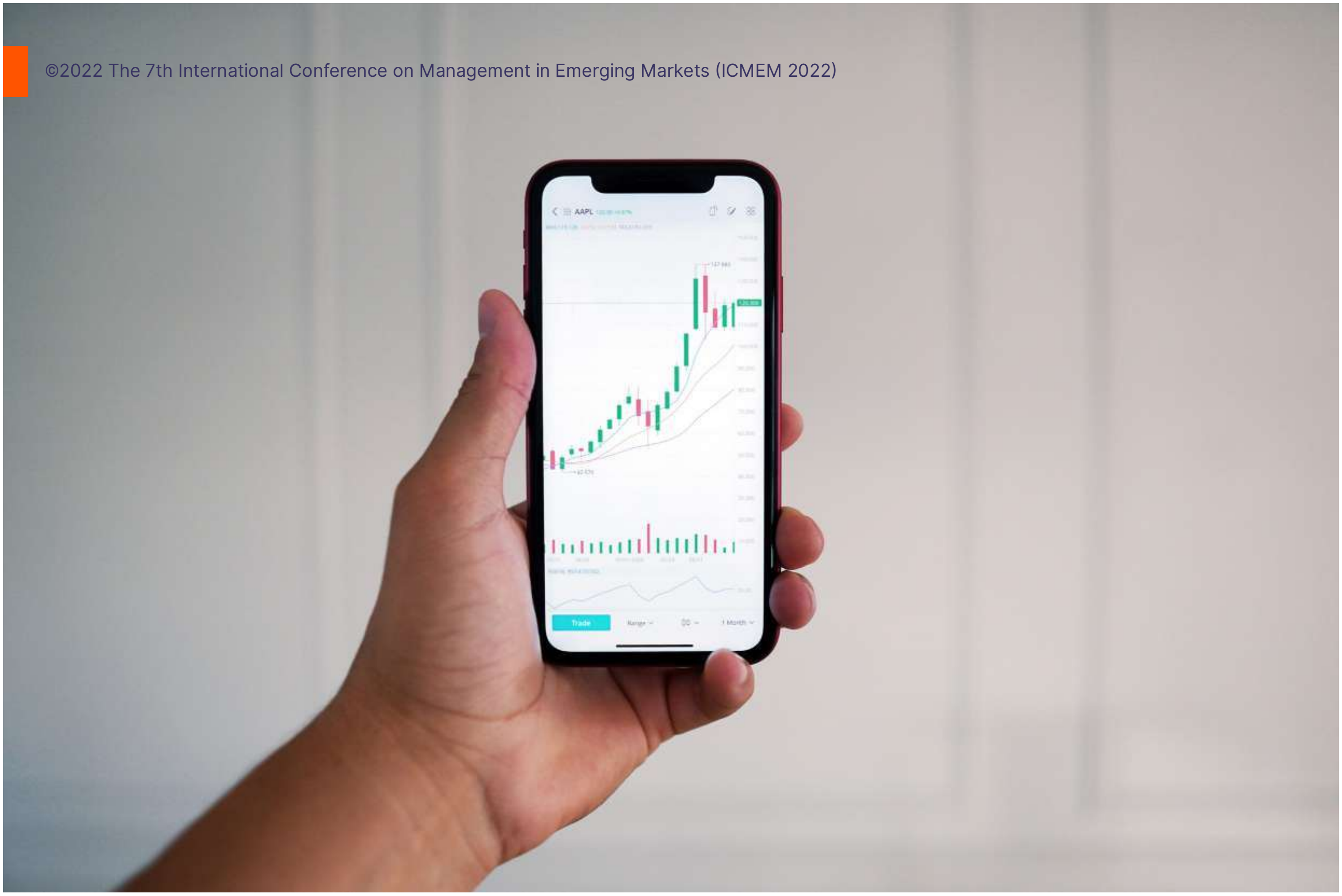

Paper 42

CAPM Test In Indonesian Stock Market Using Mean-Variance Optimal Portfolio As Market Return Proxy

Irfan Hilman and Deddy P Koesrindartoto

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Abstract - **This study examines the validity of the market return proxy used in the standard capital asset pricing model (CAPM) test. CAPM describes the relationship between the risk and the expected return of assets and is commonly used to estimate the cost of capital and measure the performance of a managed portfolio. Unfortunately, the value-weighted Jakarta Composite Index (JCI) used in standard CAPM tests as a market proxy fails to satisfy the assumption of mean-variance efficiency. Using mean-variance portfolio optimization of Kompas 100, LQ45, and IDX30 index components to generate an optimal portfolio to be used as a market proxy in CAPM, this study shows that "optimal beta" has less error in the expected return prediction than "market beta". Furthermore, the presence of bias in the value-weighted market index is also analyzed. The findings of this study imply that the mean-variance efficient portfolio from the portfolio optimization process should replace the value-weighted market index as a market proxy for CAPM's beta estimation.**

Keywords – **CAPM, portfolio optimization, market proxy**

I. INTRODUCTION

CAPM is introduced by Sharpe (1964) and Lintner (1965) to determine the theoretically appropriate required rate of return of assets, particularly common stocks. Since its introduction, CAPM has gained widespread acceptance from academics and professionals, resulting in a Nobel Prize for Sharpe in 1990.

Although CAPM gains strong support in early research (Jensen, 1968 and Jensen, 1969), subsequent researches document poor empirical evidence (Blume and Friend, 1973; Fama and MacBeth, 1973; Fama and French, 1992). Most explanations for the model's failure focus on irrational pricing and the market proxy approach (Fama & French, 2004). The irrational pricing argument states that investors' decisions are fundamentally affected by psychological biases, hence irrational pricing which is not captured by market beta in CAPM exists systematically. This explanation stems from the failure of CAPM to explain expected returns on stocks sorted according to characteristics, such as earning-prices ratio (Basu, 1977), size (Banz, 1981), and book-to-market ratio (Chan, Hamao, and Lakonishok, 1991). As a result, CAPM is expanded to multifactor models with additional "common risk factors" to increase the explanatory power. For instance, the three-factor model (market risk, size, and value premium) by Fama and French (1992), the four-factor model (market risk, size, value, and momentum premium) by Carhart (1997), and the five-factor model (market risk, size, value, profitability, and investment premium) by Fama and French (2015).

