How to optimize the CPO Share Portfolio in the Composite Stock Price Index

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Abstract

The decision-making process in investing in the composite stock price index will not be separated from risk and fluctuating market performance, but by considering asset correlation, assessing how these assets move together or apart, it is important to identify assets with low or negative correlation, which will effectively lower the overall portfolio risk. This research aims to optimize the Crude Palm Oil (CPO) stock portfolio from 2016 to 2022 using a customized risk ranking approach, linear programming, and Analysis of variance (ANOVA). in other words, this research is to create a theoretical portfolio that will achieve optimal performance based on the latest historical data that is available. The study incorporates factors like volatility, market performance, and company fundamentals to evaluate stock risks comprehensively. Linear programming aids in allocating funds optimally among selected CPO stocks while considering budget limits, diversification, and risk. Results highlight the potential for a balanced portfolio that maximizes returns while managing risk. Practical applications include guiding investors, fund managers, and bankers in making informed decisions for portfolio management, especially within the Indonesian stock market. During the research period there were 10 stocks that consistently formed the LQ-45 index, whereas based on the Coefficient of Variance (CV) ranking criteria, only 4 stocks were selected for the portfolio optimization process. The study's novelty lies in combining refined risk assessment, linear programming, and ANOVA analysis, enhancing portfolio optimization for CPO stocks in the Jakarta Composite Index.

Keywords: Portfolio Optimization, Crude Palm Oil Stocks, Adjusted Risk Ranking, Linear Programming, Risk-return trade-off.

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Introduction

The global economy has shown remarkable resilience, defying earlier predictions that increased interest rates and sluggish economic activity would severely hamper growth in 2023. This resilience can be attributed in large part to the alleviation of inflationary pressures and stable employment, which have facilitated sustained growth in spending and provided crucial support.

With the global economy continuing to perform well, there has been a slight upward revision in the GDP forecast for 2023, reflecting the ongoing progress made in the first half of the year. The projected global GDP growth now stands at 2.6% year-on-year (YoY), up from the previous estimate of 2.5% YoY. This positive adjustment in the GDP forecast has generated optimism for a smooth economic slowdown and suggests that any potential recession might be brief and mild.

Turning to Malaysia, the Crude Palm Oil (CPO) house production conducts the outlook for its GDP in 2023 has also been moderately upgraded to 4.2% YoY following a stronger-than-anticipated performance in the first quarter. The country's economy will be buoyed by domestic demand, as external factors have led to uncertainties affecting its export capabilities. Robust employment prospects and reduced inflationary pressures are set to underpin domestic activities, fostering consumer spending throughout the remainder of the year.

For most of 2Q2023, key economic indicators were still mixed with the U.S. remaining resilient while other regions and countries saw softness. The easing inflation, both for consumers and producers, has allowed for much of the stability but is still tempered by the higher interest rates as Central Banks continued to lift rates in the hope to bring the CPI down to their targeted rate of 2.0%. Apart from the reduced inflation,amoresubdued Russia/Ukraine conflict and an ample supply of food and energy commodities helped to ease the supply concerns. Also, transport issues were alleviated, and this added to the more stable supply environment and lowered the inflationary threat

Throughout the second quarter of 2023, global services activities built upon the positive momentum observed in the first quarter. This was driven by continued growth in spending, which was supported by robust employment figures and a reduction in inflationary pressures. In contrast, the global manufacturing Purchasing Managers' Index (PMI) continued to contract due to reduced demand, leading to decreased output. This contraction trend has persisted since the beginning of the year. Interestingly, while the services sector initially experienced a strong surge at the start of the year, its growth rate now appears to be moderating somewhat.

In 2020, Indonesia's oil palm plantations encountered a range of factors that influenced their operations. These included a decline in global demand for Crude Palm Oil (CPO) driven by the spread of COVID-19, resulting in reduced consumption by importers. The industry also grappled with subdued production levels and a gradual replanting initiative in Indonesia and Malaysia, both major CPO producers. On the domestic front, the B30 program provided support for local CPO consumption. Additionally, concerns arose about the possibility of a drought season similar to that experienced in 2019, potentially impacting plantation yields. The trends in Crude Oil and Soybean Oil prices also played a role in shaping the landscape for Indonesia's oil palm industry during this period.

The COVID-19 pandemic has emerged as a primary factor influencing the oil palm industry. Our projections indicate that the pandemic will lead to a reduction in CPO supply, bringing it down to 134.5 million tonnes, reflecting a decrease of 1.3% year-on-year (YoY). This decline can be attributed to decreased plantation activity in Indonesia and Malaysia, the two largest CPO producers. In particular, the combined production of these countries is anticipated to reach 61.4 million tonnes, marking a YoY decrease of 1.3%. These declines stem from the imposition of restrictions on oil palm farmers' activities since March.

