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Optimal portfolio strategy: A stock index-based analysis

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Abstract

The classification of stock indices published by Indonesia Stock Exchange (2021) has resulted in variations of stock indices, whereby a stock index may contain stocks that are the same, similar, or different from other stock indices. Based on the portfolio theory in Hartono (2014) and the Markowitz model in Lutfi and Hendrian (2020), variations or differences in portfolio performance can be influenced by the variations or differences in stock indices. This article analyzes the differences between optimal portfolio performances based on these variations of stock indices. Based on a sample of 88 stocks from 10 stock indices over the last 10 years, divided into 3 data periods of stock price, we found no significant difference between optimal portfolio performances based on stock indices. We also found that no stock index can be the suitest for constructing a portfolio exhibiting optimal performance. Thus, the ability of a stock index to represent the performance of IHSG or whole stocks is the same as other stock indices. In this research, we also found that the line of risk-free returns to optimal portfolio performances, which were constructed without a short-selling approach, did not effectively engage the outermost boundary of the efficient portfolio frontier.

Keywords: Portfolio performance; optimal portfolio; stock index; Markowitz model; sharpe ratio; short selling

1. Introduction

Investment instruments, such as stocks, are typically categorized alongside stocks within a collective asset group represented by a stock index. Based on the publication of the Indonesia Stock Exchange (2021), stock indices in Indonesia are classified into multiple classifications, sub-classifications, and distinct stock indices. This classification results in variations of stock indices, whereby a stock index may contain stocks that are the same, similar, or different from other stock indices. Based on the stock price data published by Yahoo Finance (2024), stock prices consist of the opening price, the highest price, the lowest price, the closing price, and the adjusted closing price. These stock price types result in another phenomenon of variations of stock indices, whereby a stock index may contain stocks that have the same, similar, or different prices to another stock price in other stock indices. The primary inquiry of this analysis centers on the existence of differences between optimal portfolio performances based on these variations of stock indices.

According to Hartono (2014), traditional portfolio theory elucidates that an asset with a certain return and risk can mitigate its risk by diversifying risk into other assets by constructing a portfolio. Otherwise Hartono (2014), stated modern portfolio theory and post-modern portfolio theory further elucidate that portfolio's return and risk can be optimized by applying statistical and mathematical methodologies, including the Markowitz model and sharpe ratio. According to Lutfi and Hendrian (2020), the Markowitz model effectively addresses the limitations of naive diversification by utilizing available information to select assets, determine asset allocation, and provide an efficient portfolio set that matches certain investors' risk preferences. This implies that variations in the selection process and

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asset allocation determination can influence the overall portfolio performance. In this context, the optimal portfolio performance that contains stocks with specific allocations and is selected based on specific stock indices may result in the same, similar, or different optimal portfolio performances that contain stocks with other allocations and are selected based on other stock indices. Thus, portfolio theory and the Markowitz model imply that differences between optimal portfolio performances may influenced by differences in stock indices.

The comparison between the stock portfolio performances from the studies conducted by Octovian (2017); Jayana and Sihombing (2019); Iskandar and Julianto (2020); Zivkov *et al.*, (2022); Ghaemi *et al.* (2024); Gozah *et al.* (2020); Huni and Sibindi (2020); Lai *et al.* (2020); Ben Ameur *et al.* (2024); and Purwanto *et al.* (2020) indicate that there are differences between optimal portfolio performances based on diverse stock indices. Consequently, from a theoretical and practical perspective, there are differences between optimal portfolio performances based on stock indices. In this research, we conduct a comprehensive statistical analysis of the differences between optimal portfolio performances based on stock indices across 3 data periods of stock price, as well as the implications of these differences for investors.

In general, the studies conducted by Octovian (2017); Jayana and Sihombing (2019); Iskandar and Julianto (2020); Zivkov *et al.* (2022); Ghaemi *et al.* (2024); Gozah *et al.* (2020); Huni and Sibindi (2020); Lai *et al.* (2020); Ben Ameur et al. (2024); and Purwanto et al. (2020) utilized Markowitz model to construct optimal portfolios and sharpe ratio to evaluate portfolio performances. The distinguishing factor among these studies lies in the types and quantities of stock indices utilized. These variations arise from the differences in the classification of stock indices. Huni and Sibindi (2020) utilized a sectoral classification of stock indices. Lai *et al.* (2020) utilized a classification of stock indices based on geographical regions. Zivkov *et al.* (2022) utilized a classification of stock indices based on ASEAN and non-ASEAN countries. Ben Ameur *et al.* (2024) utilized a classification of stock indices based on criteria of green assets versus non-green assets. And Ghaemi *et al.* (2024) utilized a classification of stock indices based on sharia indices versus conventional indices. Furthermore, Octovian (2017); Jayana and Sihombing (2019); Gozah *et al.* (2020); Iskandar and Julianto (2020); and Purwanto *et al.* (2020) utilized stock indices without any specific classification based on defined criteria.

In this research, we utilized different approaches to select stocks and determine the stock allocation in constructing an optimal portfolio. We adopted the classification of stock indices as published by the Indonesia Stock Exchange (2021) to identify stock indices that adequately represent the entire spectrum of stocks in Indonesia across multiple dimensions. Consequently, the classification, subclassification, and stock indices employed in this research are anticipated to provide foundational guidelines for future research and for the development of optimal portfolios in the identification of pertinent stock indices in various contexts.

In this research, we utilized 3 data periods of stock price to analyze differences between optimal portfolio performances based on stock indices. These data periods of stock price are before the COVID-19 pandemic, since the COVID-19 pandemic, and before and since the COVID-19 pandemic. According to "*Keputusan Presiden Republik Indonesia Nomor 11 tahun 2020 tentang Penetapan Kedaruratan Kesehatan Masyarakat Corona Virus Disease 2019 (Covid- 19)*", pandemic Covid-19 was officially recognized on March 31, 2020. Thus, before the pandemic COVID-19 refers to stock price data collected before March 31, 2020, whereas the period since the pandemic COVID-19 refers to stock price data collected since March 31, 2020. The period before and since the COVID-19 pandemic refers to stock price data collected before and since March 31, 2020. It is imperative to analyze the discrepancies in optimal portfolio performance as influenced by stock indices across these 3 data periods of stock price to ensure the consistency of our analytical findings under varied economic conditions over both short and long-term horizons.

2. Method

To analyze the differences between optimal portfolio performances based on stock indices, we construct optimal portfolios utilizing the Markowitz model, sharpe ratio, and short-selling approach based on diverse stock indices. Subsequently, we conducted a statistical differential analysis of the performance data of these optimal portfolios.

Optimal portfolio

According to Hartono (2014), an optimal portfolio is a portfolio with optimal performance. The assessment of portfolio performance is derived from portfolio data and inputs, including stock price, realized stock return, risk-free return, expected stock return, stock standard deviation, coefficient of variation of stocks, stock variance, covariance of stocks, coefficient of correlation of stocks, realized portfolio return, expected portfolio return, portfolio variance, and portfolio standard deviation, culminating in the calculation of the sharpe ratio value.

Stock price refers to the adjusted closing stock price, which is subject to adjustment. The adjustment to this data operates under the premise that the stock price on a date lacking stock price is equivalent to the stock price from the preceding date.

Realized stock return (R_i) is calculated by the following formula:

$$R_i = \frac{P_t - P_{t-1}}{P_{t-1}} \ldots (1)$$

R_i refers to realized stock return, P_t refers to the stock price at period t, and P_{t-1} refers to the stock price at period t-1.

Risk-free return (R_{fr}) refers to the yield of retail government bonds ("*Obligasi Negara Ritel*" or ORI), as obtained from the official website of the Directorate General of Financing and Risk Management under the Indonesian Ministry of Finance, spanning data from 2014 to 2023. The following formula calculates risk-free return:

$$R_{fr} = \sum_{t=1}^{n} w_i \,.\, R_{fri} \ldots (2)$$

Where R_{fr} refers to risk-free return, w_i refers to the weight of risk-free return i, and R_{fri} refers to risk-free return i.

Expected stock return E(Ri) refers to the weighted average or arithmetic mean of realized stock returns. The following formula calculates expected stock return:

$$E(R_i) = \sum_{t=1}^{n} R_{it} / n \ldots (3)$$

Where $E(R_i)$ refers to expected stock return; R_{it} refers to realized returns of stock-i at period t; and n refers to the total of realized stock returns.

Stock standard deviation (σ_i) refers to the risk or deviation between realized and expected stock returns. The following formula calculates stock standard deviation:

$$\sigma_i = \sqrt{\sum_{i=1}^{n} \frac{[R_i - E(R_i)]^2}{n}} \ldots (4)$$

Where σ_i refers to stock standard deviation; $E(R_i)$ refers to expected stock return; R_i refers to realized stock return; and n refers to the total of realized stock returns.

The following formula calculates coefficient of variation of stocks (CV_i):

$$CV_i = \frac{\sigma_i}{E(R_i)} \ldots (5)$$

Where CV_i refers to the coefficient of variation of stocks, σ_i refers to stock standard deviation, and $E(R_i)$ refers to expected stock return.

Stock variance (σ^2_i) refers to the square of stock standard deviation, and covariance of stocks (σ_{ij}) is calculated by the following formula:

$$Cov\ (R_A, R_B) \sum_{i=1}^{n} \frac{[(R_{Ai} - E\ (R_A)).(R_{Bi} - E\ (R_B))]}{n} \ldots (6)$$

Where Cov(R_A, R_B) refers to the covariance between realized returns of stock A and realized returns of stock B; R_{Ai} refers to the realized return of stocks A under condition i; R_{Bi} refers to the realized return of stocks B under condition i; E(R_A) refers to expected returns of stock A; E(R_B) refers to expected returns of stock B; and n refers to the total of realized stock returns.

The coefficient of correlation of stocks (r_{AB}) is calculated by the following formula:

$$r_{AB} = \frac{Cov\ (R_A, R_B)}{\sigma_A . \sigma_B} \ldots (7)$$

Where r_{AB} refers to the coefficient of correlation of stocks; Cov(R_A, R_B) refers to the covariance between realized returns of stock A and realized returns of stock B; σ_A refers to the standard deviation of stock A; and σ_B refers to the standard deviation of stock B.

Realized portfolio return (R_p) refers to the weighted average or arithmetic mean of the realized stock returns within the portfolio, each multiplied by its respective weight. Realized portfolio return is calculated by following the formula:

$$R_p = \sum_{t=1}^{n} w_i . R_i \ldots (8)$$

Where R_p refers to realized portfolio return, w_i refers to weight of realized returns of stock i, and R_i refers to realized returns of stock i.

