is a model to assist investment decisions in risky assets. Modern Portfolio Theory by Harry Markowitz in 1952 explained that portfolio weighting uses a calculation. It considers the risk of each investment called the mean-variance model, where the expected return is calculated using the average method (mean) and variance as a risk measure used ( Hartono, 2014).

The concept of Modern Portfolio Theory relates stock market risk to return volatility as measured by variance. Some investors do not accept this measure because the measure gives the exact weight between positive and negative returns, while most investors determine risk based on negative returns (Angelovska, 2013). Hartono (2017) states that the standard deviation and variance risk measures raise much criticism.

Campbell et al. (2001) stated that it is possible to establish a framework for portfolio selection that moves away from the standard mean-variance approach with VaR. Ismanto (2016) explained that an optimal portfolio with the mean-variance model approach from Markowitz, which uses standard deviation as a risk proxy, needs to be adjusted. The risk proxy is changed to a measure that focuses more on downside risk, namely Value at Risk.

Previous research by Wicaksono et al. (2014) carried out risk measurements on mutual funds. The results proved that the historical simulation method accurately measured an enormous potential loss on mutual fund investments. Thim & San (2018) applied VaR measurements using the historical process in banking proved the historical simulation method is not an accurate method for measuring Value at Risk in commercial banks. Machfiroh (2016) showed that Value at Risk (VaR) with historical simulation methods to measure stock risk on the LQ-45 index is said to be accurate. Musa et al. (2020) revealed that the Value at Risk (VaR)

historical simulation method was the most suitable method in estimating the minimum capital at 3 banks out of 5 estimated banks. Susanti et al. (2020) also applied VaR to banking single stocks and portfolios by proving historical simulation was the best and consistent method in assessing VaR of single stocks (BNI shares) and portfolios.

Due to the COVID-19 pandemic, the crisis has influenced the stock market, making the risks faced need a better estimation. Historical simulation provides the advantage of using actual historical data that reflects the actual state of the market and is easy for investors and management to understand. The study results prove that historical simulation accurately estimates bank risk in the 2009-2011 crisis (Fadhila & Rizal, 2013). Amin et al. (2018) supported these results by proving that in the crisis period, the historical simulation method is a more accurate method than the standard delta method through the calculation of Mean Square Error (MSE). Kourouma et al. (2011) estimated the potential loss during the 2008 crisis, rejecting the historical simulation approach as an accurate model in predicting the level of casualties. In contrast to this, Raghavan et al. (2017) conducted a study to evaluate the performance of VaR in developing stock markets using the crisis period. The results prove that the historical simulation approach is appropriate for developing markets, namely Russia and India.

Analysis of risk measurement and portfolio investment that is not based on the assumption of normality becomes crucial. Many studies reported that financial data tend not to follow the normal distribution of data, and the assumption of normality is considered less relevant. In addition, the crisis phenomenon due to the COVID-19 pandemic has influenced the stock market and caused the potential for losses in investment to be more significant. This fact shows the need to study portfolios that move away from assumptions that require data normality.

Lwin et al. (2017) used historical simulation VaR on the mean-VaR framework in portfolio optimization and tried to add an algorithm model to solve problems in more complex portfolios. The results proved that the mean-VaR portfolio framework provided a more realistic picture, and the algorithm formed could solve problems in more complex portfolios.

Arthini et al. (2012) estimate the VaR of stock portfolios using the Markowitz method using historical data and Monte Carlo simulation data, then compare them. The results showed that the VaR value of the Monte Carlo portfolio gave a higher estimate than the VaR value of historical data. Sukono et al. (2017) modeled the mean—VaR in optimizing portfolios with risk tolerance at the utility level squared. Their results revealed the level of return and risk of the portfolio at a certain tolerance level. Rahmi and Juniar (2019) used VaR to measure stock risk and included the Markowitz optimal portfolio stocks. Their research showed that the VaR of the portfolio was smaller than the VaR of each stock.

Ismanto (2016) forms an optimal portfolio with the concept of a VaR risk measure, namely developing a mean-variance model to mean-VaR, both for individual investors and for financial institutions. The results show the proportion formed by market risk (VaR) and the risk value. Chairrunisa et al. (2018) also conducted a similar study and used the mean-VaR model on banking stocks. The results showed that the portfolio weight with minimum risk and obtaining a small portfolio risk value was considered safe for investors.