While CPO demands contributions from Indonesia and Malaysia are not expected to decline significantly due to their biodiesel programs bolstering domestic consumption, China's consumption, which contributes 9.6% to global CPO consumption, is predicted to decrease to 6.9 million tonnes, reflecting a YoY decline of 1.3% in 2020. This reduction is attributed to import restrictions resulting from logistic closures. However, we anticipate an improvement in these conditions starting from the third quarter of 2020, factoring in a decrease in COVID-19 cases.

Another influencing factor in the oil palm industry is the need for consistent replanting and the impact of weather conditions. Ensuring a steady and sufficient supply of crude palm oil (CPO) requires the regular regeneration of oil palm trees. The absence of effective replanting programs poses a risk to global CPO supply. This year, there is an anticipated slowdown in production from oil palm plantations. Optimal yields are typically generated by oil palm trees aged between 7 and 14 years. However, as these trees reach the age of 23 to 25 years, their fruit bunches' yields tend to decrease. Replanting becomes necessary once the trees surpass 25 years of age to maintain productivity. Notably, the average ages of oil palm trees in Indonesia and Malaysia are approximately 16 and 20 years, respectively. In 2020, both countries are gradually approaching the phase of lower fruit bunch production.

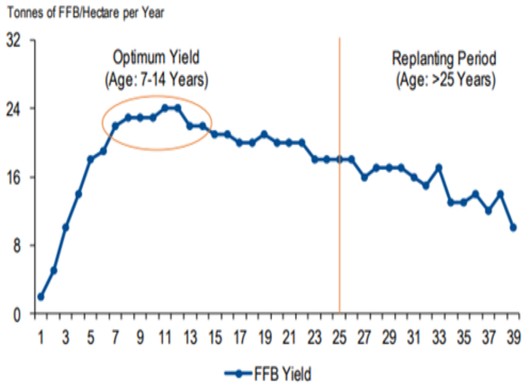
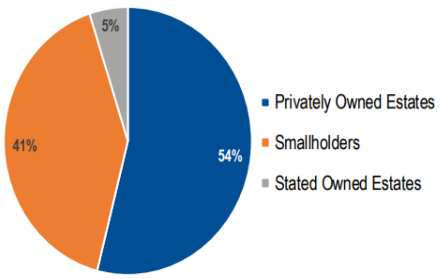


Figure 1. Yield Pattern of Oil Palm Trees

In light of this, the prevailing conditions create a potential advantage for soybean oil, a primary competitor, particularly if the rate of replanting activities does not witness a significant increase by year-end. The strategic implementation of replanting efforts becomes pivotal in sustaining the competitiveness of the oil palm industry and countering the potential impact of aging trees and unfavorable weather conditions.

Indonesia, holding the position of the largest contributor to global Crude Palm Oil (CPO) supply at 30%, confronts a challenging scenario within its plantations. These plantations are predominantly managed by smallholders and plasma farmers, who often face capital constraints that hinder their ability to undertake essential replanting efforts. The effectiveness and progress of the replanting program, involving both smallholders and state-owned plantations through PT Perusahaan Perkebunan Negara (PTPN), remain uncertain. This uncertainty is exacerbated by the absence of clearly defined implementation procedures and incentives to drive the program forward



arefacing an Ageing Crisis.

The existing situation concerning plasma trees in Indonesia is poised to lead to a decline in production strength over the forthcoming two to four years. The limited financial resources available to smallholders and the ambiguity surrounding the replanting initiative underscore the need for cohesive strategies and support mechanisms to ensure the sustained productivity of Indonesia's oil palm industry.

Regarding the weather patterns expected for the entirety of 2023, the projections indicate a repetition of the same cycle observed in 2019. This suggests that the impact on global Crude Palm Oil (CPO) production will remain relatively insignificant. As a result, this predicted weather condition is unlikely to cause significant fluctuations in the supply and demand dynamics of CPO, thus preventing extreme volatility in global CPO prices. Up until May 2023, the Southern Oscillation Index (SOI) data has consistently remained above the -7 threshold. This data pattern indicates that the imminent onset of El Niño is improbable, as sea surface temperatures continue to exceed historical averages. Consequently, this sustained temperature trend mitigates the potential effects of El Niño on weather conditions and reinforces the stability of the oil palm industry's landscape.