Expected portfolio return E(R_p) refers to the weighted average or arithmetic mean of the expected stock returns within the portfolio, each multiplied by its respective weight. The expected portfolio return is calculated by the following formula:

$$\mathrm{E}\ (R_p) = \sum_{t=1}^{n} (w_i . E(R_i)) \ldots (9)$$

Where E(R_p) refers to expected portfolio return, w_i refers to the weight of expected returns of stock i, and E(R_i) refers to expected returns of stock i.

Portfolio variance (σ^2_p) is calculated by the following formula:

$$\sigma^2{}_p = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i . w_j . \sigma_{ij} \ldots (10)$$

Where σ^2_p refers to portfolio variance; w_i refers to the proportion of stock i in the portfolio; w_j refers to the proportion of stock j in the portfolio; and σ_{ij} refers to the covariance of stock i and stock j.

Portfolio standard deviation (σ_p) refers to the square root of portfolio variance, and sharpe ratio or reward to variability (RVAR) is calculated by the following formula:

$$\mathrm{RVAR} = \frac{TR_p - R_{BR}}{\sigma_p} \ldots (11)$$

Where RVAR refers to sharpe ratio or reward to variability; TR_p refers to an average realized portfolio returns over a specific period; R_{BR} refers to average risk-free asset return over the same period, and σ_p refers to portfolio standard deviation.

Data and sample

We utilize a population of 852 stocks listed in the Indonesia Composite Index (*Indeks Harga Saham Gabungan*-IHSG) as published by the Indonesia Stock Exchange on December 31, 2023. We utilize judgment sampling based on 3 sample criteria consisting of non-composite index criteria that are suitable for representing composite indices, highest realized index return criteria across all index sub-classifications, and availability of stocks criteria for trading over a decade-long period from January 1, 2014, to December 31, 2023. Consequently, the sample utilized consists of 10 stock indices. Accordingly, each stock index is expected to construct three optimal portfolios, culminating in 30 sharpe ratios for optimal portfolio performance assessment.

Statistical testing

This research employed a series of statistical tests, including a normality test for data distribution, a homogeneity test for data variance, and a variance difference test specifically designed for the 30 sharpe ratios derived from diverse stock indices. The normality of the data was assessed using the Kolmogorov-Smirnov test, while the homogeneity of data was assessed using the Levene test. In addition, the variance difference test was evaluated using analysis of variance (ANOVA). Consequently, the normality and homogeneity of the dataset about the 30 sharpe ratios can be ascertained statistically before conducting variance difference testing of sharpe ratio data.

3. Results and discussion

Optimal portfolio

The optimal portfolios without short sales that we construct utilizing the solver function within Microsoft Excel 2021 software result in optimal expected returns and optimal standard deviations through the strategic modification of stock selection and allocation, thereby maximizing the sharpe ratio. These sharpe ratios derived from these diverse optimal portfolios are presented in Table 1. below.

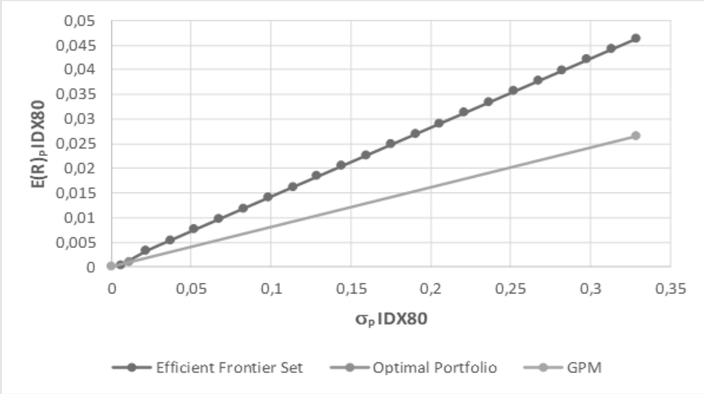
Table 1. Sharpe ratios by stock index

Sharpe ratio				Before pandemic	Since pandemic	Before and since the pandemic
Stock index	Headline	Liquidity	IDX80	0.0798	0.1349	0.0829
		Liquidity co-branding	Investor33	0.0397	0.1006	0.0472
	Sector	Investable sector	infobank15	0.0394	0.0718	0.0420
	thematic	ESG	SRI-KEHATI	0.0309	0.0807	0.0355
		Sharia	JII70	0.0683	0.1188	0.0684
		Others	PEFINDO i-grade	0.0711	0.1050	0.0688
	Factor	Size	IDX SMC liquid	0.0451	0.1116	0.0528
		Growth/ value	IDX value30	0.0280	0.1099	0.0483
		Dividend	IDX high dividend 20	0.0332	0.1165	0.0537
		Quality	IDX quality30	0.0380	0.0930	0.0469

The optimal portfolios we constructed result in diverse stock compositions, expected portfolio returns, standard deviations, and sharpe ratios, as presented in Figure 1. - Figure 10. below. Nevertheless, no line of risk-free returns to optimal portfolio performances that effectively engages the outermost boundary of each efficient portfolio frontier. This result indicates that optimal portfolios constructed without short sales possess the potential to enhance the portfolio scope once more if stock trading involves short selling. In essence, investors who engage in borrowing stocks, executing sales of stocks, repurchasing those stocks, and returning them to the original stocks lender can still improve their portfolio performance, even in instances where their portfolio performance has been optimal.

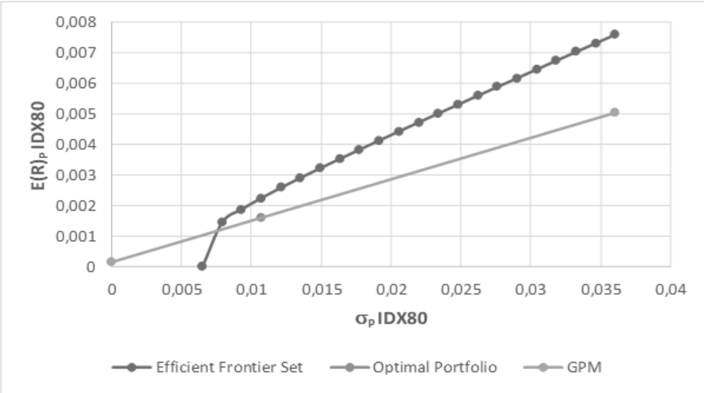
Optimal Portfolio based on IDX80 Before Pandemic

Stock	σ_i	E(Ri)	Allocation
ACES	0,0201	0,0006	5,70%
AMRT	0,0203	0,0004	5,12%
BBCA	0,0117	0,0006	18,17%
BFIN	0,0203	0,0004	3,51%
BRPT	0,0256	0,0015	20,82%
EMTK	0,0281	0,0004	2,02%
INKP	0,0270	0,0009	2,11%
MAPI	0,3286	0,0108	1,47%
SIDO	0,0152	0,0004	3,66%
TKIM	0,0296	0,0009	1,59%
TPIA	0,0176	0,0012	35,83%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0113	0,0011	0,0798
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,3286	0,0264	End Point



Optimal Portfolio based on IDX80 Since Pandemic

Stock	σ_i	E(Ri)	Allocation
AKRA	0,0219	0,0014	4,34%
AMRT	0,0219	0,0013	11,23%
ASSA	0,0325	0,0013	0,23%
BFIN	0,0258	0,0016	8,82%
BRMS	0,0327	0,0015	3,27%
ENRG	0,0335	0,0016	3,47%
HRUM	0,0284	0,0017	4,09%
ISAT	0,0267	0,0019	10,62%
ITMG	0,0220	0,0016	9,98%
MAPI	0,0242	0,0013	7,00%
MPMX	0,0209	0,0013	5,55%
SMDR	0,0300	0,0025	14,89%
SRTG	0,0251	0,0011	0,54%
TBIG	0,0205	0,0010	3,38%
TPIA	0,0198	0,0012	12,60%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0107	0,0016	0,1349
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,0361	0,0050	End Point



Optimal Portfolio based on IDX80 Before Pandemic and Since Pandemic

Stock	σ_i	E(Ri)	Allocation
AMRT	0,0209	0,0008	11,83%
ASSA	0,0272	0,0007	2,98%
BBCA	0,0120	0,0005	13,85%
BBRI	0,0164	0,0006	0,40%
BFIN	0,0225	0,0008	10,96%
BRMS	0,0328	0,0005	0,38%
BRPT	0,0270	0,0013	9,14%
DOID	0,0324	0,0009	1,63%
EMTK	0,0287	0,0004	1,37%
ESSA	0,0316	0,0008	1,27%
HRUM	0,0246	0,0006	1,10%
INDY	0,0308	0,0008	0,23%
INKP	0,0260	0,0009	1,28%
MAPI	0,2607	0,0073	1,34%
SIDO	0,0152	0,0004	1,28%
SMDR	0,0262	0,0012	11,86%
SRTG	0,0232	0,0005	0,79%
TKIM	0,0282	0,0009	0,72%
TPIA	0,0185	0,0012	27,63%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0102	0,0010	0,0829
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,2607	0,0218	End Point

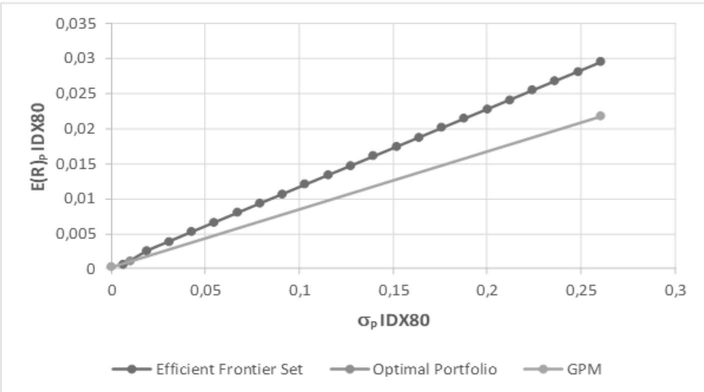
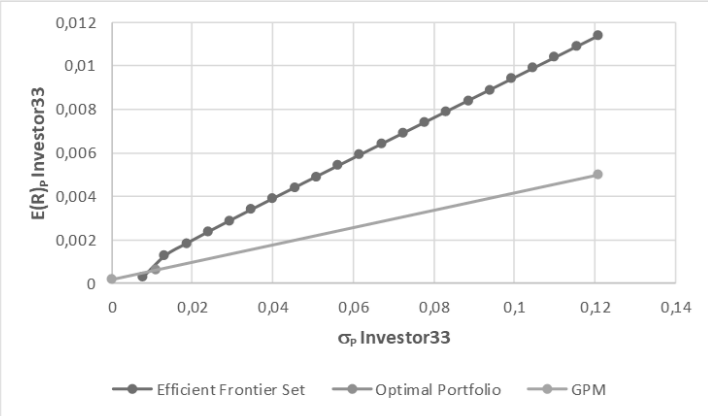