This research can be helpful as input and reference material to assist investment policymaking. Bank shares as a sample can provide more benefits in implementing Value at Risk. As explained by The Basel Committee On Banking Supervision, Value at Risk is adopted as a tool to measure risk. The estimation results of Value at Risk can determine the minimum capital requirement for banks. The development of the mean-VaR model can assist in making decisions to form an optimal portfolio of bank stocks with risk measured using Value at Risk. In this study, Value at Risk (VaR) was estimated using the historical simulation method. Testing the accuracy (backtesting) of the historical simulation method was carried out with the

Kupiec Test. The VaR value obtained will be used to form an optimal portfolio based on the mean-VaR, namely the development of the Markowitz mean-variance model to mean-VaR.

## **REVIEW OF LITERATURE**

### **Value at Risk (VaR)**

Jorion (1996) explained the concept of Value at Risk (VaR), which is defined as a risk measurement method that statistically estimates the maximum possible loss on an investment over a specific time horizon target at a certain confidence level in the normal market conditions. In other words, the worst loss over some time will not exceed the given confidence level. Therefore, VaR shows how much investors will lose within a specific investment period with a confidence level of " $1-\alpha$ " (in percentage units or currency). Purnamasari (2017) explained that statistically, VaR with a confidence level  $(1-\alpha)$  is expressed as the  $-t$ -th quantile of the return distribution.

### **Historical Simulation**

VaR can be estimated through one of the primary methods, called historical (non-parametric) simulation. The non-parametric approach based on historical data does not require the assumption of normality of the data (Thanh et al., 2018). Historical simulations are based on the belief that the distribution of possible changes in market factors over the next period is identical to the distribution observed in the previous period (Christoffersen, 2012). The historical simulation method involves using past data as a reference to determine what will happen in the future (Hull, 2015). The historical simulation method uses historical data to build the distribution of future returns from an asset or a portfolio (Mostafa et al., 2017). Bessis (2015) stated that the output of the historical simulation method is an empirical rather than parametric return distribution, such as the normal distribution.

### **Backtesting**

Backtesting is a statistical technique to test the accuracy and validate the risk estimate by comparing the estimated risk from a model with what happened in a specific time (Purnamasari, 2017). Putri et al. (2013) explained that one of the methods used in backtesting is the Kupiec Test. Kupiec Test based on the failure rate (failure rate) measures the number of exceptions is consistent with the level of confidence. This test is used to determine whether the failure rate corresponds significantly to  $(1-\text{level of confidence VaR})$ .

### **Portfolio Theory**

Markowitz introduced modern portfolio theory in 1952 and 1959. This theory assumes that investment decisions made by investors are based on expected returns and portfolio risk. The expected return of the portfolio is calculated using the average approach (mean), and portfolio risk is measured by the concept of standard deviation (standard deviation) or variance (variance), so this method is also called mean-variance (Hartono, 2014).

The optimal portfolio has the best combination of expected return and risk. The attainable set provides a possible portfolio formed from the available assets, and the efficient set is a set of efficient portfolios. An efficient portfolio offers the most significant expected return with the same level of risk or a portfolio containing the slightest risk with the same expected return level. The Markowitz model assumes that investors are rational people so that the optimal portfolio chosen is in the set of efficient portfolios (Hartono, 2017).

### **Mean-VaR Portfolio**

Ismanto (2016) explained that forming an optimal portfolio with the mean-VaR approach is developing a model from Markowitz, namely, changing the risk measure from standard

deviation to VaR. Campbell et al. (2001) became one of the pioneers in developing VaR in portfolio analysis. The focus on downside risk as an alternative measure for financial market risk has made it possible to establish a framework for portfolio selection that moves away from the standard mean-variance approach. The measure of risk depends on the potential loss, which is a function of the VaR of the portfolio. The efficient frontier VaR is similar to the mean-variance frontier except for the definition of risk, where risk is reflected by the VaR and not the standard deviation.

## RESEARCH METHOD

This research is quantitative descriptive research with the sample was obtained using a purposive sampling method and based on the author's criteria. This study used secondary data divided into period 1 (normal) and period 2 (crisis). The data used was the closing price of shares on January 1, 2018 – January 31 and February 1 – September 30, 2020. The research data came from accessing the data through the website, while the data sources were from the websites [www.idx.co.id](http://www.idx.co.id) and [www.yahooofinance.com](http://www.yahooofinance.com). The normality test on stock returns would assess the normality of the data distribution to determine that the data used had an abnormal tendency as assumed. Normality test was performed using the Kolmogorov Smirnof (K-S) test.

