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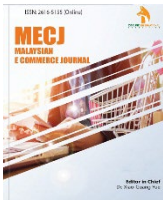

RESEARCH ARTICLE

OPTIMAL INVESTMENT PORTFOLIO WITH TRANSACTION LOT: DOES PRICE MATTER

Ezra Putranda Setiawan*

Department of Mathematics Education, Universitas Negeri Yogyakarta, Indonesia
****Corresponding Author Email: ezra.ps@uny.ac.id***

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ABSTRACT

Transaction lot as a rule in real stock market had implemented in several portfolio optimization models. In almost all these models, the stock price became part of the constraint(s), but the role is not well understood. In this study, we compare the effectiveness of portfolio optimization models with transaction lot in different asset price level. We conduct a simulation study using 15 portfolios, each consists of four assets with various price range. We find that the usage of different stock price did not affect the performance of minimum-variance portfolio optimization with transaction lots. On the other hand, the performance of minimum-CVaR portfolio optimization with transaction lots is largely affected by stock price.

KEYWORDS

Genetic algorithm, price, efficient frontier, CvaR

1. INTRODUCTION

Asset diversification is a common way to diminish the investment risk, which frequently done by creating a portfolio consist of several assets, i.e. stocks. To determine the proportion of each stock in an investment portfolio, Markowitz in 1952 introduce the mean-variance model. (Markowitz, 1952). In this model, the variance is used as a risk measure which would be minimized with several constraints. Several risk measures other than the variance also developed, such as the semi-variance, the mean absolute deviation (MAD), and the conditional value at risk (CVaR) (Markowitz, 1959; Konno, 1991; Artzner et al., 1999). These risk measures were used in portfolio optimization, as did by (Ballestero, 2005; Rockafellar and Uryasev, 1999; Da Silva et al., 2017; Chang et al., 2009; Pia-Santamaria and Bravo, 2013).

Another development on the portfolio optimization strategy is the use of transaction lot. Numerous optimization method generates the solution as the rational number representing the proportion of investment in each stock. On the other hand, almost all stock market around the world regulates the minimum number of shares to be bought or sold by the investor regularly, which known as the lot. The investor only can buy or sell the stock in a round number times the shares each lot.

Many methods have been proposed to implement the minimum transaction lot in the portfolio optimization model. In the model with the mean absolute deviation (MAD), a heuristic method had implemented by (Mansini and Speranza, 1999). For the Markowitz mean-variance model, the transaction lot solution based on genetic algorithm and particle swarm algorithm were introduced by (Lin and Liu, 2008; Cura, 2009). Later, other solution using a fuzzy method were developed by (Liu and Zhang, 2015). And a simpler solution with solver were obtained by (Chin et al., 2018). Most researchers solve the portfolio selection problem with transaction lot based on CVaR using mixed integer linear programming and genetic algorithm (Angelelli et al., 2008; Setiawan and Rosadi, 2016). Although requires complex calculation, portfolio optimization with transaction lot could be easily implemented by the investor in the stock market.

It should be noted that each portfolio selection model with minimum transaction lot related to the stock price per lot. On the other hand, the price of each stock in the stock market differs. In the Indonesia Stock Exchange, for example, the price range could be from IDR 50 up to IDR 25,000 each share, which is more than a hundred times the smallest price. Another data from the London Stock Exchange show that the price range is from £ 1,66 per share up to £ 5,854 per share, which is more than two thousand times the smallest price. Therefore, the investor should know how the asset price will affect the portfolio selection model with minimum transaction lot. However, previous study related to the portfolio with transaction lot did not give attention to the stock price.

The main aim of this study is to examine how the stock price affects the portfolio optimization model regarding transaction lot. Hence, the next section describes the portfolio optimization models with transaction lot. The third section describes the simulation procedure used in this study. The fourth section would discuss the simulation result. The last section presents the conclusion and several notes for future research.

2. OPTIMAL PORTFOLIO WITH TRANSACTION LOT

Suppose that an investor has total capital b that would be invested in n available stock. The main objective here is to determine $x_1, x_2, \ldots, x_n$, where x_j represent the number of lot of the j-th available stock. Other available information is p_{jt}, which represent the price of j-th asset at time t. Assume that all available stocks are used in the portfolio, the portfolio is calculated at time $t = T$, and the short sale is prohibited. Let r denote the minimal expected percentage return.