Figure 1. Optimal portfolios based on IDX80

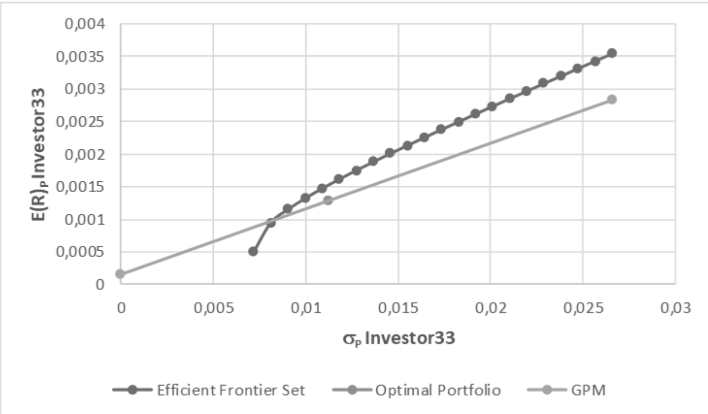
Optimal Portfolio based on Investor33 Before Pandemic

Stock	σ_i	E(Ri)	Allocation
AMRT	0,0203	0,0004	10,61%
BBCA	0,0117	0,0006	60,26%
BBRI	0,0166	0,0006	3,64%
ICBP	0,0144	0,0004	5,04%
MYOR	0,0167	0,0004	4,12%
SIDO	0,0152	0,0004	10,95%
TOWR	0,1208	0,0030	5,39%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0110	0,0006	0,0397
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,1208	0,0050	End Point



Optimal Portfolio based on Investor33 Since Pandemic

Stock	σ_i	E(Ri)	Allocation
AKRA	0,0219	0,0014	11,97%
AMRT	0,0219	0,0013	20,41%
ANTM	0,0266	0,0014	3,81%
BBNI	0,0170	0,0010	0,64%
BMRI	0,0163	0,0009	3,48%
BNGA	0,0156	0,0011	25,03%
ITMG	0,0220	0,0016	22,68%
KLBF	0,0175	0,0005	0,27%
TBIG	0,0205	0,0010	11,70%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0112	0,0013	0,1006
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,0266	0,0028	End Point



Optimal Portfolio based on Investor33 Before Pandemic and Since Pandemic

Stock	σ_i	E(Ri)	Allocation
ADRO	0,0238	0,0007	9,79%
AKRA	0,0201	0,0004	2,24%
AMRT	0,0209	0,0008	25,33%
BBCA	0,0120	0,0005	34,50%
BBRI	0,0164	0,0006	12,59%
BNGA	0,0175	0,0004	0,94%
ITMG	0,0224	0,0006	0,79%
MYOR	0,0166	0,0004	2,34%
PTBA	0,0221	0,0006	2,00%
SIDO	0,0152	0,0004	2,95%
TBIG	0,0203	0,0004	1,95%
TOWR	0,0962	0,0021	4,58%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0107	0,0007	0,0472
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,0962	0,0047	End Point

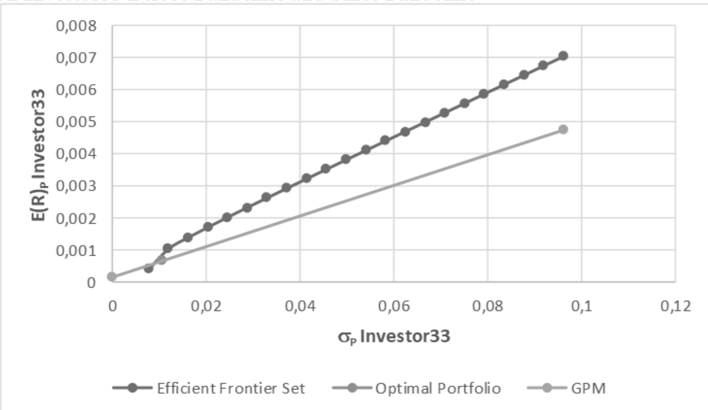
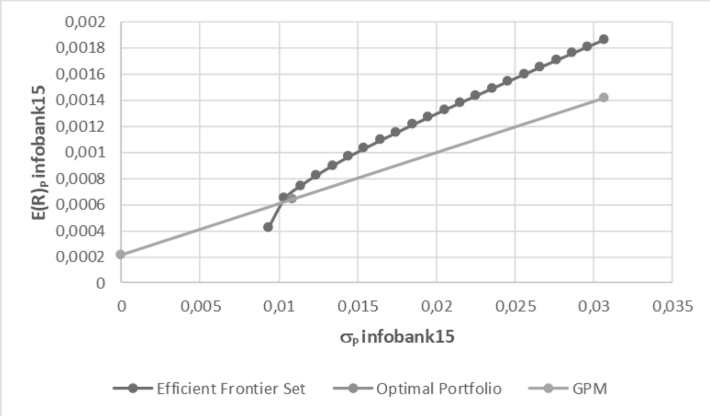


Figure 2. Optimal portfolio based on Investor33

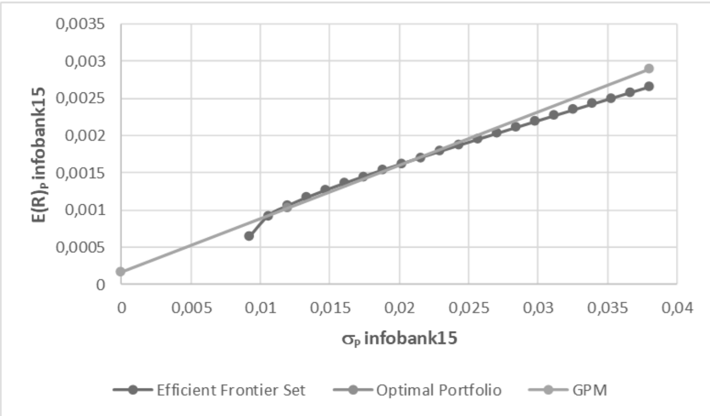
Optimal Portfolio based on infobank15 Before Pandemic

Stock	σ_i	E(Ri)	Allocation
AGRO	0,0307	0,0004	0,35%
BBCA	0,0117	0,0006	61,02%
BBRI	0,0166	0,0006	8,80%
MEGA	0,0235	0,0008	29,83%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0109	0,0006	0,0394
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,0307	0,0014	End Point



Optimal Portfolio based on infobank15 Since Pandemic

Stock	σ_i	E(Ri)	Allocation
AGRO	0,0380	0,0016	8,52%
BBNI	0,0170	0,0010	10,52%
BJBR	0,0150	0,0007	3,73%
BMRI	0,0163	0,0009	18,76%
BNGA	0,0156	0,0011	47,30%
MEGA	0,0211	0,0005	11,17%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0120	0,0010	0,0718
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,0380	0,0029	End Point



Optimal Portfolio based on infobank15 Before Pandemic and Since Pandemic

Stock	σ_i	E(Ri)	Allocation
AGRO	0,0336	0,0008	8,73%
BBCA	0,0120	0,0005	41,41%
BBRI	0,0164	0,0006	17,91%
BJBR	0,0198	0,0005	3,26%
BNGA	0,0175	0,0004	3,79%
MEGA	0,0226	0,0007	24,46%
PNBN	0,0219	0,0004	0,44%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0106	0,0006	0,0420
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,0336	0,0016	End Point

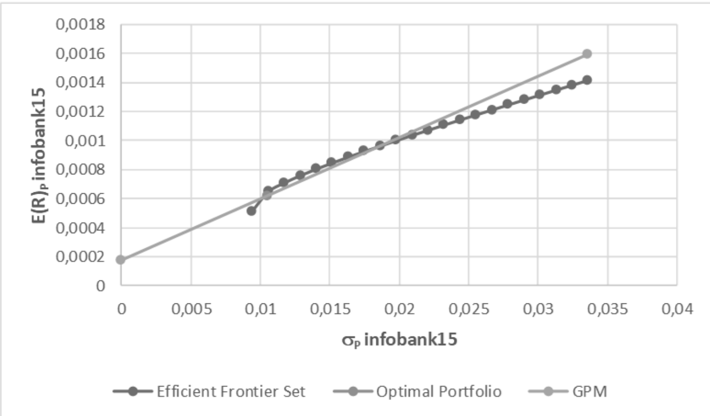
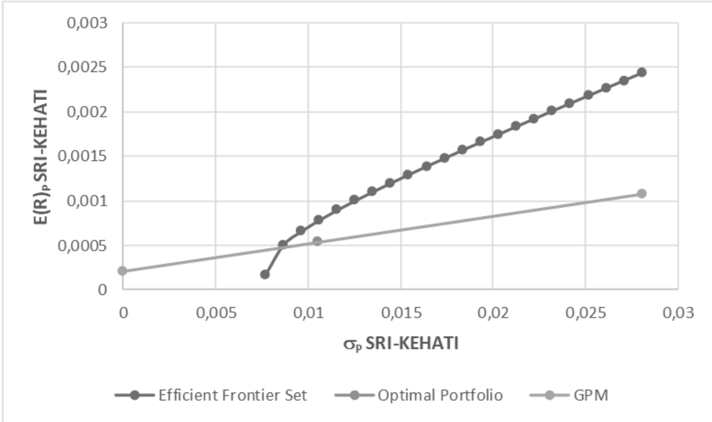


Figure 3. Optimal portfolio based on infobank15

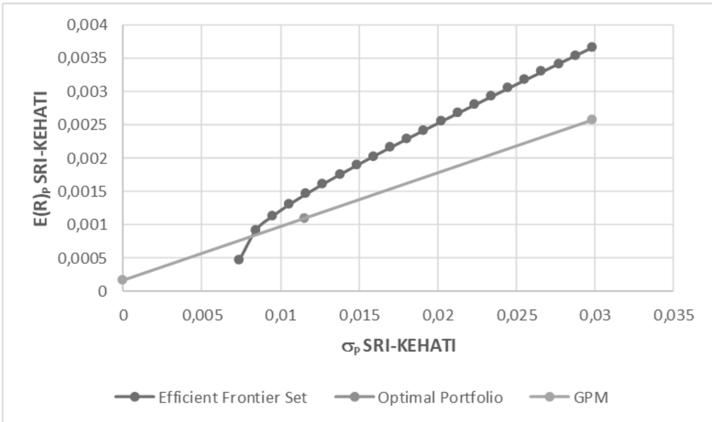
Optimal Portfolio based on SRI-KEHATI Before Pandemic