The historical simulation method determined the holding period and confidence level first, then compiling the order of the return distribution. The holding period was the period set by an investor to estimate the risk level of the asset. The holding period used in this study was one week. The level of confidence given is 95% ( $\alpha = 0.05\%$ ). After obtaining the return value, the returns were sorted from the smallest to the largest value. The VaR value came from the  $\alpha$  quantile of the return distribution ordered with the confidence level given by the following formula (Purnamasari, 2017).

$$VaR_{(1-\alpha)}(t) = Q * \sqrt{t}$$

Description:

$VaR_{(1-\alpha)}(t)$  = VaR with confidence level (1- $\alpha$ ) after (t) period

$Q * \sqrt{t}$  = the  $\alpha$  quantile of the distribution return

The investment loss in each stock multiplied the VaR value by the investment amount. This research assumed that the amount of investment was (Rp 1,000,000,000,-). Purnamasari (2017) explained that this calculation could follow the formula approach below.

$$VaR_{(1-\alpha)}(t) = W_0 Q * \sqrt{t}$$

Description:

$VaR_{(1-\alpha)}(t)$  = VaR with confidence level (1- $\alpha$ ) after (t) period

$W_0$  = initial investment of assets

$Q * \sqrt{t}$  = the  $\alpha$  quantile of the distribution return

## Kupiec Test

Backtesting utilized the Kupiec Test with an unconditional coverage approach developed by Kupiec (1995) based on the Loglikelihood Ratio (LR) value. Purnamasari (2017) mentioned that the unconditional coverage Loglikelihood Ratio (LR<sub>UC</sub>) based on Jorion (2007) could follow the below calculations.

$$LR_{UC} = -2 \ln[(1-p)^{(T-N)} p^N] + 2 \ln \left[ 1 - \left( \frac{N}{T} \right) \right] ((T-N) \left( \frac{N}{T} \right)^N$$

Description:

$LR_{UC}$  = Loglikelihood Ratio unconditional coverage

- T = number of observations
- N = number of failures between VaR values and actual losses
- p = probability (1-level of confidence)

The ratio value is compared with the Chi-square value with a degree of freedom 1 (one), with the following hypothesis.

- H0 = accurate VaR model
- Ha = VaR model is not accurate

The test criteria are as follows with a confidence level of 95% ( $\alpha = 0.05\%$ ).

- 1) If the statistical value exceeds the critical value of the Chi-square distribution for the given confidence level, then H0 is rejected, and Ha is accepted.
- 2) If the statistical value does not exceed the critical value of the Chi-square distribution for the given confidence level, then H0 is accepted, and Ha is rejected.

**Portfolio Stock Selection**

The selected stocks into the portfolio were stocks with positive expected returns. Stocks with a positive expected return indicate that the stock is estimated to make a profit. The following calculation obtains realized return. The expected return came from the geometric mean (geometric mean) calculation as follows.

$$E(R_{ig}) = [(1 + R_1)(1 + R_2) \dots (1 + R_n)]^{\frac{1}{n}-1}$$

Description:

- $(E)R_{ig}$  = geometric mean expected return
- $R_i$  = return asset i
- $n$  = return amount

**Efficient frontier based on Mean-VaR**

The efficient set came from arranging several portfolios into a collection that formed an efficient line where a certain level of return had a minimum VaR. An efficient frontier with VaR as a risk measure was obtained by doing quadratic programming. The VaR value for a portfolio and the expected return are set as follows.

$$VaR_p = \frac{C.E(R_p)^2 - 2.B.E(R_p) + A}{D}$$

The VaRp function is quadratic, so the expected return E(Rp) function consists of two functions written as follows.

$$E(R_p) = \frac{B}{C} \pm \frac{1}{C} \sqrt{D(C.VaR_p - 1)}$$

These values are:

$$A = \sum_{k=1}^n \sum_{j=1}^n [\sigma_{kj}]^{-1} E(R_j). E(R_k)$$

$$B = \sum_{k=1}^n \sum_{j=1}^n [\sigma_{kj}]^{-1} E(R_k)$$

$$C = \sum_{k=1}^n \sum_{j=1}^n [\sigma_{kj}]^{-1}$$

$$D = A.C - B$$

Notation  $[\sigma_{kj}]^{-1}$  is a covariance matrix, where the diagonal part of the matrix is the variance converted to VaR, and the outer diagonal is the covariance.