In contrast, market proxy arguments draw inspiration from Roll's (1977) critics. Roll focuses on the theoretical aspect of CAPM regarding the validity of the value-weight market portfolio proxy used in standard CAPM tests. In addition to the mean-variance efficient requirement, Roll states that the market proxy must be a "true market portfolio" which includes all marketable assets beyond common stocks. Nevertheless, Stambaugh (1982) finds that the addition of several asset classes beyond common stocks to market proxy does not result in a better approximation of the original CAPM. The problem of market proxy continues to become a debate among academics. Currently, value-weight market proxies used in most CAPM tests are assumed to be on the mean-variance frontier.

This research uses optimal portfolios resulting from mean-variance portfolio optimization as a market proxy in CAPM, replacing value-weight market indices which are commonly used. We believe value-weight market indices to be inefficient since inherent biases such as large-cap bias (Chaudhary and Bakhshi, 2021) and price floor policy (capping the minimum price of 50 for the main index) in Jakarta Composite Index (JCI) components cause value-weight market portfolio' risks and returns to be below efficient frontier. Contrary to most research, we do not focus on the irrational pricing approach which tests for the multifactor model because CAPM is impeccable from an academic viewpoint. Furthermore, various studies document inconsistency in multifactor model test results, such as the tendency of other risk premiums such as size and momentum to be time-varying and disappear after academic publications (McLean and Pontiff, 2013).

The scope of this study is limited to the Indonesian stock market and the analysis consists of monthly data. The main objective of this study is to compare the CAPM performance by using the value-weight market index (represented by JCI) and mean-variance optimal portfolio (represented by the optimized Kompas 100, LQ45, and IDX30 index) as a market proxy. The usage of the value-weighted market index as a market proxy in CAPM regression will result in "market beta". On the other hand, the usage of the optimal portfolio as the market proxy will result in "optimal beta". Both variables will be substituted to beta in CAPM to produce different predictions of the expected return. The performance of CAPM is measured by the accuracy of its prediction. To carry out the objective, we will compare the prediction errors of "market beta" and "optimal beta".

Key assumptions for this research are built upon earlier studies. Assumptions for the mean-variance model on which the foundation of CAPM is built are all investors are rational, risk-averse, and utility maximizers (Markowitz, 1952). Furthermore, assumptions for Sharpe-Linter CAPM are unrestricted borrowing and lending at the risk-free rate and homogenous expectations (Sharpe, 1964; Lintner, 1965). In addition, it is also assumed that CAPM completely explains returns, and no other risk premiums besides market risk premium are added to the original model, so that intercept (alpha) value is zero.

We hope this research can significantly contribute to a gap in current research since most contemporary studies tend to focus on the development of multifactor models. In addition, the amount of research that discusses the market proxy problem of CAPM in the emerging market, including Indonesia, is rare, hence this research can open the door for further research in this field.

II. METHODOLOGY

2.1 Data and Sample Selection

This research uses the monthly adjusted close price of Kompas 100, LQ45, and IDX30 index components. These monthly price data are then converted to monthly returns to be used as inputs to the portfolio optimization process. Stock components of Kompas 100, LQ45, and IDX30 index consist of 94, 45, and 30 stocks, respectively. Six stocks are excluded from Kompas 100 index due to incomplete data. Stock components are from the index's list for the August 2021-January 2022 period as referenced by the IDX website. The period of data selection is from 1 February 2017-1 January 2022. In total, there are 10.140 data for monthly stock returns from 169 stock tickers. Furthermore, the yield of a 10-year Indonesian government bond is used as a risk-free rate proxy in CAPM. For the value-weighted market proxy, the monthly return of JCI is used. This research uses Matlab 2021 for portfolio optimization and CAPM regression.

The return data are arranged into sample groups according to the choice of a market index (Kompas 100, LQ45, and IDX30) and periodicity (2, 3, 4, and 5 years).

2.2 Research Methodology

The methodology for this research can be divided into mean-variance portfolio optimization and the CAPM regression process for finding beta and expected return. In the portfolio optimization process, the mean and variance of return data of each index's components are computed for finding the mean of return, risk, and weight of the portfolio in the efficient frontier. The problem of portfolio selection for constructing an efficient frontier diagram can be formulated as risk minimization, expressed as a set of equations in the matrix form:

$$\min_{\omega} \frac{1}{2}\omega'\Sigma\omega \qquad (1)$$

$$s.t.\ \omega'\mu = r_p \qquad (2)$$

$$\omega'\iota = 1 \qquad (3)$$

where _i is the weight of stock i, cov(r_i,r_j) is the covariance of return of stock i and j, E(r_i) is the expected return of stock i, and r_i, r_j and r_p are the return of stock i, j, and portfolio p, respectively.

By solving a set of Equations 1-3, a set of portfolios with minimum variance for various levels of r_p can be calculated by quadratic programming and plotted as the portfolio points along the efficient frontier. These portfolios are also known as mean-variance efficient portfolios.

Located in the efficient frontier, there are two global optimum portfolios: maximum Sharpe ratio (MSR) and minimum variance (MV) portfolio. Each portfolio has different criteria for optimality. MSR portfolio has a global optimum Sharpe ratio among the efficient portfolios and is connected with a line to the risk-free rate point in the vertical axis (Fabozzi et al, 2015). The MSR portfolio can be found directly by solving the maximization problem in the form of a matrix:

$$\max_{\omega} \frac{\mu'\omega - r_f}{\sqrt{\omega'\Sigma\omega}} \qquad (4)$$

where is the mean of return, r_f is the risk-free rate and r_f R^N. On the other hand, the MV portfolio has a global minimum risk among the efficient portfolios and is located at the bottom end of the efficient frontier, or in the curve's "nose".

The results of portfolio optimization are the mean of return, risk, and weight of the optimal portfolio for each sample. Next, the weight of each component will be multiplied by its price to construct an optimal portfolio index. The returns of the optimal portfolio index are calculated and then used in CAPM regression for finding beta. The specification for CAPM is the original model as proposed by Sharpe (1964) and Lintner (1965), expressed as:

$$E[r_i] = \alpha_i + r_f + \beta_i \times (E[R_m] - r_f) \qquad (5)$$

where E[r_i] is the expected return of stock i, is the model's intercept, (beta) is the systematic risk, and E[R_m] is the expected return of market proxy. Market beta is obtained by using JCI returns as a market proxy in CAPM. On the other hand, optimal beta is obtained from using MSR and MV portfolio returns of Kompas 100, LQ45, and IDX30 in each periodicity as a market proxy. Furthermore, CAPM regression is carried out again using optimal beta and market beta to find the expected return.