Stock	σ_i	E(Ri)	Allocation
BBCA	0,0117	0,0006	75,32%
BBRI	0,0166	0,0006	8,84%
EMTK	0,0281	0,0004	6,47%
ICBP	0,0144	0,0004	9,37%
	Total		100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0105	0,0005	0,0309
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,0281	0,0011	End Point



Optimal Portfolio based on SRI-KEHATI Since Pandemic

Stock	σ_i	E(Ri)	Allocation
ANTM	0,0266	0,0014	15,17%
AUTO	0,0177	0,0011	29,18%
BBNI	0,0170	0,0010	7,07%
BBRI	0,0161	0,0008	1,77%
BMRI	0,0163	0,0009	16,35%
DSNG	0,0216	0,0007	6,41%
KLBF	0,0175	0,0005	3,71%
SILO	0,0236	0,0012	19,94%
SSMS	0,0232	0,0005	0,41%
	Total		100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0116	0,0011	0,0807
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,0298	0,0026	End Point



Optimal Portfolio based on SRI-KEHATI Before Pandemic and Since Pandemic

Stock	σ_i	E(Ri)	Allocation
ANTM	0,0243	0,0005	3,13%
BBCA	0,0120	0,0005	49,83%
BBRI	0,0164	0,0006	22,98%
DSNG	0,0215	0,0004	6,95%
EMTK	0,0287	0,0004	6,89%
ICBP	0,0141	0,0004	0,47%
SILO	0,0219	0,0004	7,64%
SSMS	0,0197	0,0003	2,11%
	Total		100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0099	0,0005	0,0355
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,0287	0,0012	End Point

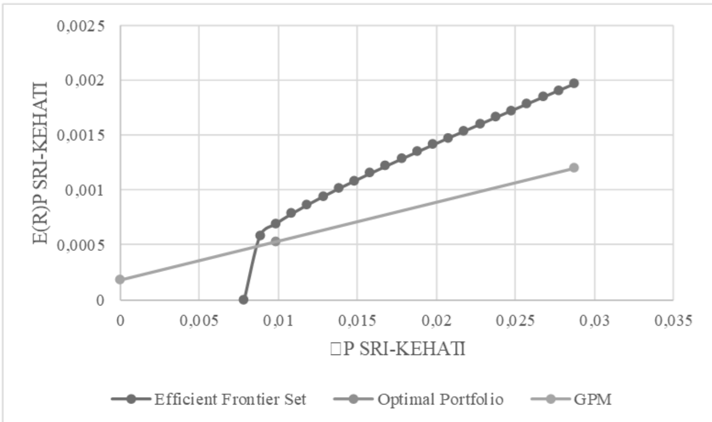
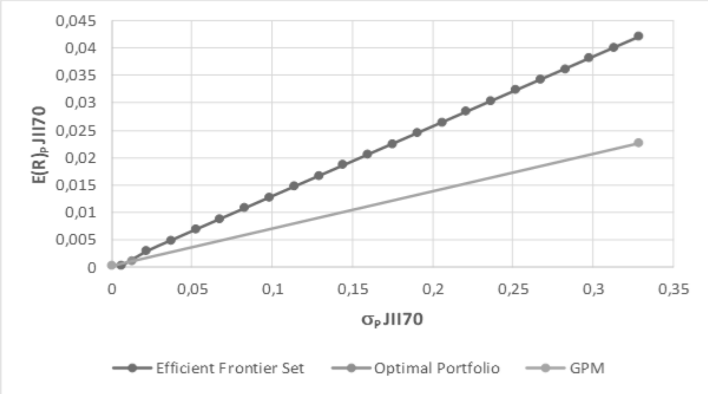


Figure 4. Optimal portfolio based on SRI-KEHATI

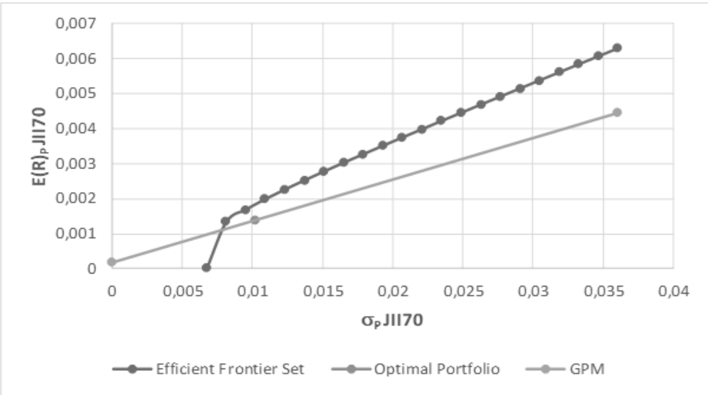
Optimal Portfolio based on JII70 Before Pandemic

Stock	σ_i	E(Ri)	Allocation
ACES	0,0201	0,0006	11,84%
EMTK	0,0281	0,0004	3,01%
ICBP	0,0144	0,0004	6,34%
INKP	0,0270	0,0009	5,65%
MAPI	0,3286	0,0108	1,82%
MYOR	0,0167	0,0004	3,03%
SIDO	0,0152	0,0004	8,76%
SMSM	0,0166	0,0004	0,74%
TKIM	0,0296	0,0009	5,07%
TPIA	0,0176	0,0012	53,52%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0126	0,0011	0,0683
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,3286	0,0227	End Point



Optimal Portfolio based on JII70 Since Pandemic

Stock	σ_i	E(Ri)	Allocation
AKRA	0,0219	0,0014	5,88%
AUTO	0,0177	0,0011	10,01%
BRMS	0,0327	0,0015	4,85%
ENRG	0,0335	0,0016	3,74%
ERAA	0,0233	0,0010	1,03%
ESSA	0,0361	0,0017	1,42%
HRUM	0,0284	0,0017	5,90%
ISAT	0,0267	0,0019	11,34%
ITMG	0,0220	0,0016	12,22%
MAPI	0,0242	0,0013	8,46%
MPMX	0,0209	0,0013	7,64%
SMSM	0,0186	0,0007	7,04%
SRTG	0,0251	0,0011	2,60%
TPIA	0,0198	0,0012	17,49%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0102	0,0014	0,1188
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,0361	0,0044	End Point



Optimal Portfolio based on JII70 Before Pandemic and Since Pandemic

Stock	σ_i	E(Ri)	Allocation
ADRO	0,0238	0,0007	2,65%
AKRA	0,0201	0,0004	1,09%
BRMS	0,0328	0,0005	2,43%
DSNG	0,0215	0,0004	0,73%
EMTK	0,0287	0,0004	2,80%
ERAA	0,0265	0,0006	1,27%
ESSA	0,0316	0,0008	4,51%
HRUM	0,0246	0,0006	3,46%
ICBP	0,0141	0,0004	2,30%
INDY	0,0308	0,0008	0,54%
INKP	0,0260	0,0009	4,83%
ISAT	0,0240	0,0006	2,38%
MAPI	0,2607	0,0073	1,67%
MPMX	0,0202	0,0005	3,71%
MYOR	0,0166	0,0004	4,15%
PTBA	0,0221	0,0006	1,19%
SIDO	0,0152	0,0004	3,05%
SMSM	0,0174	0,0005	9,94%
SRTG	0,0232	0,0005	2,87%
TKIM	0,0282	0,0009	1,68%
TPIA	0,0185	0,0012	42,74%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0110	0,0009	0,0684
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,2607	0,0180	End Point

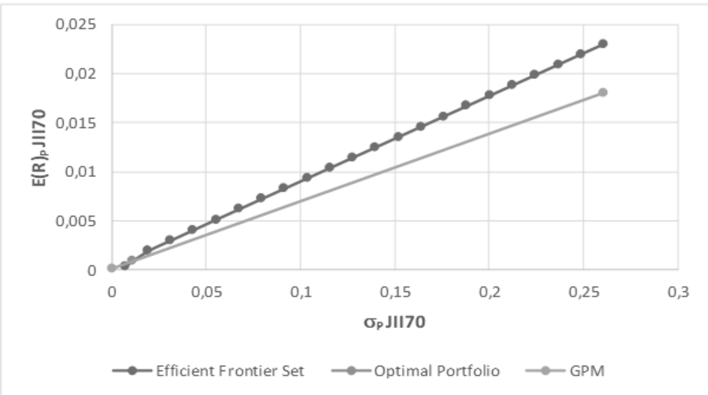
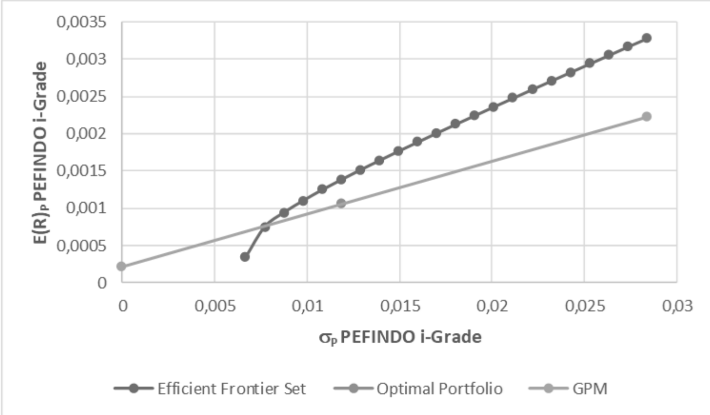


Figure 5. Optimal portfolio based on JII70

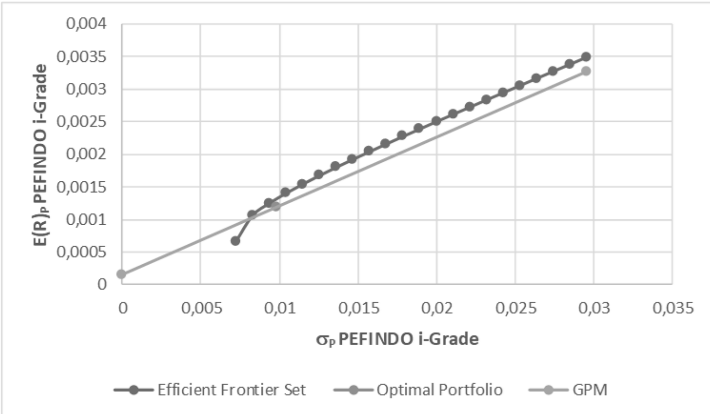
Optimal Portfolio based on PEFINDO i-Grade Before Pandemic