### Mean-VaR Optimal Portfolio Proportion

Based on Hartono (2014), the optimization solution determines the optimal portfolio proportion by the following calculation approach to get the balance of each asset in the optimal portfolio.

$$w_k = \frac{\sum_{k=1}^n w_1 [\sigma_{kj}]^{-1}}{C}$$

Description:

- $w_k$  = the proportion of the k shares in the portfolio  
 $w_1$  = matrix of entire proportions (identity) with a value of 1  
 $[\sigma_{kj}]^{-1}$  = inverse covariance matrix  
 $C$  =  $\sum_{k=1}^n \sum_{j=1}^n [\sigma_{kj}]^{-1}$

## RESULT AND DISCUSSION

### Normality Test Results

Based on the Kolmogorov-Smirnov test, overall stock return data shows a smaller significance value (asyp. Sig. < 0.05). The data are declared not to follow the normal distribution and support the assumptions in the historical simulation. These results support Hull (2015), stating that the assumption of normality of the data allows the measurement of risk to be irrelevant. These results also support Machfiroh's (2016) research, showing that stock returns do not follow the normal distribution based on the skewness test. The results of this study agree with Thanh et al. (2018), proving that VaR based on the assumption of normality is irrelevant.

### Value at Risk (VaR) and Potential Losses

**Table 1. VaR Value based on Historical Simulation Method**

Code Share	Period 1 (normal) (n = 107 weeks)		Period 2 (COVID-19 crisis) (n = 35 weeks)	
	VaR Quantile	Historical VaR (95%)	VaR Quantile	Historical VaR (95%)
BBRI	5/107	-5,94%	2/35	-13,51%
BBNI	5/107	-8,07%	2/35	-21,48%
BBCA	5/107	-4,55%	2/35	-10,32%
BBKP	5/107	-8,38%	2/35	-24,70%
BBTN	5/107	-11,22%	2/35	-19,58%
BMRI	5/107	-6,69%	2/35	-12,41%
BDMN	5/107	-9,14%	2/35	-24,14%
BNLI	5/107	-9,57%	2/35	-8,30%
BNGA	5/107	-6,87%	2/35	-13,77%
BTPN	5/107	-5,82%	2/35	-18,22%
BNII	5/107	-6,00%	2/35	-15,89%
BNBA	5/107	-3,88%	2/35	-4,61%

The amount of loss multiplies the VaR value by the investment amount. According to Jorion (1996), VaR is the maximum loss at a specific target horizon and a certain confidence level. The VaR value in this study interpreted that BBRI shares in the first period with an assumed initial investment of (Rp1,000,000,000,-) had a 95% chance to suffer a maximum loss of (-Rp59,360,730.59,-) in the next 1-week after January 31, 2020. In other words, with an initial investment of (Rp1,000,000,000,-), there was a 95% possibility that the loss of BBRI shares would not exceed (Rp59,360,730.59,-). Based on the second period, there was a 95%

chance that BBRI shares would suffer a maximum loss of (–Rp135,135,135,14,-) in the next 1-week after September 30, 2020, with an initial investment of (Rp1,000,000,000,-). In other words, with an initial investment of (Rp1,000,000,000,-), there was a 95% chance that the loss of BBRI shares would not exceed (Rp135,135,135,14,-).

**Accuracy Test Results (Backtesting) with Kupiec Test**

Based on the Loglikelihood Ratio unconditional coverage calculation in the first period, the ratio value (LRUC1) is 0.3914 with a critical Chi-Square value of 3.841. The value of this ratio is less than the critical value of Chi-Square (LRUC1 < 3.841), so at the 95% confidence level, the historical simulation method used is valid and is an accurate method for estimating the VaR value. In the second period, the ratio value (LRUC2) obtained is 0.3976 with a critical Chi-Square value of 3.841. The value of this ratio is less than the critical value of Chi-Square (LRUC1 < 3.841), at the 95% confidence level, the historical simulation method is valid and is an accurate method for estimating the VaR value in the crisis market period.