Using the mean-variance model as proposed in Lin and Liu in 2008, we obtain the portfolio optimization model with transaction lot as follows.

$$\min\ \sigma_p^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \sigma_{ij} \tag{1}$$

With constraints:

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- $\sum_{i=1}^{n} x_i c_i \le b$
- $e_p = \sum_{i=1}^{n} x_i c_i r_i \ge br$
- $w_i = \frac{c_i x_i}{\sum_{i=1}^{m} c_i x_i}$, $i = 1, 2, ..., n$
- x_i is an integer.

Another portfolio optimization method using Conditional Value-at-Risk (CVaR) only examine the average of the return below the pre-defined quantile β. The definition of CVaR and its properties can be seen in (Rockafellar and Uryasev, 2000). Hence in this model, the objective function (1) become

$$\min\ CVaR_\beta = -\left(E\left[X\mathbf{1}_{\{X\le x_\beta\}}\right] + x_\beta\left(\beta - P\left[X \le x_\beta\right]\right)\right) \quad (2)$$

while X denote the random variable represent the portfolio's return, calculated by sum each asset's return multiplied by its weight.

One of the important components in the portfolio optimization model (above is the minimum expected return percentage *r*. By ignoring this component (or, equivalently, set $r = 0$), we obtain the minimum-variance portfolio. Otherwise, by solving the portfolio optimization model for several different *r* and plot the result between risk and return, the efficient frontier curve can be obtained.

Related to the optimization, recall that Lin and Liu in 2008 said that the portfolio with transaction lot is an NP-hard problem. They also state that genetic algorithm, as proposed by Holland in 1975 could be used to solve the portfolio optimization (Lin and Liu, 2008; Holland, 1975). Several research, show the superiority of genetic algorithm compared to the Tabu search and simulated annealing (Chang et al., 2000; Woodside-Oriakhi et al., 2008). For this reason, in this study we use the genetic algorithm method.

3. Methods

We choose twelve different stocks available in Indonesia Stock Market (IDX) with different level of price. The price data of these stocks were obtained from Yahoo! Finance (http://finance.yahoo.com). Descriptive statistics for these assets' price and daily return are presented in table 1.

Table 1: Descriptive Statistics of stocks used in the study

Stock code	Price (IDR)			Return			
	Min	Max	Mean	Mean	Stdev.	Skewness	Kurtosis
A1	15,550	29,000	22,492.1	0.019	0.120	0.292	2.406
A2	62,025	94,400	75,590.8	0.015	0.180	0.159	1.232
A3	23,100	40,425	31,239.1	-0.111	0.201	0.002	0.978
A4	7,875	11,235	9,570.7	-0.018	0.142	0.171	2.458
B1	4,200	6,675	5,366.9	-0.051	0.210	1.189	9.370
B2	1,155	20,500	9,360.9	0.103	0.347	-0.469	4.040
B3	5,525	8,925	7,371.5	-0.105	0.161	-0.155	2.256
B4	6,150	10,175	8,030.1	0.094	0.167	0.302	2.364
C1	280	404	345.1	-0.217	0.210	0.385	6.438
C2	95	299	175.6	-0.433	0.226	0.867	5.340
C3	196.8	662.6	384.9	-0.115	0.213	0.263	2.474
C4	298	820	523.1	-0.296	0.237	0.836	3.960

Based on the asset's price average and range, we determine several portfolios as follows. Several portfolios consist of assets with similar price (P01, P02, P03), while the others consist of two paired assets with similar price (P04, P05, P06, P07, P08, P09). We also calculate portfolios that include three assets with similar price plus an asset with different price, as shown in table 2.

Table 2: Portfolio used in this study

Portfolio	Assets	Portfolio	Assets
P01	A1, A2, A3, A4	P09	B1, C2, C3, B4
P02	B1, B2, B3, B4	P10	C1, C2, C3, A4
P03	C1, C2, C3, C4	P11	C1, A2, C3, C4
P04	B1, A2, A3, B4	P12	C1, C2, B3, C4
P05	C1, C2, A3, A4	P13	A1, C2, A3, A4
P06	C1, A2, A3, C4	P14	B1, A2, A3, A4
P07	B1, B2, C3, C4	P15	B1, A2, B3, B4
P08	C1, C2, B3, B4		

In this study, we adopt the rolling horizon procedure to replicate the portfolio optimization and obtain return data to calculate the optimal portfolio (DeMiguel and Nogales, 2002). For each portfolio above, we calculated an optimal portfolio using minimum-variance method without transaction lot and another minimum-variance portfolio with transaction lot. This procedure was repeated several times after remove the first data and add one more recent data.