Stock	σ_i	E(Ri)	Allocation
ADMF	0,0121	0,0003	4,02%
BBCA	0,0117	0,0006	23,11%
BRPT	0,0256	0,0015	24,65%
INKP	0,0270	0,0009	5,93%
TPIA	0,0176	0,0012	42,29%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0118	0,0011	0,0711
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,0284	0,0022	End Point



Optimal Portfolio based on PEFINDO i-Grade Since Pandemic

Stock	σ_i	E(Ri)	Allocation
ADMF	0,0139	0,0008	24,11%
AKRA	0,0219	0,0014	11,95%
BMRI	0,0163	0,0009	3,30%
BNGA	0,0156	0,0011	20,71%
DSNG	0,0216	0,0007	3,45%
ISAT	0,0267	0,0019	14,94%
MEDC	0,0296	0,0015	3,57%
TPIA	0,0198	0,0012	17,98%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0098	0,0012	0,1050
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,0296	0,0033	End Point



Optimal Portfolio based on PEFINDO i-Grade Before Pandemic and Since Pandemic

Stock	σ_i	E(Ri)	Allocation
ADMF	0,0128	0,0005	20,61%
AKRA	0,0201	0,0004	0,24%
BBCA	0,0120	0,0005	18,07%
BBRI	0,0164	0,0006	5,13%
BRPT	0,0270	0,0013	12,16%
DSNG	0,0215	0,0004	0,96%
INKP	0,0260	0,0009	5,22%
ISAT	0,0240	0,0006	1,03%
MEDC	0,0288	0,0007	2,66%
MYOR	0,0166	0,0004	0,39%
TPIA	0,0185	0,0012	33,52%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0099	0,0009	0,0688
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,0288	0,0022	End Point

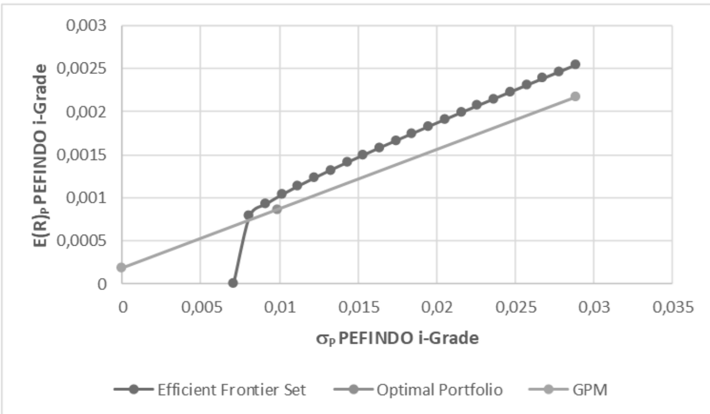
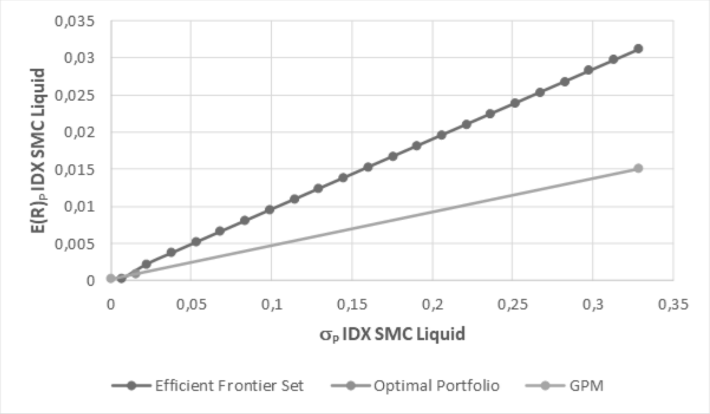


Figure 6. Optimal portfolio based on PEFINDO i-grade

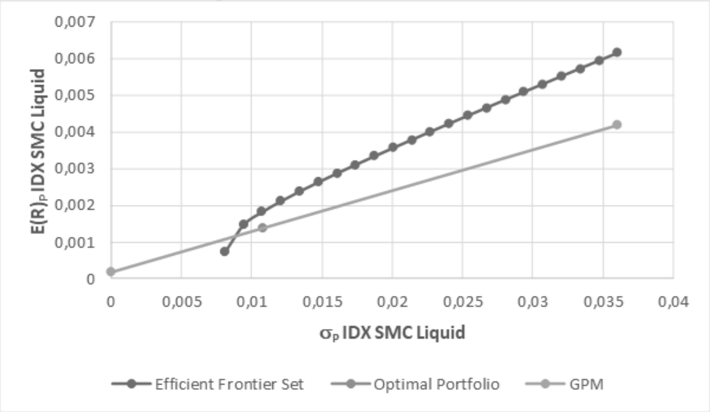
Optimal Portfolio based on IDX SMC Liquid Before Pandemic

Stock	σ_i	E(Ri)	Allocation
ACES	0,0201	0,0006	27,87%
ASSA	0,0235	0,0004	3,72%
BFIN	0,0203	0,0004	11,58%
EMTK	0,0281	0,0004	7,57%
INDY	0,0323	0,0006	5,05%
INKP	0,0270	0,0009	22,94%
MAPI	0,3286	0,0108	3,48%
SIDO	0,0152	0,0004	17,79%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0158	0,0009	0,0451
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,3286	0,0150	End Point



Optimal Portfolio based on IDX SMC Liquid Since Pandemic

Stock	σ_i	E(Ri)	Allocation
AKRA	0,0219	0,0014	7,02%
ASSA	0,0325	0,0013	1,34%
BFIN	0,0258	0,0016	14,20%
BNGA	0,0156	0,0011	19,63%
DSNG	0,0216	0,0007	0,33%
ERAA	0,0233	0,0010	0,07%
ESSA	0,0361	0,0017	2,44%
HRUM	0,0284	0,0017	6,77%
ITMG	0,0220	0,0016	16,90%
MAPI	0,0242	0,0013	9,81%
SILO	0,0236	0,0012	13,22%
SRTG	0,0251	0,0011	2,57%
TBIG	0,0205	0,0010	5,69%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0108	0,0014	0,1116
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,0361	0,0042	End Point



Optimal Portfolio based on IDX SMC Liquid Before Pandemic and Since Pandemic

Stock	σ_i	E(Ri)	Allocation
AKRA	0,0201	0,0004	0,56%
ASSA	0,0272	0,0007	9,24%
BFIN	0,0225	0,0008	24,38%
BJBR	0,0198	0,0005	1,26%
BNGA	0,0175	0,0004	1,23%
DSNG	0,0215	0,0004	3,01%
EMTK	0,0287	0,0004	4,18%
ERAA	0,0265	0,0006	1,66%
ESSA	0,0316	0,0008	6,78%
HRUM	0,0246	0,0006	4,25%
INDY	0,0308	0,0008	3,60%
INKP	0,0260	0,0009	12,75%
ITMG	0,0224	0,0006	2,90%
MAPI	0,2607	0,0073	2,43%
MEDC	0,0288	0,0007	2,77%
PTBA	0,0221	0,0006	2,34%
SIDO	0,0152	0,0004	4,38%
SILO	0,0219	0,0004	6,05%
SRTG	0,0232	0,0005	4,76%
TBIG	0,0203	0,0004	1,48%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0124	0,0008	0,0528
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,2607	0,0139	End Point

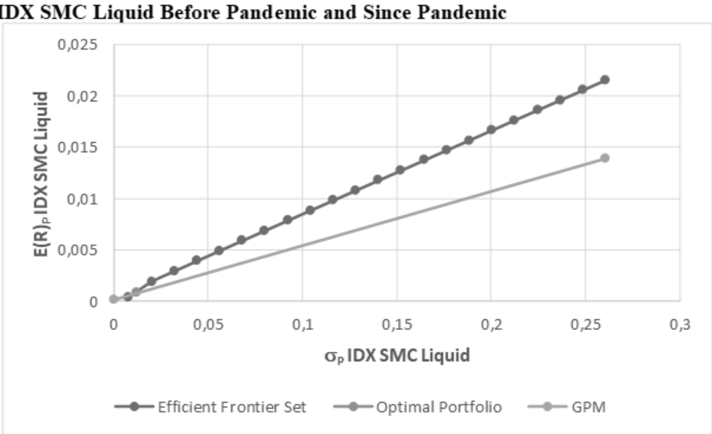
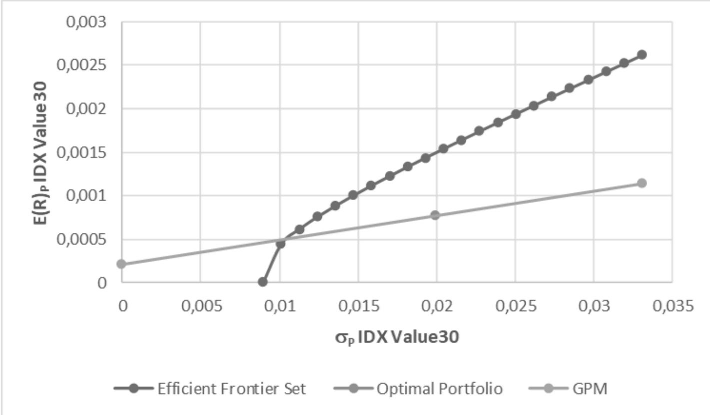


Figure 7. Optimal portfolio based on IDX SMC liquid

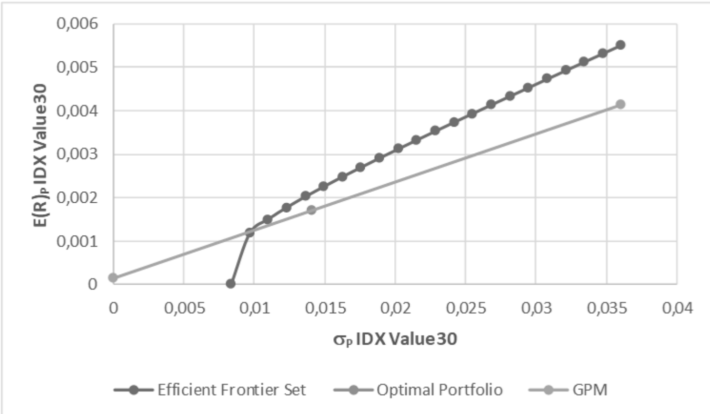
Optimal Portfolio based on IDX Value30 Before Pandemic