2.3 Error Estimation

The results of the expected return from optimal beta and a market beta of CAPM regression are compared to the realized return of each stock component. The error of prediction ( ) is expressed as:

$$\varepsilon = E(r_i) - r_i \qquad (6)$$

where E(r_i) and r_i is the expected return and realized return, respectively, for stock i. From a set of error data, the mean-squared error (MSE) is expressed as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \qquad (7)$$

where Y_i and Y _i is the actual and average value of component i. The value of MSE for each sample will be used to judge the performance of CAPM for each sample of optimal and market beta.

The commonly accepted assumption is that the usage of the optimal portfolio from mean-variance optimization as a market proxy must not result in better CAPM performance, than simply using a value-weighted market index. The null hypothesis is developed from this assumption, which states that the error of CAPM prediction by using a value-weighted market proxy is lower than or equal to the error resulting from the usage of an optimal portfolio as a market proxy. On the other hand, the alternative hypothesis must support the notion the error of CAPM prediction by using a value-weighted market proxy is higher than the error resulting from the usage of an optimal portfolio as a market proxy.

III. RESULTS

3.1 General Descriptive Statistics

The descriptive statistics of monthly returns of Kompas 100, LQ45, and IDX30 components for the full period of February 2017-January 2002 are given in Table 1.

Table 1 - DESCRIPTIVE STATISTICS OF THE MONTHLY RETURNS OF INDEX COMPONENTS

	Kompas 100	LQ45	IDX30
Min	-0,575	-0,555	-0,506
Max	1,295	1,000	1,000
Mean	0,012	0,013	0,015
Median	-0,004	0,000	0,003
Stdev	0,144	0,129	0,122
Skewness	1,543	0,972	1,200
Kurtosis	8,345	4,976	5,966
N	5640	2700	1800

Furthermore, monthly returns of Kompas 100, LQ45, IDX30, and JCI calculated from their monthly index prices are obtained for February 2017-January 2022. The results are presented in Table 2:

Table 2 - DESCRIPTIVE STATISTICS OF THE MONTHLY RETURNS OF INDEX PRICES

	Kompas 100	LQ45	IDX30	JCI
Min	-0,201	-0,214	-0,203	-0,168
Max	0,111	0,117	0,117	0,094
Mean	0,002	0,002	0,002	0,005
Median	0,006	0,009	0,008	0,007
Stdev	0,050	0,051	0,050	0,041
Skewness	-1,075	-1,301	-1,182	-1,248
Kurtosis	3,647	4,775	4,124	4,312
N	60	60	60	60

3.2 Data Results

The results of the portfolio optimization process are the efficient frontier diagrams that depict a set of mean-variance efficient portfolios. The efficient frontier diagrams for Kompas 100, LQ45, and IDX30 optimization results in 2-5 years period of returns are shown in Figures 1-12.

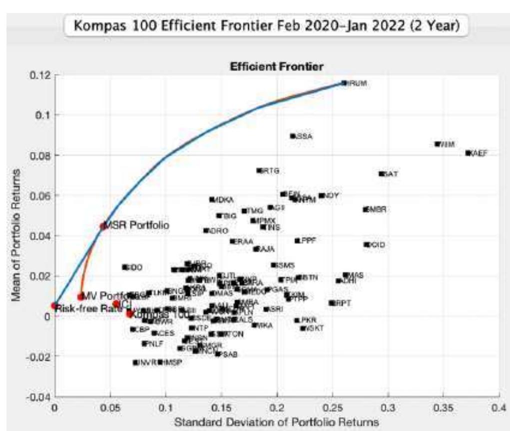

Fig. 1. Efficient frontier diagram for 2 years sample of Kompas 100 optimization results.

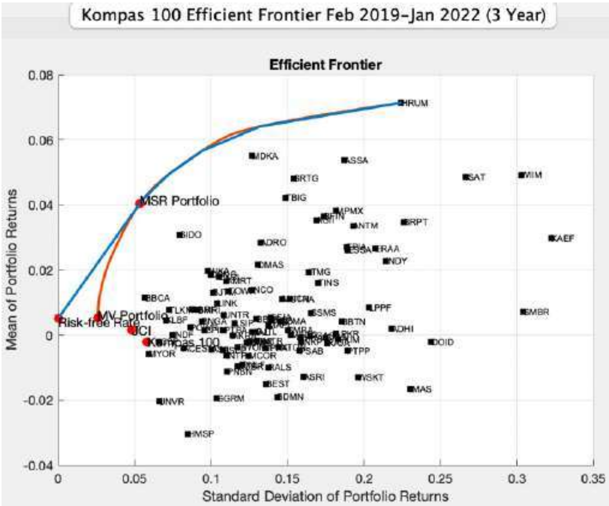

Fig. 2. Efficient frontier diagram for 3 years sample of Kompas 100 optimization results.

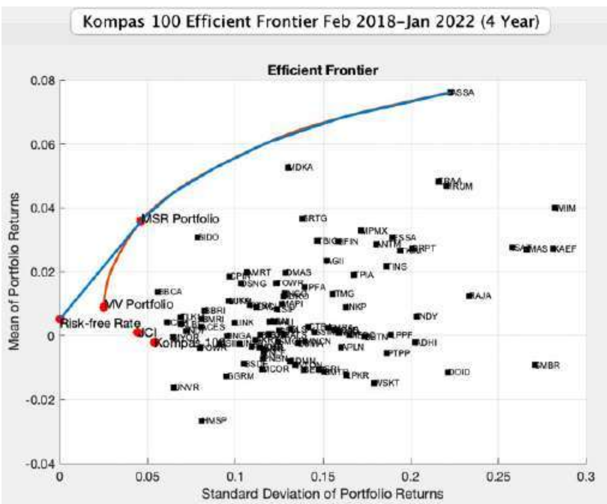

Fig. 3. Efficient frontier diagram for 4 years sample of Kompas 100 optimization results.