To compare these portfolio's performance, we use the Sharpe Ratio, which defined as the ratio between investment excess return and the standard deviation as risk measure. Higher Sharpe Ratio implies better portfolio performance. Another portfolio risk measure used in this study is the Average of Grinblatt-Titman (AGT), a holdings-based performance measurement which measure investor's ability to adjust portfolios' weight each period (Grinblatt and Titman, 1993; Reilly and Brown, 2012). Higher AGT means that the change of asset's weight in the portfolio yield higher portfolio return. Last, we calculate the portfolio turnover (PT), which measure the average change of asset's weight. Following De Miguel and Nogales in 2009, lower portfolio turnover indicates a "resistant" portfolio, in which assets' weight did not change much every day (De Miguel and Nogales, 2009).

Beside the minimum-variance, we consider the mean-variance and mean-CVaR optimal portfolio by calculate the efficient frontier curve. Both curves are produced using the portfolio optimization with and without transaction lot. Consequently, these curves can be used to compare the performance of portfolio optimization with transaction lot in different price.

4. Results and Discussion

Our study show that the Genetic Algorithm (GA) performs well on obtaining the optimal mean-variance as well as mean-CVaR portfolio with transaction lot. These results are in-line with Setiawan and Rosadi (2016) and Rosadi *et al.* (2020). As presented in figure 1, the fitness function has reached its maximum. Genes that yield highest fitness were taken as the weight of the optimal portfolio with transaction lot. For each procedure, these steps are repeated three times so that the presence of best portfolio can be ensured.

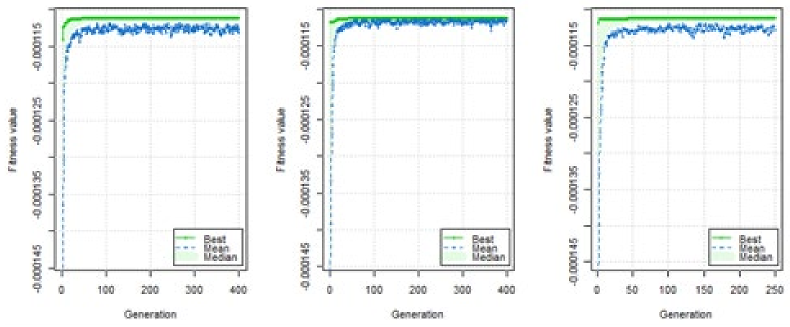

Figure 1: Performance of Genetic Algorithm (GA) for Portfolio Optimization

In this study, we used the rolling horizon method. Consequently, we can compare the change of portfolio weight calculated using same method. Figures 2 and 3 present these changes in optimal portfolio calculated using minimum-variance and minimum-CVaR, respectively.