Musa et al. (2020) showed that historical simulations were accurate and had minimum mean square error (MSE). Wicaksono et al. (2014) and Machfiroh (2016) proved that the historical simulation method accurately estimated the VaR value. Susanti et al.'s research. (2020) also supported the results by proving that the historical simulation method was the best and consistent method in estimating the VaR of single stocks and portfolios based on backtesting.

Fadhila and Rizal (2013) proved the risk estimation (VaR) in the crisis period 2009-2011 on BRI and BNI bank stocks with a historical simulation approach provided accurate results. Another study on the evaluation of the performance of VaR in emerging stock markets conducted by Raghavan et al. (2017) supported the results of this study by proving the historical simulation method was appropriate to use on the Russian and Indian stock markets during the crisis market. Amin et al. (2018) also showed that based on the Mean Square Error (MSE) calculation, the historical simulation method was more accurate for crisis markets than the standard delta method.

**Portfolio Selection and Formation of an Efficient Frontier**

The stock's expected return needs to be determined first to ensure which stocks will be included in the portfolio and the risk of each stock. The expected return E(Ri) is calculated using the geometric mean.

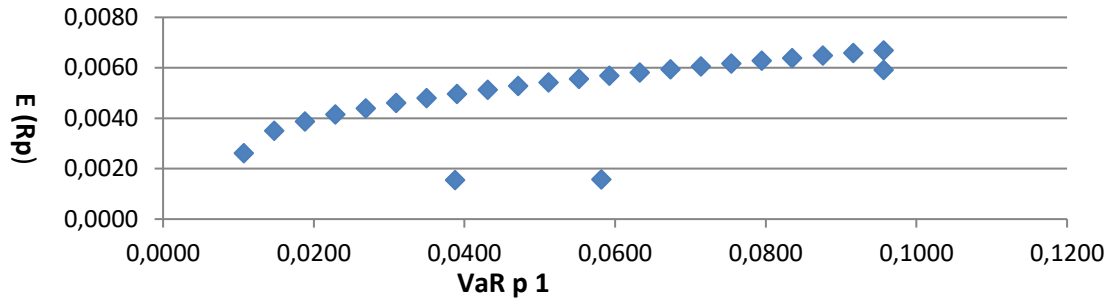
**Table 2. Expected Return of Portfolio Shares and Individual Risk Value of Each Share**

Code Share	Period-1 (normal)	
	E(Ri)	VaR i
<b>BBRI</b>	0,0019	-0,0594
<b>BBCA</b>	0,0037	-0,0455
<b>BNLI</b>	0,0059	-0,0957
<b>BTPN</b>	0,0016	-0,0582
<b>BNBA</b>	0,0015	-0,0388
Code Share	Period-2 (COVID-19 crisis)	
	E(Ri)	VaR i
<b>BNII</b>	0,0006	-0,1589
<b>BNBA</b>	0,0014	-0,0461

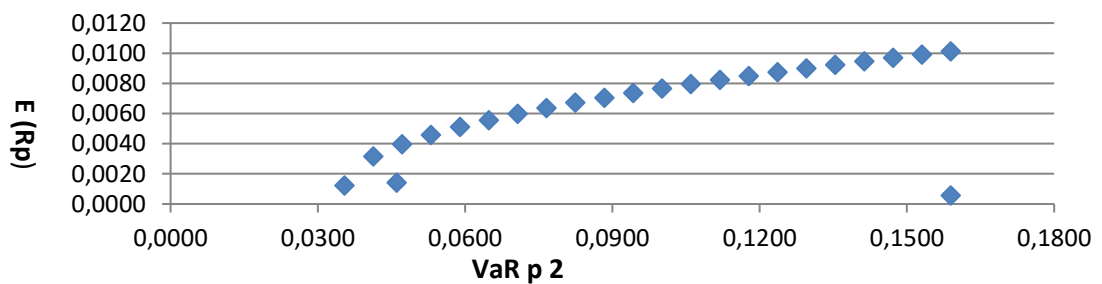
A positive expected return indicates that the stock estimate will provide a profit, while a negative expected return means that the stock estimate will give a loss. Thus, stocks with positive returns will be included in the portfolio. Based on Table 2, stock returns in period-1 with positive values are BBRI, BBCA, BNLI, BTPN, and BNBA. In period-2, the positive stock returns are BNII and BNBA.