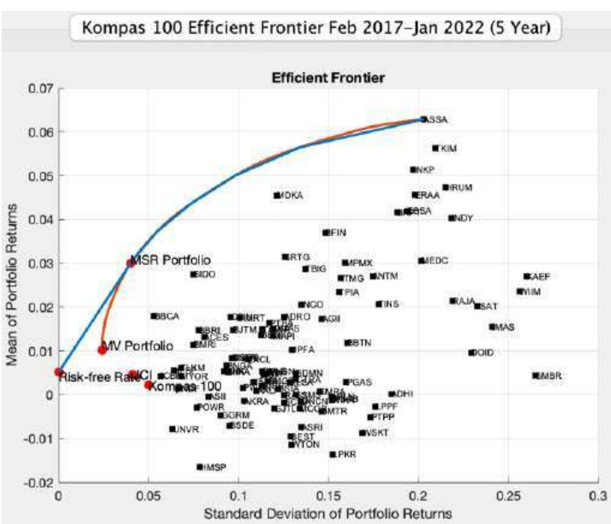

Fig. 4. Efficient frontier diagram for 5 years sample of Kompas 100 optimization results.

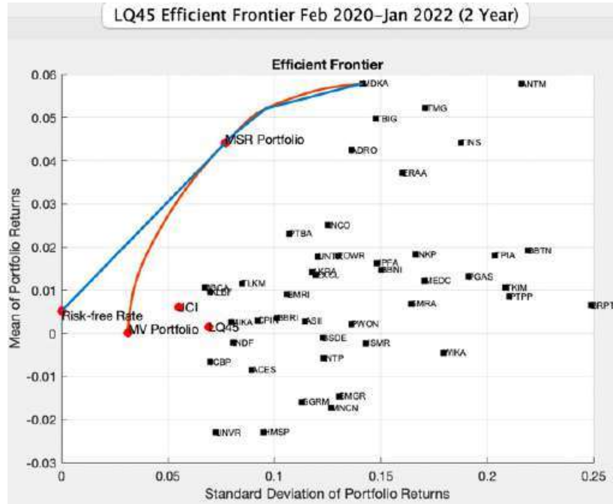

Fig. 5. Efficient frontier diagram for 2 years sample of LQ45 optimization results.

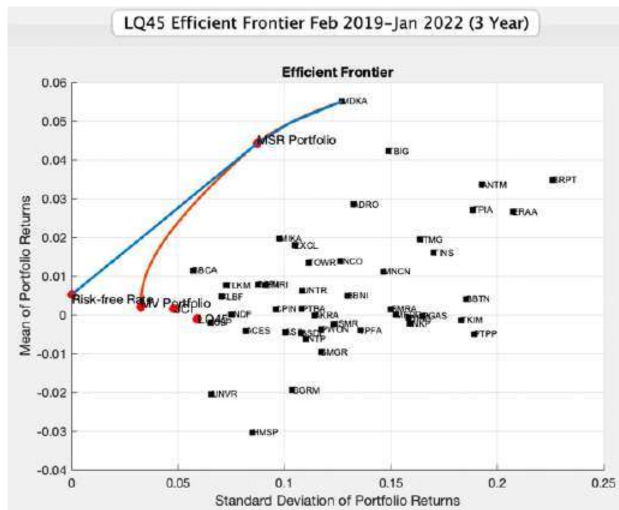

Fig. 6. Efficient frontier diagram for 3 years sample of LQ45 optimization results.

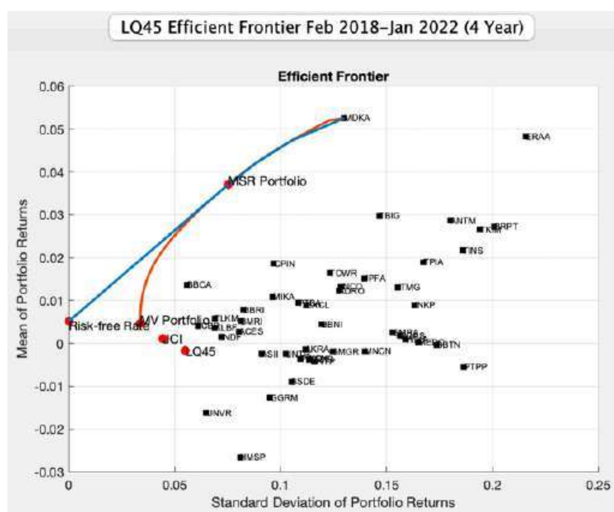

Fig. 7. Efficient frontier diagram for 4 years sample of LQ45 optimization results.

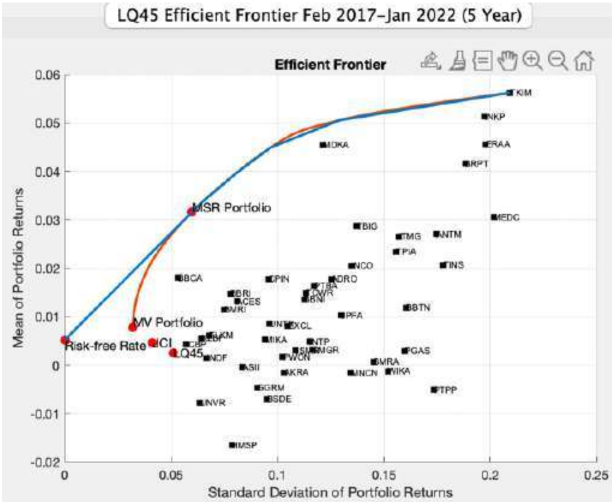

Fig. 8. Efficient frontier diagram for 5 years sample of LQ45 optimization results.

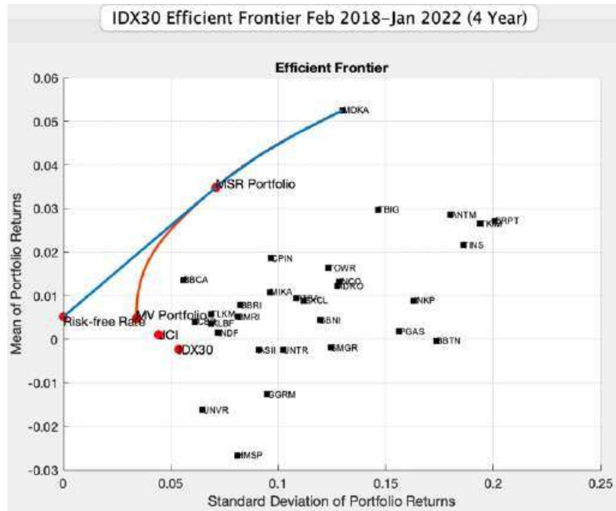

Fig. 11. Efficient frontier diagram for 4 years sample of IDX30 optimization results.