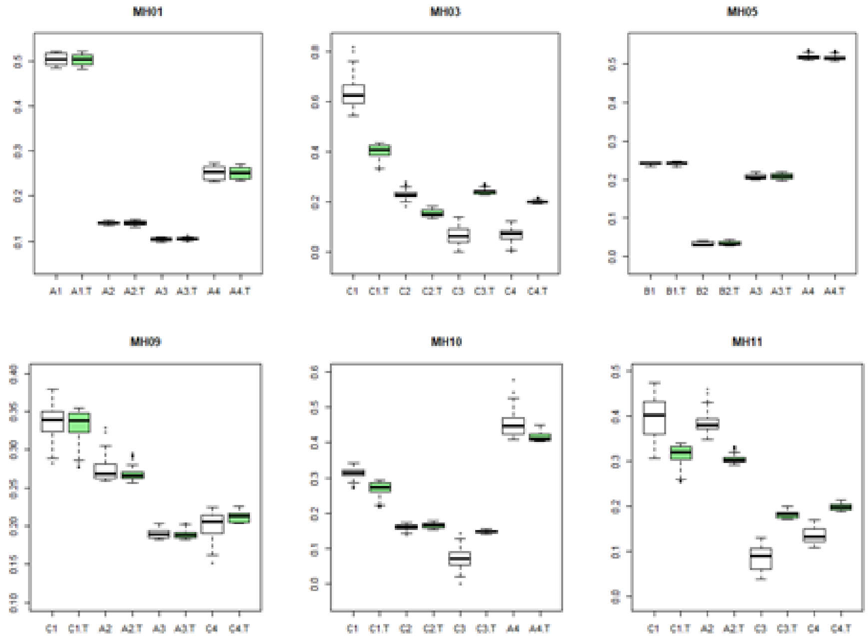

Figure 2: Stability of Asset's weights for the minimum-variance portfolios

Figure 2 show that the presence of transaction lot in the minimum-variance portfolio optimization sometimes does not affect the movement of asset's weight. This result mostly finds in the portfolio dominated by higher asset price such as P01, P02, and P04. Different result found in P03, P09, P10, P11, and P12, where the minimum-variance portfolio with transaction lot yield smaller change on asset's weight compared to the one without transaction lot. In other word, the presence of transaction lot in the minimum-variance portfolio optimization would reduce the variability of the portfolio weight during a period.

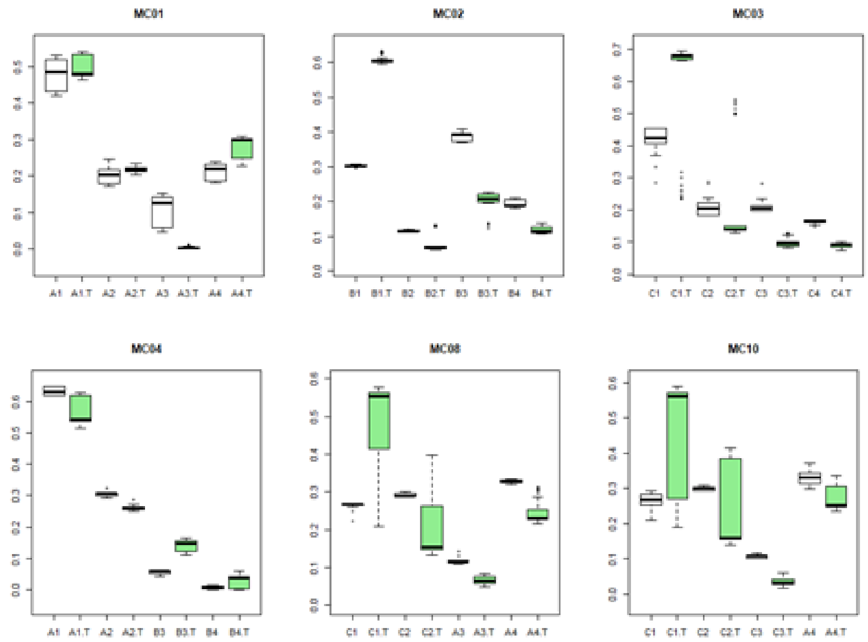

Figure 3: Stability of asset's weights for the minimum-CVaR portfolios

Based on figure 3, the minimum-CVaR models exhibit different result when modified with transaction lot. Unlike in the minimum-variance method, the implementation of transaction lot in almost all portfolios yield different weight compared to the optimization without them. For example, in portfolio P01, P02, P04, P05, and P10, the optimal portfolio with transaction lot yield portfolio with unstable weight that represented by wider range of the boxplots. Other assets exhibit same weight range but with different median.

Comparison of assets' weight calculated using both mean-variance and mean-CvaR optimization show various result. As an example, for portfolio 1, Figure 2 shows that the assets' weight for this portfolio with transaction lot were like the one without transaction lot. However, Figure 3 shows some differences in two assets' weight between portfolio with and without transaction lot. In addition, large differences are found in portfolio 10, where Figure 3 shows that the minimum-CvaR method with transactions lots failed to produce stable assets' weight. This result might relate to the composition of Portfolio 10, which consists of two assets with higher price and two assets with much lower price.