Stock	σ_i	E(Ri)	Allocation
DOID	0,0331	0,0006	9,50%
INDY	0,0323	0,0006	13,65%
INKP	0,0270	0,0009	32,92%
SMDR	0,0236	0,0004	9,89%
TKIM	0,0296	0,0009	34,04%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0200	0,0008	0,0280
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,0331	0,0011	End Point



Optimal Portfolio based on IDX Value30 Since Pandemic

Stock	σ_i	E(Ri)	Allocation
CTRA	0,0231	0,0010	1,77%
ENRG	0,0335	0,0016	8,05%
ERAA	0,0233	0,0010	9,80%
ESSA	0,0361	0,0017	4,31%
HRUM	0,0284	0,0017	10,04%
ITMG	0,0220	0,0016	20,15%
MPMX	0,0209	0,0013	20,22%
SMDR	0,0300	0,0025	25,66%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0141	0,0017	0,1099
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,0361	0,0041	End Point



Optimal Portfolio based on IDX Value30 Before Pandemic and Since Pandemic

Stock	σ_i	E(Ri)	Allocation
ADRO	0,0238	0,0007	5,30%
DOID	0,0324	0,0009	8,12%
ERAA	0,0265	0,0006	6,05%
ESSA	0,0316	0,0008	7,34%
HRUM	0,0246	0,0006	2,67%
INDY	0,0308	0,0008	2,97%
INKP	0,0260	0,0009	13,79%
MEDC	0,0288	0,0007	5,08%
MPMX	0,0202	0,0005	7,78%
SMDR	0,0262	0,0012	36,09%
TKIM	0,0282	0,0009	4,81%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0148	0,0009	0,0483
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,0324	0,0017	End Point

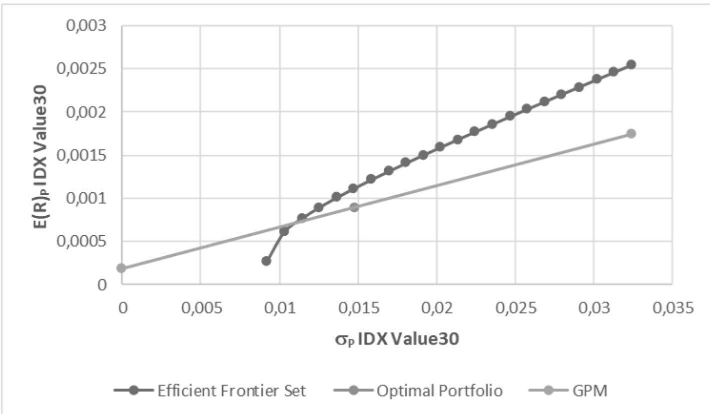
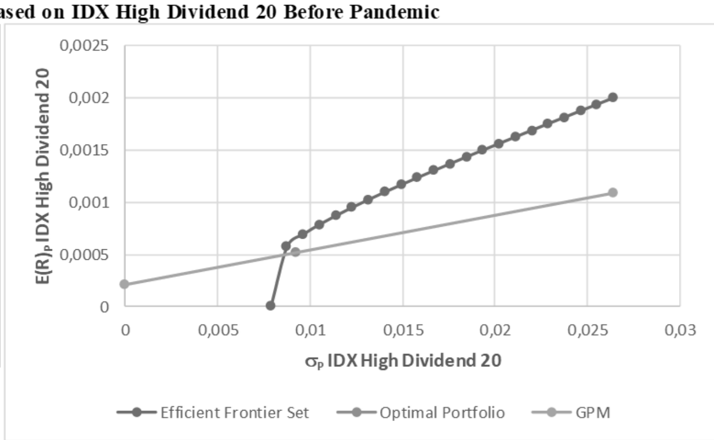


Figure 8. Optimal portfolio based on IDX value30

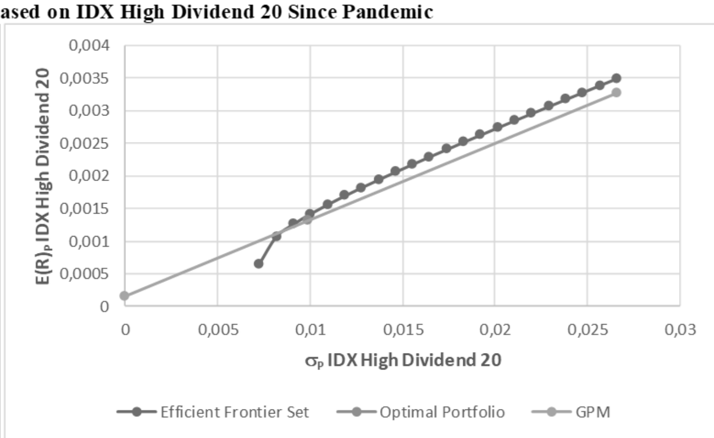
Optimal Portfolio Based on IDX High Dividend 20 Before Pandemic

Stock	σ_i	E(Ri)	Allocation
AMRT	0,0203	0,0004	10,95%
BBCA	0,0117	0,0006	60,32%
BBRI	0,0166	0,0006	5,93%
BJTM	0,0149	0,0004	5,16%
BSSR	0,0264	0,0005	9,15%
HEXA	0,0223	0,0005	8,48%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0093	0,0005	0,0332
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,0264	0,0011	End Point



Optimal Portfolio based on IDX High Dividend 20 Since Pandemic

Stock	σ_i	E(Ri)	Allocation
AMRT	0,0219	0,0013	15,70%
ANTM	0,0266	0,0014	2,31%
BBNI	0,0170	0,0010	1,13%
BMRI	0,0163	0,0009	0,70%
BNGA	0,0156	0,0011	16,03%
BSSR	0,0261	0,0015	9,63%
HEXA	0,0152	0,0013	28,63%
ITMG	0,0220	0,0016	11,73%
MPMX	0,0209	0,0013	14,14%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0099	0,0013	0,1165
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,0266	0,0033	End Point



Optimal Portfolio based on IDX High Dividend 20 Before Pandemic and Since Pandemic

Stock	σ_i	E(Ri)	Allocation
ADRO	0,0238	0,0007	3,33%
AMRT	0,0209	0,0008	19,53%
BBCA	0,0120	0,0005	23,79%
BBRI	0,0164	0,0006	7,82%
BJTM	0,0148	0,0005	6,89%
BSSR	0,0263	0,0008	14,31%
HEXA	0,0200	0,0008	19,31%
MPMX	0,0202	0,0005	5,02%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0092	0,0007	0,0537
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,0263	0,0016	End Point

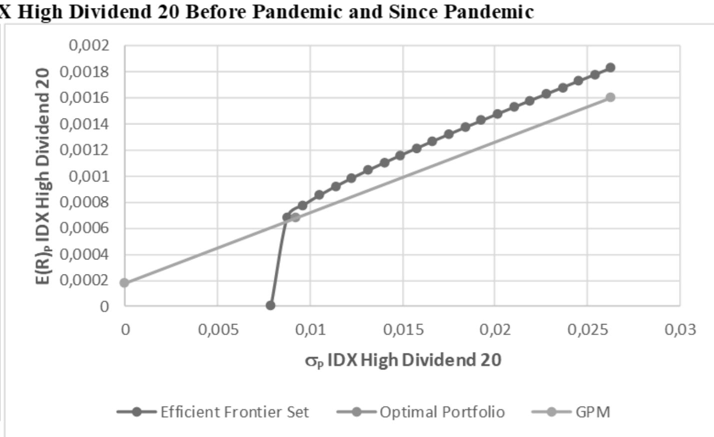
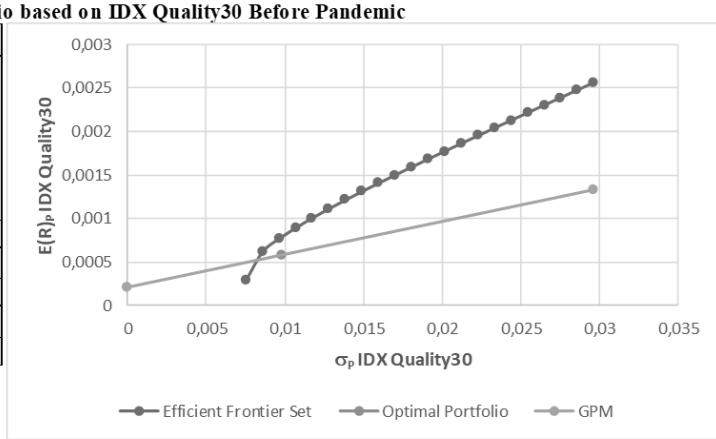


Figure 9. Optimal portfolio based on IDX high dividend 20

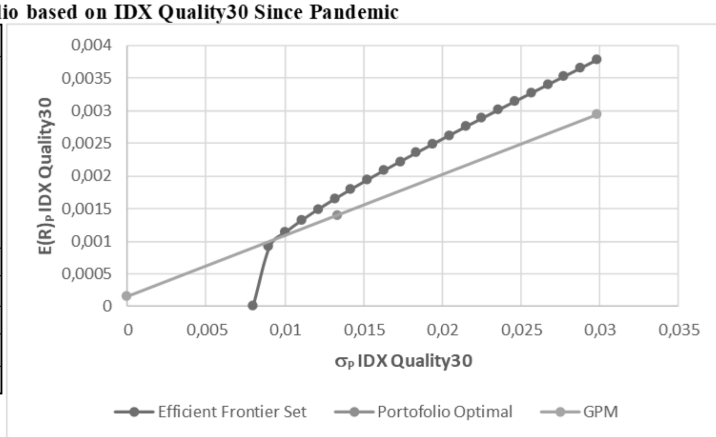
Optimal Portfolio based on IDX Quality30 Before Pandemic

Stock	σ_i	E(Ri)	Allocation
ACES	0,0201	0,0006	13,87%
BBCA	0,0117	0,0006	51,14%
BFIN	0,0203	0,0004	7,29%
EMTK	0,0281	0,0004	5,20%
SIDO	0,0152	0,0004	7,61%
TKIM	0,0296	0,0009	14,89%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0098	0,0006	0,0380
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,0296	0,0013	End Point



Optimal Portfolio based on IDX Quality30 Since Pandemic

Stock	σ_i	E(Ri)	Allocation
BBRI	0,0161	0,0008	1,08%
BFIN	0,0258	0,0016	24,70%
BMRI	0,0163	0,0009	20,37%
HRUM	0,0284	0,0017	11,74%
ITMG	0,0220	0,0016	30,40%
KLBF	0,0175	0,0005	4,35%
SRTG	0,0251	0,0011	7,36%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0133	0,0014	0,0930
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,0298	0,0029	End Point