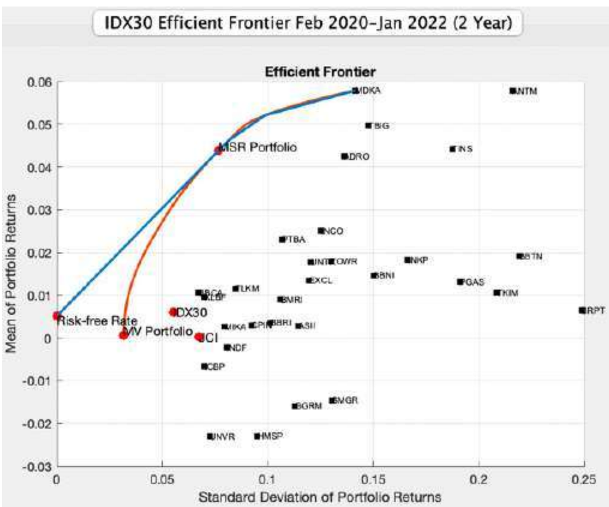

Fig. 9. Efficient frontier diagram for 2 years sample of IDX30 optimization results.

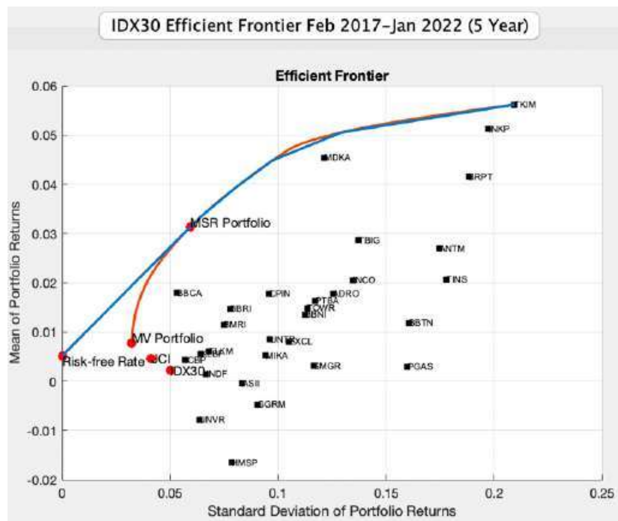

Fig. 12. Efficient frontier diagram for 5 years sample of IDX30 optimization results.

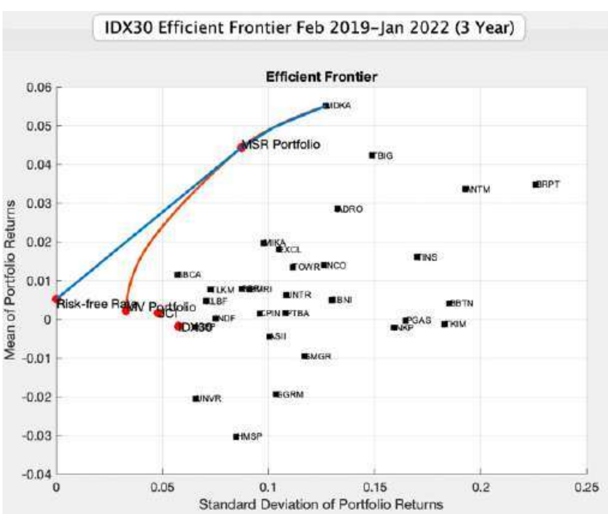

Fig. 10. Efficient frontier diagram for 3 years sample of IDX30 optimization results.

Figure 1-12 shows the mean of return and risk of Kompas 100, LQ45, and IDX30 index components, index returns, and JCI. As the theory suggests, the MSR and MV portfolio are both located at the efficient frontier. The MSR portfolio is connected to the point of the risk-free rate, while the MV portfolio is located at the bottom end of the efficient frontier. The mean of returns of index components is located below the efficient frontier. In addition, the mean of return and risk of unoptimized value-weighted indices (Kompas 100, LQ45, and IDX30) and JCI are located below the efficient frontier, indicating their inherent inefficiency in the mean-variance framework. Although these efficient frontier diagrams represent only a small portion of samples, we believe that the construction of efficient frontier diagrams by using other samples will result in a similar location for the value-weight index, since the portfolio weight is not optimal.

Following the results of portfolio optimization, the mean of return and risk of each optimal portfolio will be compared to that of a value-weighted portfolio for each index in Table 3-5.

Table 3 - THE MEAN OF RETURN AND RISK OF OPTIMAL PORTFOLIO AND VALUE-WEIGHTED PORTFOLIO OF KOMPAS 100

	MSR		MV		Kompas 100	
	Return	Risk	Return	Risk	Return	Risk
2 year	0,045	0,044	0,009	0,024	0,001	0,068
3 year	0,040	0,053	0,005	0,026	-0,002	0,058
4 year	0,036	0,046	0,009	0,025	-0,002	0,054
5 year	0,030	0,040	0,010	0,024	0,002	0,050
Mean	0,038	0,046	0,008	0,025	0,000	0,057

Table 4 - THE MEAN OF RETURN AND RISK OF OPTIMAL PORTFOLIO AND VALUE-WEIGHTED PORTFOLIO OF LQ45

	MSR		MV		LQ45	
	Return	Risk	Return	Risk	Return	Risk
2 year	0,044	0,077	0,000	0,031	0,001	0,069
3 year	0,044	0,087	0,002	0,032	-0,001	0,059
4 year	0,037	0,075	0,005	0,034	-0,002	0,055
5 year	0,032	0,060	0,008	0,032	0,002	0,051
Mean	0,039	0,075	0,004	0,032	0,000	0,059

Table 5 - THE MEAN OF RETURN AND RISK OF OPTIMAL PORTFOLIO AND VALUE-WEIGHTED PORTFOLIO OF IDX30

	MSR		MV		IDX30	
	Return	Risk	Return	Risk	Return	Risk
2 year	0,044	0,077	0,001	0,031	0,000	0,067
3 year	0,044	0,087	0,002	0,033	-0,002	0,057
4 year	0,035	0,071	0,005	0,034	-0,002	0,054
5 year	0,031	0,059	0,008	0,032	0,002	0,050
Mean	0,039	0,073	0,004	0,033	0,000	0,057

Looking at the average returns and risk for the 2-5 years sample period, the average returns of the value-weighted index are always lower than that of the optimal portfolios (MSR and MV). On the other hand, the risk is higher. The average risk in the MV portfolio is the lowest compared to that of MSR and the value-weighted index. In contrast, the average return in the MSR portfolio is the highest compared to that of MV and the value-weighted index. The results in Table 3-5 are consistent with the location of the respective portfolios in the efficient frontier (Figure 1-12).