Table 3: Minimum Variance Portfolio Performance

Portfolio	Without transaction lot				With Transaction lot			
	Return	Sharpe Ratio	Average GT	Portfolio Turnover	Return	Sharpe Ratio	Average GT	Portfolio Turnover
P01	0.087	5.564	0.0264	0.0062	0.087	5.410	-0.034	0.0095
P02	0.102	5.420	0.0416	0.0056	0.103	5.529	0.0406	0.0073
P03	0.106	5.537	-0.416	0.0778	0.103	5.640	-0.015	0.0082
P04	0.088	5.061	0.0708	0.0069	0.090	5.024	0.0201	0.0114
P05	0.085	4.355	0.0905	0.0051	0.086	4.481	0.0912	0.0101
P06	0.056	1.193	0.0563	0.0064	0.055	1.087	0.0664	0.0077
P07	0.086	5.556	-0.027	0.0046	0.086	5.556	-0.047	0.0067
P08	0.101	6.452	-0.033	0.0062	0.100	6.357	0.0676	0.0066
P09	0.047	0.290	0.0379	0.0206	0.047	0.290	0.0517	0.0074
P10	0.101	6.390	0.2516	0.0417	0.105	6.899	0.0061	0.0065
P11	0.023	-2.786	0.3842	0.0465	0.045	0.001	0.0079	0.0042
P12	0.122	7.966	0.5373	0.0874	0.112	7.001	-0.003	0.0072
P13	0.121	9.131	0.0366	0.0053	0.122	9.245	0.0883	0.0082
P14	0.049	0.553	0.0231	0.0050	0.049	0.553	-0.002	0.0074
P15	0.082	3.289	0.0118	0.0057	0.080	3.126	-0.019	0.0068

Note: GT = Grinblatt-Titman Ratio

Comparing the Sharpe Ratio in Table 3, optimizing portfolio with transaction lot did not always lead to higher return compared to the portfolio without transaction lot. The difference of average return is ranging from 0.000 (i.e. same) to 0.022 on portfolio P11. In addition, higher Sharpe Ratio on portfolio with transaction lot only found in several portfolios, namely P02, P03, P05, P10, P11, and P13, which dominated by assets with mid and low price. Compared to the total return, higher Sharpe ratio might correspond to lower risk instead of higher return. Therefore, we can say that the presence of transaction lot might reduce the investment risk, as represented by the standard deviation.

From the portfolio turnover (PT) which measure the change of assets' weight, it appeared that portfolio without transaction lot exhibit lower PT than the portfolio with transaction lot, except for P03, P09, P10, P11, and P12. A look on Table 2 show that these five portfolios consist of asset with lower price. In contrast, when assets with higher price is included on the portfolio, the turnover of portfolio with transaction lot is much higher than the one without transaction lot. Henceforth from the turnover view, the portfolio optimization with transaction lot works well on assets with lower price instead of higher price.

Regarding the Average Grinblatt-Titman (AGT) statistics, it appeared that portfolio optimization with transaction lot yield lower AGT than the portfolio optimization without transaction lot. This result indicated that following the change of asset's weight resulted from portfolio optimization with transaction lot not always a better decision (resulting higher return). On the contrary, in portfolio P03, P05, P06, P08, P09, and P13, the portfolio optimization with transaction lot yield higher AGT than the other. Therefore, it seems that the asset's weight change will be more likely to increase the total return of portfolio with transaction lot when the portfolio consists of assets with lower price.

Table 4: Minimum CVaR Portfolio Performance

Portfolio	Without transaction lot				With Transaction lot			
	Return	Sharpe Ratio	Average GT	Portfolio Turnover	Return	Sharpe Ratio	Average GT	Portfolio Turnover
P01	0.077	3.920	0.6507	0.0212	0.071	3.227	-0.047	0.0198
P02	0.131	6.661	0.0538	0.0025	0.213	10.85	0.0398	0.0128
P03	0.108	6.077	-0.234	0.0119	0.094	4.450	2.7664	0.1105
P04	0.007	2.953	-0.022	0.0035	0.079	3.860	0.0281	0.0165
P05	0.099	5.507	-0.021	0.0010	0.165	8.295	-0.069	0.0145
P06	0.059	1.583	0.2419	0.0110	0.177	9.241	0.0532	0.0125
P07	0.066	2.672	-0.066	0.0043	0.084	3.426	-0.081	0.0117
P08	0.119	7.514	-0.002	0.0051	0.092	5.180	1.8738	0.0887
P09	0.046	0.134	-0.004	0.0039	0.048	0.346	-0.947	0.1107
P10	0.120	7.469	0.0291	0.0071	0.086	4.420	0.8694	0.0655
P11	0.042	-0.343	0.1225	0.0057	0.045	0.001	4.9954	0.2168
P12	0.110	6.822	-0.095	0.0119	0.092	4.979	1.3615	0.0785
P13	0.138	10.449	0.0938	0.0082	0.158	10.051	0.0053	0.0089
P14	0.052	0.940	0.0182	0.001	0.175	9.112	0.1214	0.0167
P15	0.106	5.141	-0.007	0.002	0.220	11.424	-0.047	0.0145

Note: GT = Grinblatt-Titman Ratio

For minimum-CVaR portfolio optimization, Table 4 show that the portfolio with transaction lot mostly had higher portfolio turnover than the portfolio without transaction lot. This result indicated that the assets' weight generated by minimum- CVaR without transaction lot is more 'robust' than the assets' weight calculated with transaction lot. The AGT statistics also show that following the assets' weight change in P02, P05, P06, P09, P13, and P15 calculated without transaction lot yield higher return than the assets' weight change in those that calculated with transaction lot.