Optimal Portfolio based on IDX Quality30 Before Pandemic and Since Pandemic

Stock	σ_i	E(Ri)	Allocation
ADRO	0,0238	0,0007	4,76%
BBCA	0,0120	0,0005	33,69%
BBRI	0,0164	0,0006	10,84%
BFIN	0,0225	0,0008	23,39%
EMTK	0,0287	0,0004	3,94%
HRUM	0,0246	0,0006	4,35%
ITMG	0,0224	0,0006	1,28%
PTBA	0,0221	0,0006	0,10%
SIDO	0,0152	0,0004	2,68%
SRTG	0,0232	0,0005	4,79%
TKIM	0,0282	0,0009	10,19%
Total			100%
Portfolio	σ_p	E(Rp)	Sharpe Ratio
Optimal	0,0101	0,0007	0,0469
GPM (R_{BR})	-	0,0002	Start Point
GPM	0,0287	0,0015	End Point

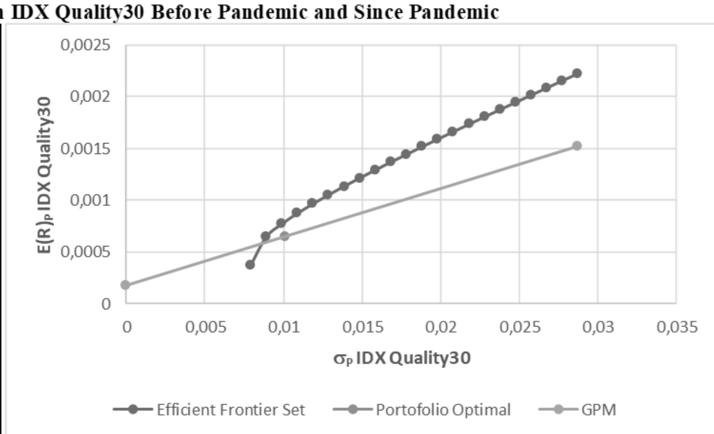


Figure 10. Optimal portfolio based on IDX quality30

Descriptive statistics

We analyzed optimal portfolio performances grounded in descriptive statistics concerning the sharpe ratio data, employing IBM SPSS statistics 27 software. The resultant descriptive statistical findings concerning the sharpe ratio data are presented in Table 2. below. In general, optimal portfolio based on IDX80 demonstrate the highest average sharpe ratio (0.0992) when juxtaposed with optimal portfolios based on other stock indices. This result indicates that optimal portfolios based on IDX80 confer the highest performance compared to optimal portfolios based on other stock indices.

Table 2. Descriptive statistics of sharpe ratios

Stock index	N	Mean	Std. dev.	Std. error	95% Confidence interval for mean		Min.	Max.
					Lower bound	Upper bound		
IDX80	3	0.0992	0.0309	0.0179	0.0224	0.1761	0.0798	0.1349
Investor33	3	0.0625	0.0332	0.0191	-0.0199	0.1449	0.0397	0.1006
infobank15	3	0.0511	0.0180	0.0104	0.0064	0.0958	0.0394	0.0718
SRI-KEHATI	3	0.0490	0.0275	0.0159	-0.0194	0.1175	0.0309	0.0807
JII70	3	0.0852	0.0291	0.0168	0.0128	0.1576	0.0683	0.1188
PEFINDO i-grade	3	0.0817	0.0203	0.0117	0.0313	0.1320	0.0688	0.1050
IDX SMC liquid	3	0.0698	0.0364	0.0210	-0.0205	0.1601	0.0451	0.1116
IDX value30	3	0.0621	0.0427	0.0246	-0.0439	0.1686	0.0280	0.1099
IDX high dividend 20	3	0.0678	0.0434	0.0251	-0.0400	0.1757	0.0332	0.1165
IDX quality30	3	0.0593	0.0295	0.0170	-0.0141	0.1326	0.0380	0.0930
Total	30	0.0688	0.0307	0.0056	0.0573	0.0802	0.0280	0.1349

Discussion

Statistical testing

The results of the Kolmogorov-Smirnov test on sharpe ratio data are presented in Table 3. below. The Asymp value Sig. (2-tailed) of 0.066 exceeds the significance level of 0.05. This result signifies that sharpe ratio data adhere to a normal distribution. thus permitting the execution of advanced parametric statistical tests on the dataset.

Table 3. Kolmogorov-Smirnov test of sharpe ratio data

			RVAR
N			30
Normal parameters[a.b]	Mean		0.0688
	Std. deviation		0.0307
Most extreme differences	Absolute		0.1540
	Positive		0.1540
	Negative		-0.0920
Test statistic			0.1540
Asymp. Sig. (2-tailed)[c]			0.0660
Monte Carlo Sig. (2-tailed)[d]	Sig.		0.0640
	99% Confidence interval	Lower bound	0.0570
		Upper bound	0.0700

a. Test distribution is normal.
b. Calculated from data.
c. Lilliefors significance correction.
d. Lilliefors' method is based on 10000 Monte Carlo samples with a starting seed of 2000000.

Table 4. Levene test of sharpe ratio data

Sharpe ratio	Levene statistic	df1	df2	Sig.
Based on mean	0.813	9	20	0.610
Based on median	0.128	9	20	0.998
Based on median and with adjusted df	0.128	9	17.887	0.998
Based on trimmed mean	0.705	9	20	0.697

The results of the Levene test on sharpe ratio data are presented in Table 4. above. The Sig. Based on mean of 0.610 exceeds the significance level of 0.05. This result indicates that sharpe ratio data exhibits homogeneity, fulfilling the requisite conditions of variance homogeneity necessary for statistical analysis of variance.

The results of one-way ANOVA on sharpe ratio data are presented in Table 5. below. The F-value of 0.726 is less than F-critical of 2.393. Furthermore, the Sig. of 0.681 exceeds the significance level of 0.05. These results indicate no significant difference between sharpe ratio data based on stock indices. There is no significant difference between optimal portfolios based on stock indices. This finding is inconsistent with the comparison's result in descriptive statistics from the studies conducted by Octovian (2017); Jayana and Sihombing (2019); Gozah *et al.* (2020); Huni and Sibindi (2020); Iskandar and Julianto. (2020); Lai *et al.* (2020); Purwanto *et al.* (2020); Zivkov *et al.* (2022); Ghaemi *et al.* (2024); and Ben Ameur *et al.* (2024), all of which result in there are differences between optimal portfolios based on stock indices.

Table 5. One-way ANOVA of sharpe ratio data

Sharpe ratio	Sum of squares	df	Mean square	F	Sig.	F-Crit
Between groups	0.007	9	0.001	0.726	0.681	2.393
Within groups	0.021	20	0.001			
Total	0.027	29				

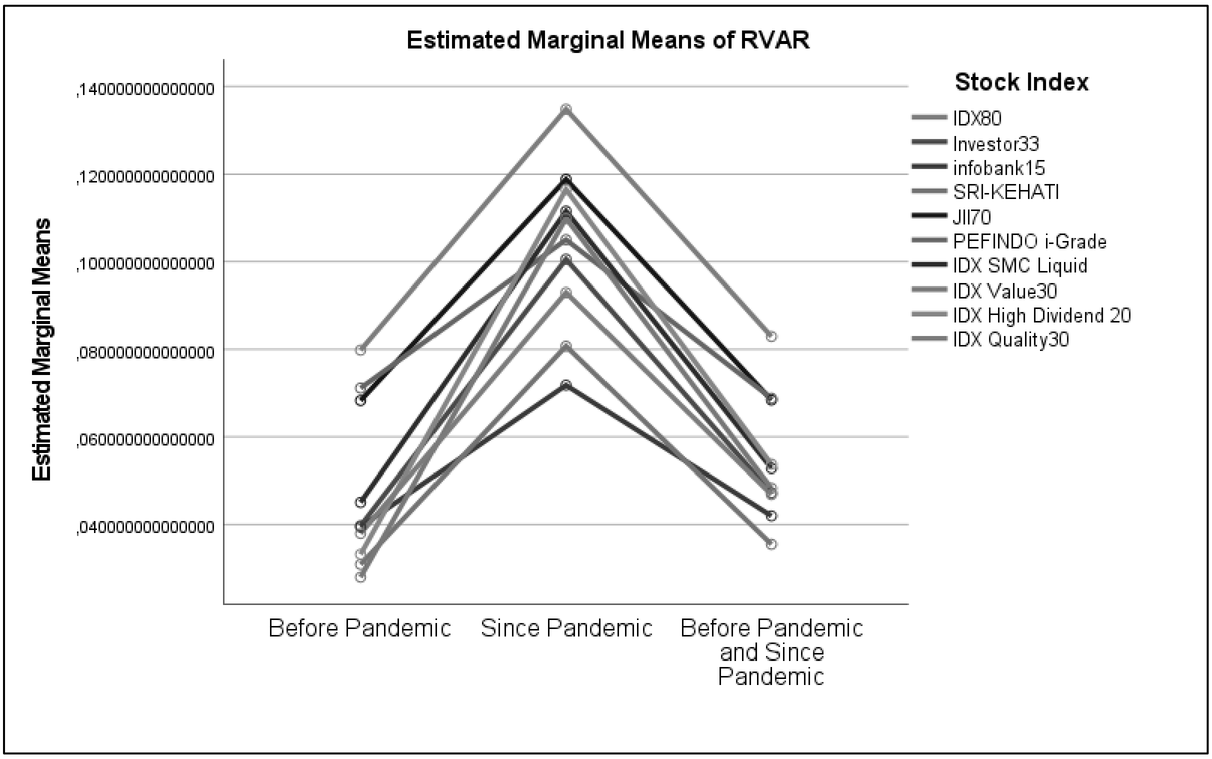


Figure 11. Mean plot of sharpe ratio data

The results of mean plot and LSD on sharpe ratio data are presented in Figure 11. and Table 6. Nearly all average stock index depicted in the mean plot graph exhibit proximity to one another, the IDX80 index averages. which are positioned at a relatively closer distance. Additionally, the Sig. for all stock index comparisons is recorded as exceeding the significance level of 0.05. This finding implies that optimal portfolio performances based on the IDX80 stock index from those based on other stock indices. However, those differences lack statistical significance in comparison to other stock indices. When integrated with the findings from the preliminary descriptive statistics, it becomes evident that although optimal portfolios based on IDX80 confer the highest performance, that performance differential is not substantial when juxtaposed with optimal portfolios based on other stock indices. In summary, a comparative analysis of portfolio performance reveals that no stock index can be the suitest for the construction of a portfolio exhibiting optimal performance.