In CAPM regression, the returns of the optimal portfolio index for each Kompas 100, LQ45, and IDX30 will be substituted for the returns of the market proxy to obtain the optimal beta. On the other hand, the returns of JCI will be substituted for the returns of the market proxy in CAPM to obtain the market beta. The statistics of beta values for each stock component and their measure of statistical significance (p-value) are provided in Tables 6-8.

Table 6 - THE RESULTS OF BETA AND P-VALUE OF OPTIMAL AND VALUE-WEIGHTED MARKET PROXY IN KOMPAS 100 COMPONENTS

	MSR					
	Beta			p-value		
	Min	Max	Mean	Min	Max	Mean
2 years	-0,37	1,89	0,68	0	0,81	0,09
3 years	-0,18	2,11	0,48	0	0,81	0,13
4 years	-0,02	1,56	0,64	0	0,56	0,07
5 years	0,14	2,57	1,20	0	0,32	0,03
Total	-0,37	2,57	0,75	0	0,81	0,08
	MV					
	Beta			p-value		
	Min	Max	Mean	Min	Max	Mean
2 years	-0,87	3,09	0,93	0	0,93	0,19
3 years	-0,86	3,31	1,22	0	0,95	0,11
4 years	-0,63	2,92	1,25	0	0,85	0,08
5 years	-0,69	3,93	1,32	0	0,91	0,07
Total	-0,87	3,93	1,18	0	0,95	0,11
	JCI					
	Beta			p-value		
	Min	Max	Mean	Min	Max	Mean
2 years	-1,16	3,62	1,62	0	0,80	0,04
3 years	-0,80	4,06	1,64	0	0,76	0,03
4 years	-0,51	3,59	1,61	0	0,71	0,03
5 years	-0,35	3,75	1,57	0	0,67	0,02
Total	-1,16	4,06	1,61	0	0,80	0,03

Table 7 - THE RESULTS OF BETA AND P-VALUE OF OPTIMAL AND VALUE-WEIGHTED MARKET PROXY IN IDX30 COMPONENTS

	MSR					
	Beta			p-value		
	Min	Max	Mean	Min	Max	Mean
2 years	-0,12	1,60	0,66	0	0,75	0,09
3 years	-0,09	1,30	0,49	0	0,77	0,10
4 years	0,01	1,27	0,52	0	0,47	0,07
5 years	0,09	2,47	0,79	0	0,26	0,05
Total	-0,12	2,47	0,61	0	0,77	0,08
	MV					
	Beta			p-value		
	Min	Max	Mean	Min	Max	Mean
2 years	-0,46	2,92	0,73	0	0,89	0,24
3 years	0,09	2,57	1,11	0	0,44	0,06
4 years	-0,39	0,99	0,49	0	0,90	0,12
5 years	0,04	1,68	0,91	0	0,45	0,06
Total	-0,46	2,92	0,81	0	0,90	0,12
	JCI					
	Beta			p-value		
	Min	Max	Mean	Min	Max	Mean
2 years	0,17	2,91	1,32	0	0,26	0,03
3 years	0,12	2,86	1,32	0	0,30	0,03
4 years	0,21	3,01	1,31	0	0,15	0,01
5 years	0,22	2,77	1,30	0	0,10	0,01
Total	0,12	3,01	1,31	0	0,30	0,02

Table 8 - THE RESULTS OF BETA AND P-VALUE OF OPTIMAL AND VALUE-WEIGHTED MARKET PROXY IN IDX30 COMPONENTS

	MSR					
	Beta			p-value		
	Min	Max	Mean	Min	Max	Mean
2 years	-0,12	1,60	0,66	0	0,75	0,09
3 years	-0,09	1,30	0,49	0	0,77	0,10
4 years	0,01	1,27	0,52	0	0,47	0,07
5 years	0,09	2,47	0,79	0	0,26	0,05
Total	-0,12	2,47	0,61	0	0,77	0,08
	MV					
	Beta			p-value		
	Min	Max	Mean	Min	Max	Mean
2 years	-0,46	2,92	0,73	0	0,89	0,24
3 years	0,09	2,57	1,11	0	0,44	0,06
4 years	-0,39	0,99	0,49	0	0,90	0,12
5 years	0,04	1,68	0,91	0	0,45	0,06
Total	-0,46	2,92	0,81	0	0,90	0,12
	JCI					
	Beta			p-value		
	Min	Max	Mean	Min	Max	Mean
2 years	0,17	2,91	1,32	0	0,26	0,03
3 years	0,12	2,86	1,32	0	0,30	0,03
4 years	0,21	3,01	1,31	0	0,15	0,01
5 years	0,22	2,77	1,30	0	0,10	0,01
Total	0,12	3,01	1,31	0	0,30	0,02

Based on data in Table 6-8, the average beta values for JCI are higher than those resulting from optimal market proxies. In general, the average beta values are significant (p-value<0,1) except for those resulting from MV optimal portfolio as a market proxy for the periodicity of 1-2 years. The higher beta values for the JCI proxy imply that the usage of a value-weighted market proxy tends to overestimate the risk of individual securities. These findings lead to higher expected returns from CAPM prediction, as will be explained in the later section.

The expected returns resulting from optimal and market beta in CAPM regression are later compared to the realized returns of each stock to obtain the prediction errors. Next, the MSE values for all stock components of Kompas 100, LQ45, and IDX30 are presented in Tables 9-11.