Regarding portfolio performance, it is interesting to note that the Sharpe ratio is in line with the total return. When a portfolio calculated with transaction lot has higher return than the one calculated without transaction lot, they also exhibit higher Sharpe ratio. Higher return (and higher Sharpe Ratio) in portfolio with transaction lot is found for portfolio P02, P04, P05, P06, P07, P09, P11, P13, P14, and P15.

The result of Table 3 and Table 4 confirms that the minimum-variance and minimum-CvaR, with and without transaction lot, exhibit different performance although calculated based on same return and price dataset. Table 5 shows the rank of each portfolio based on their Sharpe Ratio and Return among portfolios calculated using same methods.

Table 5: Ascending rank of Portfolio Performance based on Total Return and Sharpe Ratio. Smaller return/sharpe ratio has smaller rank.

Portfolio	Total Return-based				Sharpe Ratio-based			
	min var	min var + lot	min-CVaR	min-CvaR + lot	min var	min var + lot	min-CVaR	min-CvaR + lot
P01	8	8	7	3	11	8	7	3
P02	12	11,5	14	14	8	9	11	14
P03	13	11,5	10	9	9	11	10	7
P04	9	9	1	4	7	7	6	5
P05	6	6,5	8	11	6	6	9	10
P06	4	4	5	13	4	4	4	12
P07	7	6,5	6	5	10	10	5	4
P08	10	10	12	7	13	12	14	9
P09	2	2	3	2	2	2	2	2
P10	10	13	13	6	12	13	13	6
P11	1	1	2	1	1	1	1	1
P12	15	14	11	7	14	14	12	8
P13	14	15	15	10	15	15	15	13
P14	3	3	4	12	3	3	3	11
P15	5	5	9	15	5	5	8	15

From Table 5, it appeared that the portfolio P11 and P09 always exhibit lowest return among the other portfolio calculated through all methods. In contrast, portfolio P13 exhibit highest performance among these portfolios across all methods except the minimum CVaR. Based on this consistent result, we can say that the performance of these portfolios is largely depend on the stocks as their building blocks.

For the minimum-variance portfolio, Table 5 shows that the usage of transaction lot in the optimization did not affect the rank of the total return and Sharpe ratio. Usage of the transaction lot in the optimization only resulting different assets' weight, which yield different total return and/or Sharpe ratio. In addition, usage of assets with similar price range might related to the difference of performance among minimum-variance portfolio with transaction lot.

Interestingly, the usage of transaction lot on the minimum-CVaR portfolio optimization leads to large difference of rank on total return and Sharpe ratio. For example, P13 is the best performance among all portfolio calculated without transaction lot but become the 5th among portfolio calculated with transaction lot. This result indicates that when transaction lot are considered in minimum-CVaR portfolio, asset price plays more important role on the asset's weight compared to the minimum variance portfolio with transaction lot.

How the price affect portfolio performance? In minimum CVaR portfolio with transaction lots, domination of high price assets (P01 and P14) reducing the performance of the portfolio. Similarly, domination of low-price assets (P03, P10, and P12) also result on performance reduction. In contrast, a large increase on performance of minimum-CVaR with transaction lots are found in portfolio P06, P14, and P15. A sharing property between these three portfolios is that they are consists of assets with various price range.

5. Conclusion and Recommendations

This study investigated the effects of stock price to the optimal portfolio constructed using minimum-variance and minimum-CvaR. In general, the usage of transaction lot in minimum-variance portfolio optimization yields more stable asset weight. However, there is no indication that assets' price affects the performance of minimum variance portfolio optimization with transaction lots. On the other hand, usage of transaction lot in minimum-CvaR portfolio optimization leads to varying asset weight. In addition, there is large difference of performance among minimum-CvaR portfolios calculated with or without transaction lot.

Choosing the suitable assets, with positive return as well as small risk, is important to improve the portfolio performance. Further study should be done to grasp the effects of another constraint beside the transaction lot, such as the cardinality constraint, number of lot constraint, and many other criteria.

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