Based on the returns and risks of the stocks in Table 2, the covariance and correlation are determined. Then, 20 portfolios are formed with the highest to lowest risk values and the expected following return. The portfolio's location with the slightest risk is in the collection of efficient portfolios (efficient frontier). Forming an efficient set (efficient frontier mean-VaR) based on Markowitz's theory, the VaR value is adjusted in an absolute way to get an efficient set in the positive area.



Gambar 1. Efficient Frontier Mean-VaR Period 1

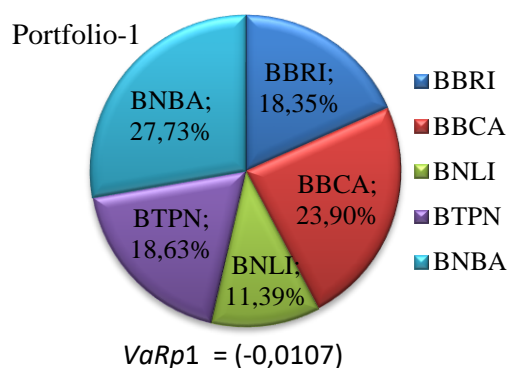


Gambar 2. Efficient Frontier Mean-VaR Period 2

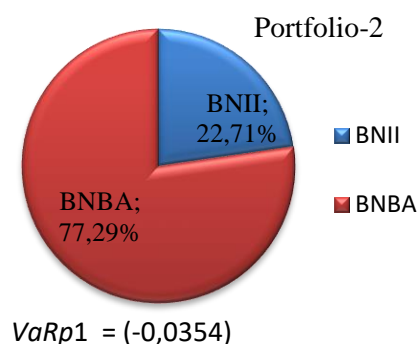
Based on the efficient frontier formed, the optimal portfolio in period 1 has a portfolio VaR value (VaRp1) of (-0.0107) with a portfolio return of (0.0026). The optimal portfolio in period 1 has a VaR value (VaRp2) of (-0.0354) with a portfolio return of (0.0012).

**Optimal Portfolio Proportion Based on Mean-VaR**

The formed portfolio consists of five banking stocks based on the normal period: BBRI, BBKA, BNLI, BTPN, and BNBA. Each of these shares has a large proportion sequentially (18.35%), (23.90%), (11.39%), (18.63%), and (27.73%). BNBA shares are the shares with the largest proportion (27.73%), and BNLI shares are the shares with the smallest proportion (11.39%). During the crisis period, the portfolio formed consisted of two banking stocks, namely BNII and BNBA. Each of these shares has a large proportion of (22.71%) and (77.29%). This proportion can be described as follows.



Gambar 3. Proportion of Shares in Portfolio-1



**Gambar 2.** Proportion of Shares in Portfolio-2

Campbell et al. (2001) described that the mean-VaR method could form a portfolio that focuses on downside risk. These results support Rahmi and Juniar's (2019) research, proving that the VaR of the portfolio developed was small. The results in this study are also in line with Ismanto (2016) and Chairrunisa et al. (2018), proving that portfolio risk is formed with a mean-VaR approach that is smaller than the constituent assets and provides a relatively small risk value, and is considered safe for investors. Lwin et al. (2017) and Sukono et al. (2017) showed that the mean-VaR portfolio framework could offer investors a more realistic return and portfolio risk level.

## CONCLUSION

The historical simulation method is accurate and consistent in estimating the VaR value on single stocks (in this case, banking stocks) and portfolios in regular and crisis markets (due to the COVID-19 pandemic). The composition of Portfolio-1 is BBRI, BBKA, BNLI, BTPN, and BNBA shares. The results of the optimal proportions obtained from the five stocks are respectively (18.35%), (23.90%), (11.39%), (18.63%), and (27.73%). The VaR value of the portfolio ( $VaRp1$ ) is (-0.0107) with a portfolio return of (0.0026). The composition of Portfolio-2 is BNII and BNBA. The optimal proportions obtained from the two stocks are (22.71%) and (77.29%). The portfolio risk value ( $VaRp2$ ) is (-0.0354) with a portfolio return of (0.0012). When the market is in crisis, the portfolio has a higher risk. The results of this study can contribute as a reference for investors in making investment policies, especially investment in banking stocks. This study's application of risk measurement methods and portfolio frameworks is limited in selecting the sample used, which only focuses on banking stocks. This research can be further developed by applying more diverse samples and methods. It is hoped that further research will be able to apply more methods. It would be better if further research could add an assessment of the performance of the formed portfolio.

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