Table 9 - MEAN-SQUARED ERRORS FOR ALL STOCK COMPONENTS IN KOMPAS 100 PORTFOLIO OPTIMIZATION

	MEAN-SQUARED ERROR		
	MSR	MV	JCI
2 year	0,008838	0,008851	0,009019
3 year	0,008811	0,008894	0,009021
4 year	0,008839	0,008925	0,009013
5 year	0,008935	0,008911	0,008991
Mean	0,008856	0,008895	0,009011

Table 10 - MEAN-SQUARED ERRORS FOR ALL STOCK COMPONENTS IN LQ45 PORTFOLIO OPTIMIZATION

	MEAN-SQUARED ERROR		
	MSR	MV	JCI
2 year	0,007289	0,007307	0,007441
3 year	0,007297	0,007332	0,007442
4 year	0,007282	0,007361	0,007446
5 year	0,007346	0,007315	0,007430
Mean	0,007304	0,007329	0,007440

Table 11 - MEAN-SQUARED ERRORS FOR ALL STOCK COMPONENTS IN IDX30 PORTFOLIO OPTIMIZATION

	MEAN-SQUARED ERROR		
	MSR	MV	JCI
2 year	0,004082	0,004027	0,004129
3 year	0,004064	0,004083	0,004131
4 year	0,004049	0,004001	0,004127
5 year	0,004096	0,004036	0,004118
Mean	0,004073	0,004036	0,004126

The results in Table 9-11 show that the usage of MSR and MV portfolio as market proxy consistently produces better prediction than that of a value-weighted market index (JCI) in Kompas 100, LQ45, and IDX30 samples. For Kompas 100, the MSR portfolio has the lowest average MSE value (0,008856) than that of the MV portfolio (0,008895)and JCI (0,009011). Similarly, the MSR portfolio in LQ45 samples also has the lowest average MSE value (0,007304) than that of the MV portfolio (0,007329) and JCI (0,007440). On the other hand, different results are obtained for IDX30 samples. Their average MSE value for the MV optimal portfolio is 0,004036, which is the lowest between that of the MSR portfolio (0,004073) and JCI (0,004126).

Furthermore, a more objective comparison will be conducted for 30 selected stock components of Kompas 100, LQ45, and IDX30 in Tables 12-14. Those stock components have similar inclusion to the three indices. The purpose of this analysis is to exclude the possible bias caused by different stock components of Kompas 100, LQ45, and IDX30.

Table 12 - MEAN-SQUARED ERRORS FOR 30 SELECTED STOCKS IN KOMPAS 100 PORTFOLIO OPTIMIZATION

	MEAN-SQUARED ERROR		
	MSR	MV	JCI
2 year	0,004034	0,004039	0,004129
3 year	0,004057	0,004095	0,004131
4 year	0,004056	0,004112	0,004127
5 year	0,004108	0,004094	0,004118
Mean	0,004064	0,004085	0,004126

Table 13 - MEAN-SQUARED ERRORS FOR 30 SELECTED STOCKS IN LQ45 PORTFOLIO OPTIMIZATION

	MEAN-SQUARED ERROR		
	MSR	MV	JCI
2 year	0,004040	0,004031	0,004129
3 year	0,004064	0,004072	0,004131
4 year	0,004042	0,004062	0,004127
5 year	0,004089	0,004034	0,004118
Mean	0,004059	0,004050	0,004126

Table 14 - MEAN-SQUARED ERRORS FOR 30 SELECTED STOCKS IN IDX30 PORTFOLIO OPTIMIZATION

	MEAN-SQUARED ERROR		
	MSR	MV	JCI
2 year	0,004082	0,004027	0,004129
3 year	0,004064	0,004083	0,004131
4 year	0,004049	0,004001	0,004127
5 year	0,004096	0,004036	0,004118
Mean	0,004073	0,004036	0,004126

The results in Table 12-14 show that the MSE values for using an optimal portfolio as a market proxy are still lower than that for using the JCI value-weighted index. In Kompas 100 sample, the average MSE value for MSR portfolio (0,004064) is 1,5% lower than that of JCI (0,004126) and is 0,5% lower than that of MV portfolio (0,004085). On the other hand, the performance of prediction is better for the MV portfolio in LQ45 and IDX30 samples. In LQ45 sample, the average MSE value for MV portfolio (0,00405) is 1,84% lower than that of JCI (0,004126) and is 0,2% lower than that of MSR portfolio (0,004059). In IDX30 sample, the average MSE value for MV portfolio (0,004036) is 2,2% lower than that of JCI (0,004126) and is 0,9% lower than that of MSR portfolio (0,004073). Overall, the MV portfolio in IDX30 samples has the lowest average MSE value (0,004036) among all other samples tested.

Since the MSE values of CAPM prediction are consistently lower with optimal beta resulting from the usage of the MSR and MV optimal portfolio as a market proxy than with market beta resulting from value-weighted JCI as a market proxy, then the null hypothesis in this research is firmly rejected.

Based on the test result, the sample that produces the best CAPM performance is the 5-year sample of MV optimization in the LQ45 index. The sample has a low MSE value (0,004034), yet the p-value of the optimal beta is still significant (average p-value of 0,049). On the other hand, some samples produce lower MSE values, but their average beta values are not statistically significant. The index choice seems to not affect the CAPM performance, although Kompas 100 has relatively higher MSE values in their samples. Nevertheless, the average MSE of the MSR portfolio in the Kompas 100 sample (0,004064) has a higher value than that of the IDX30 sample (0,004073). Similarly, the choice of periodicity does not correlate with the results of MSE, but the periodicity of 1-2 years produces average beta values that are not significant (average p-value>0,1). On the other hand, MV portfolios seem to have lower values of MSE in LQ45 and IDX30 samples, yet in Kompas 100 index, their MSE values are higher.

The consistent results of higher prediction errors for market beta from value-weighted JCI proxy might be caused by a presence of bias in the portfolio composition. To test this hypothesis, the statistics of expected returns from CAPM calculation by using market beta and optimal beta are presented in Tables 15-17. In addition, the p-values of paired t-tests (with the hypothesized mean difference set to zero) between each pair of the mean expected returns resulting from the use of optimal and market beta in CAPM regression are presented in Table 18.