Table 6. LSD of data ratio sharpe

LSD						
(I) Stock index		Mean difference (I-J)	Std. error	Sig.	95% Confidence interval	
					Lower bound	Upper bound
IDX80	Investor33	0.0367	0.0262	0.177	-0.0179	0.0914
	infobank15	0.0481	0.0262	0.081	-0.0065	0.1028
	SRI-KEHATI	0.0502	0.0262	0.070	-0.0045	0.1048
	JII70	0.0140	0.0262	0.598	-0.0406	0.0687
	PEFINDO i-grade	0.0176	0.0262	0.510	-0.0371	0.0722
	IDX SMC liquid	0.0294	0.0262	0.275	-0.0252	0.0841
	IDX value30	0.0372	0.0262	0.172	-0.0175	0.0918
	IDX high Dividend 20	0.0314	0.0262	0.245	-0.0233	0.0861
	IDX quality30	0.0399	0.0262	0.143	-0.0147	0.0946
Investor33	IDX80	-0.0367	0.0262	0.177	-0.0914	0.0179
	infobank15	0.0114	0.0262	0.667	-0.0432	0.0661
	SRI-KEHATI	0.0135	0.0262	0.613	-0.0412	0.0681
	JII70	-0.0227	0.0262	0.397	-0.0773	0.0320
	PEFINDO i-grade	-0.0192	0.0262	0.473	-0.0738	0.0355
	IDX SMC liquid	-0.0073	0.0262	0.783	-0.0620	0.0474
	IDX value30	0.0004	0.0262	0.987	-0.0542	0.0551
	IDX high Dividend 20	-0.0053	0.0262	0.841	-0.0599	0.0493
	IDX quality30	0.0032	0.0262	0.903	-0.0514	0.0579
infobank15	IDX80	-0.0481	0.0262	0.081	-0.1028	0.0065
	Investor33	-0.0114	0.0262	0.667	-0.0661	0.0432
	SRI-KEHATI	0.0020	0.0262	0.939	-0.0526	0.05667
	JII70	-0.0341	0.0262	0.208	-0.0888	0.0205
	PEFINDO i-grade	-0.0306	0.0262	0.257	-0.0852	0.0241
	IDX SMC liquid	-0.0187	0.0262	0.483	-0.0734	0.0359
	IDX value30	-0.0109	0.0262	0.680	-0.0656	0.0437
	IDX high Dividend 20	-0.0167	0.0262	0.530	-0.0714	0.0379
	IDX quality30	-0.0082	0.0262	0.758	-0.0628	0.0465
SRI-KEHATI	IDX80	-0.0502	0.0262	0.070	-0.1048	0.0045
	Investor33	-0.0135	0.0262	0.613	-0.0681	0.0412
	infobank15	-0.0020	0.0262	0.939	-0.0567	0.0526
	JII70	-0.0362	0.0262	0.183	-0.0908	0.0185
	PEFINDO i-grade	-0.0326	0.0262	0.227	-0.0873	0.0220
	IDX SMC liquid	-0.0208	0.0262	0.437	-0.0754	0.0339
	IDX value30	-0.0130	0.0262	0.625	-0.0677	0.0416
	IDX high Dividend 20	-0.0188	0.0262	0.482	-0.0734	0.0359
	IDX quality30	-0.0102	0.0262	0.700	-0.0649	0.0444
JII70	IDX80	-0.0140	0.0262	0.598	-0.0687	0.0406
	Investor33	0.0227	0.0262	0.397	-0.0320	0.0773
	infobank15	0.0341	0.0262	0.208	-0.0205	0.0888
	SRI-KEHATI	0.0362	0.0262	0.183	-0.0185	0.0908
	PEFINDO i-grade	0.0035	0.0262	0.894	-0.0511	0.0582
	IDX SMC liquid	0.0154	0.0262	0.564	-0.0393	0.0700
	IDX value30	0.0231	0.0262	0.388	-0.0315	0.0778
	IDX high Dividend 20	0.0174	0.0262	0.515	-0.0373	0.0720
	IDX quality30	0.0259	0.0262	0.334	-0.0287	0.0806

Table 6. LSD of data ratio sharpe (continue)

PEFINDO i-grade	IDX80	-0.0176	0.0262	0.510	-0.0722	0.0371
	Investor33	0.0192	0.0262	0.473	-0.0355	0.0738
	infobank15	0.0306	0.0262	0.257	-0.0241	0.0852
	SRI-KEHATI	0.0326	0.0262	0.227	-0.0220	0.0873
	JII70	-0.0035	0.0262	0.894	-0.0582	0.0511
	IDX SMC liquid	0.0119	0.0262	0.656	-0.0428	0.0665
	IDX value30	0.0196	0.0262	0.463	-0.0351	0.0743
	IDX high Dividend 20	0.0138	0.0262	0.603	-0.0408	0.0685
	IDX quality30	0.0224	0.0262	0.403	-0.0323	0.0771
IDX SMC liquid	IDX80	-0.0294	0.0262	0.275	-0.0841	0.0252
	Investor33	0.0073	0.0262	0.783	-0.0474	0.0620
	infobank15	0.0187	0.0262	0.483	-0.0359	0.0734
	SRI-KEHATI	0.0208	0.0262	0.437	-0.0339	0.0754
	JII70	-0.0154	0.0262	0.564	-0.0700	0.0393
	PEFINDO i-grade	-0.0119	0.0262	0.656	-0.0665	0.0428
	IDX value30	0.0077	0.0262	0.770	-0.0469	0.0624
	IDX high Dividend 20	0.0020	0.0262	0.940	-0.0527	0.0566
	IDX quality30	0.0105	0.0262	0.692	-0.0441	0.0652
IDX value30	IDX80	-0.0372	0.0262	0.172	-0.0918	0.0175
	Investor33	-0.0004	0.0262	0.987	-0.0551	0.0542
	infobank15	0.0120	0.0262	0.680	-0.0437	0.0656
	SRI-KEHATI	0.0130	0.0262	0.625	-0.0416	0.0677
	JII70	-0.0231	0.0262	0.388	-0.0778	0.0315
	PEFINDO i-grade	-0.0196	0.0262	0.463	-0.0743	0.0351
	IDX SMC liquid	-0.0077	0.0262	0.770	-0.0624	0.0469
	IDX high Dividend 20	-0.0058	0.0262	0.828	-0.0604	0.0489
	IDX quality30	0.0028	0.0262	0.916	-0.0519	0.0575
IDX high dividend 20	IDX80	-0.0314	0.0262	0.245	-0.0861	0.0233
	Investor33	0.0053	0.0262	0.841	-0.0493	0.0599
	infobank15	0.0167	0.0262	0.530	-0.0379	0.0714
	SRI-KEHATI	0.0188	0.0262	0.482	-0.0359	0.0734
	JII70	-0.0174	0.0262	0.515	-0.0720	0.0373
	PEFINDO i-grade	-0.0138	0.0262	0.603	-0.0685	0.0408
	IDX SMC liquid	-0.0019	0.0262	0.940	-0.0566	0.0527
	IDX value30	0.0058	0.0262	0.828	-0.0489	0.0604
	IDX quality30	0.0086	0.0262	0.747	-0.0461	0.0632
IDX quality30	IDX80	-0.0399	0.0262	0.143	-0.0946	0.0147
	Investor33	-0.0032	0.0262	0.903	-0.0579	0.0514
	infobank15	0.0082	0.0262	0.758	-0.0465	0.0628
	SRI-KEHATI	0.0102	0.0262	0.700	-0.0444	0.0649
	JII70	-0.0259	0.0262	0.334	-0.0806	0.0287
	PEFINDO i-grade	-0.0224	0.0262	0.403	-0.0771	0.0323
	IDX SMC liquid	-0.0105	0.0262	0.692	-0.0652	0.0441
	IDX value30	-0.0028	0.0262	0.916	-0.0575	0.0519
	IDX high Dividend 20	-0.0086	0.0262	0.747	-0.0632	0.0461

The findings of this research diverge comparison's results in descriptive statistics from the studies conducted by Octovian (2017) and Jayana and Sihombing (2019), both of which indicate that IDX30 is the suitest stock index for constructing an optimal portfolio; Iskandar and Julianto (2020) suggest that KOMPAS100 is the suitest stock index for constructing an optimal portfolio; Zivkov *et al.* (2022) suggest that ASEAN stock index is the suitest for constructing an optimal portfolio; and Ghaemi *et al.* (2024) suggest that Sharia stock index is the suitest for constructing an optimal portfolio.

4. Conclusion

This research scrutinizes the differences between optimal portfolio performances based on stock indices. We constructed optimal portfolios based on diverse stock indices utilizing the Solver function within Microsoft Excel 2021 software. We executed a series of statistical tests concerning those optimal portfolio performances through IBM SPSS statistics 27 software. Our findings indicated no significant difference between optimal portfolios based on stock indices. Consequently, the ability of a stock index to represent the performance of IHSG or whole stocks as same as other stock indices, particularly regarding the performance of portfolios that encompass stocks from those indices. The selection of a stock index to represent the IHSG does not need to adhere to specific criteria. This consequence may arise that stock indices, despite differing criteria, are estimated to result in stock portfolio performances that do not exhibit significant variability.

In this research, we additionally discovered that the optimal portfolio based on IDX80 confers the highest performance and that the performance differential is not substantial when juxtaposed with optimal portfolios based on other stock indices. This finding implies that no stock index can be the suitest for the construction of a portfolio exhibiting optimal performance. Furthermore, this research revealed that the line of risk-free returns to optimal portfolio performances, which were constructed without a short-selling approach, did not effectively engage the outermost boundary of the efficient portfolio frontier. Our finding suggests that optimal portfolios constructed without short sales possess the potential to enhance the portfolio scope once more if stock trading involves short selling. Consequently, investors have yet to achieve a genuinely optimal portfolio without borrowing stocks, selling those stocks, repurchasing them, and then returning returning them to the original stock lender. Therefore, the fluctuation risk in stock prices during short sales may also enhance the expected return of an already optimal portfolio devoid of short selling.

It is crucial to emphasize that these findings represent only initial results from this analysis, thus necessitating further research to enrich the comprehension of the interplay between portfolio performance and stock indices. Investors and researchers may subsequently explore alternative classifications of stock indices, diverse portfolio models or methodologies, and short-selling approaches for the construction of optimal portfolios. Additionally, investors and researchers can employ various ratios and indicators to assess portfolio performance. Furthermore, investors and researchers may also use an associative approach to elucidate phenomena pertinent to the portfolio performance and stock indices.

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