Table 15 - THE EXPECTED MONTHLY RETURN OF KOMPAS 100 OPTIMAL PORTFOLIO AND JCI

	MSR			
	Min	Max	Mean	Stdev
2 years	0,0043	0,0097	0,0068	0,0009
3 years	0,0047	0,0102	0,0063	0,0009
4 years	0,0051	0,0089	0,0067	0,0008
5 years	0,0055	0,0113	0,0080	0,0015
Total	0,0043	0,0113	0,0069	0,0012
	MV			
	Min	Max	Mean	Stdev
2 years	0,0031	0,0125	0,0074	0,0019
3 years	0,0031	0,0131	0,0081	0,0019
4 years	0,0037	0,0121	0,0081	0,0018
5 years	0,0035	0,0145	0,0083	0,0019
Total	0,0031	0,0145	0,0080	0,0019

	JCI			
	Min	Max	Mean	Stdev
2 years	0,0024	0,0138	0,0090	0,0021
3 years	0,0033	0,0149	0,0091	0,0021
4 years	0,0039	0,0137	0,0090	0,0020
5 years	0,0043	0,0141	0,0089	0,0019
Total	0,0024	0,0149	0,0090	0,0020

Table 16 - THE EXPECTED MONTHLY RETURN OF THE LQ45 OPTIMAL PORTFOLIO AND JCI

	MSR			
	Min	Max	Mean	Stdev
2 years	0,0048	0,0090	0,0068	0,0010
3 years	0,0050	0,0083	0,0064	0,0008
4 years	0,0051	0,0079	0,0063	0,0006
5 years	0,0053	0,0107	0,0073	0,0014
Total	0,0048	0,0107	0,0067	0,0010
	MV			
	Min	Max	Mean	Stdev
2 years	0,0040	0,0124	0,0071	0,0018
3 years	0,0054	0,0106	0,0078	0,0013
4 years	0,0056	0,0118	0,0080	0,0013
5 years	0,0052	0,0107	0,0075	0,0011
Total	0,0040	0,0124	0,0076	0,0014
	JCI			
	Min	Max	Mean	Stdev
2 years	0,0056	0,0129	0,0087	0,0018
3 years	0,0054	0,0131	0,0087	0,0018
4 years	0,0057	0,0134	0,0087	0,0018
5 years	0,0057	0,0130	0,0087	0,0017
Total	0,0054	0,0134	0,0087	0,0018

Table 17 - THE EXPECTED MONTHLY RETURN OF IDX30 OPTIMAL PORTFOLIO AND JCI

	MSR			
	Min	Max	Mean	Stdev
2 years	0,0049	0,0090	0,0067	0,0011
3 years	0,0050	0,0083	0,0063	0,0009
4 years	0,0052	0,0082	0,0064	0,0008
5 years	0,0054	0,0111	0,0070	0,0015
Total	0,0049	0,0111	0,0066	0,0011

Total	0,0049	0,0111	0,0066	0,0011
	MV			
	Min	Max	Mean	Stdev
2 years	0,0041	0,0121	0,0069	0,0020
3 years	0,0054	0,0113	0,0078	0,0014
4 years	0,0042	0,0075	0,0063	0,0008
5 years	0,0053	0,0092	0,0073	0,0011
Total	0,0041	0,0121	0,0071	0,0015
	JCI			
	Min	Max	Mean	Stdev
2 years	0,0056	0,0121	0,0083	0,0019
3 years	0,0054	0,0120	0,0083	0,0019
4 years	0,0057	0,0123	0,0083	0,0018
5 years	0,0057	0,0118	0,0083	0,0017
Total	0,0054	0,0123	0,0083	0,0018

Table 18 - PAIRED T-TEST (P-VALUE) BETWEEN OPTIMAL AND VALUE-WEIGHTED PORTFOLIOS

	Kompas 100		
	MSR-JCI	MV-JCI	MSR-MV
2 year	0,0000	0,0000	0,0045
3 year	0,0000	0,0007	0,0000
4 year	0,0000	0,0021	0,0000
5 year	0,0005	0,0294	0,2492
Total	0,0000	0,0000	0,0000
	LQ45		
	MSR-JCI	MV-JCI	MSR-MV
2 year	0,0000	0,0000	0,3547
3 year	0,0000	0,0065	0,0000
4 year	0,0000	0,0273	0,0000
5 year	0,0000	0,0003	0,3128
Total	0,0000	0,0000	0,0000
	IDX30		
	MSR-JCI	MV-JCI	MSR-MV
2 year	0,0003	0,0070	0,7082
3 year	0,0000	0,2388	0,0000
4 year	0,0000	0,0000	0,7182
5 year	0,0045	0,0133	0,4116

In Table 15-17, the mean of expected returns from the JCI proxy is consistently above those from the MSR and MV portfolio proxies. The difference in the mean of expected returns between MSR and JCI, and between MV and JCI, is also significant according to the paired t-test results in Table 18 (the p-value of MSR-JCI and MV-JCI is far below the significance level of 10%). The results are consistent for each periodicity in Kompas 100, LQ45, and IDX30 components. On average, the standard deviations of expected returns in the JCI proxy are also higher. These findings indicate that the usage of a value-weighted market proxy, such as JCI, leads to an overestimation of expected returns. The CAPM estimation using the JCI proxy is also subject to a larger standard deviation, thereby decreasing its reliability to be used in practice.

IV. DISCUSSION

The common assumption in standard CAPM research states that the value-weighted market index is mean-variance efficient, therefore it can be safely used for the empirical test of CAPM. The findings of this research challenge that assumption. First, the efficient frontier diagrams in Figures 1-12 show that the value-weight indices are always positioned below the efficient frontier, consequently, they can never be efficient. Second, JCI as the value-weighted market index used as a market proxy in this research produces an overestimation of beta values, leading to a higher expected return in CAPM estimation. This result is confirmed by paired t-test in Table 18 which shows that the difference in the mean of expected returns between market beta and optimal beta in the CAPM test is significant, therefore the presence of bias that causes the overestimation is confirmed. Third, the MSE values are higher in the expected returns resulting from market beta compared to optimal beta, indicating that the use of value-weighted JCI for beta estimation leads to lower CAPM performance.

V. CONCLUSION

Findings from this research imply that the validity of the value-weighted market proxy used in standard CAPM tests must be questioned. The usage of JCI as a standard market proxy in CAPM tests in Indonesia can result in a worse performance of prediction. In practice, CAPM has been used to calculate the cost of capital in capital budgeting or evaluation of investment projects. Inaccurate estimation of the cost of capital can lead to the rejection of a profitable project, or worse, the acceptance of a losing project. These reasons state the importance of using the optimal portfolio as the market proxy in CAPM.

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