Nevertheless, there remains a possibility of drought occurrence in the Kalimantan region during the June-August timeframe if the weather cycle in 2023 mirrors that of 2019. Our projections indicate that this specific period, from June to August 2023, could experience a more pronounced decrease in Crude Palm Oil (CPO) production compared to other months within the year. It is important to note that, on the whole, our assessment suggests that 2023 will not be characterized by severe weather conditions. Despite the anticipated decline in CPO production, the situation is not expected to escalate into a supply crisis.

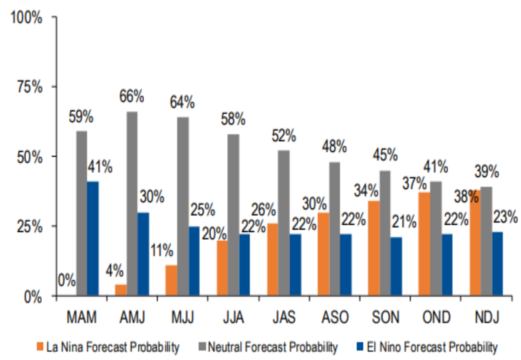


Figure 3. The probability of El Nino is Low

From 2015 to 2019, the overall expanse of oil palm plantations witnessed consistent growth, except for a decline in 2016. These plantations are distributed across 25 provinces, encompassing all provinces in Sumatra, Kalimantan, West Java, Banten, Central Sulawesi, South Sulawesi, Southeast Sulawesi, West Sulawesi, Gorontalo, Maluku, Papua, and West Papua. In 2019, the total oil palm plantation area expanded to 16.4 million hectares, marking a significant 28.5% year-on-year increase. Private-owned plantations accounted for 54%, community-owned for 41%, and state-owned for 5% of this total. Despite the presence of Presidential Instruction No. 8 of 2018, which imposed a moratorium on new land clearing, the growth of plantation areas has persisted. This trend is viewed positively due to its potential to enhance local economies and bolster the productivity of Indonesian Crude Palm Oil (CPO). Looking ahead to

2020, our projections indicate a potential increase in the oil palm plantation area to reach 17.2 million hectares.

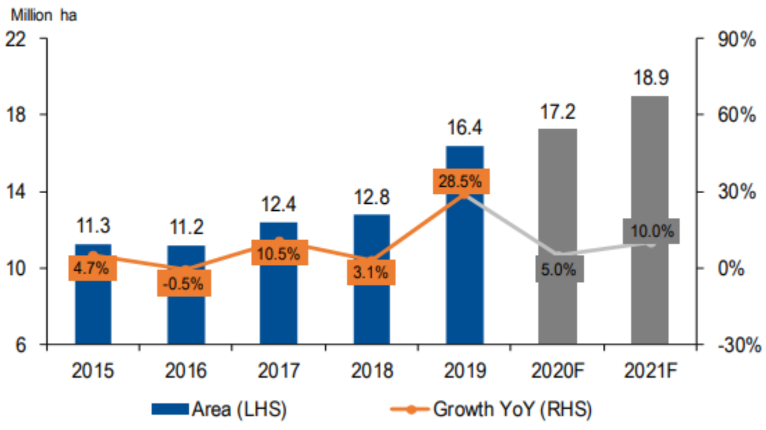


Figure 4. Indonesia Oil Palm Plantation Area

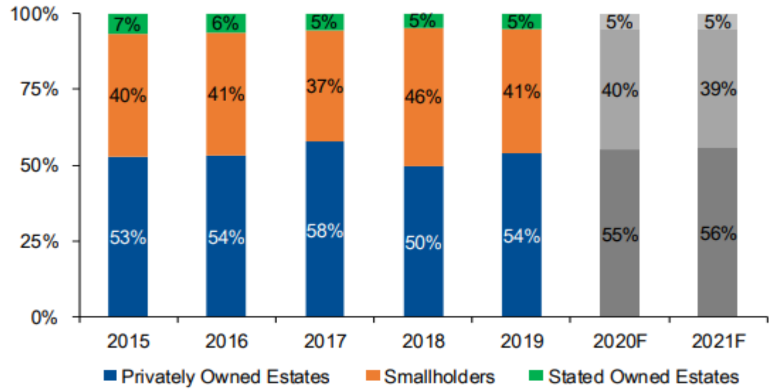


Figure 5. Indonesia's Oil Palm Plantation Area According to the Status of Exploitation

As the European Union enforces policies to curtail Crude Palm Oil (CPO) usage and India and China scale back imports due to the COVID-19 pandemic, the global demand for CPO is becoming increasingly reliant on domestic consumption within Indonesia and Malaysia to stabilize market prices. In Indonesia, a pivotal role is played by the biodiesel program, particularly through the implementation of B30 in 2020. Our estimations indicate that in the forecasted year 2020, domestic biodiesel consumption could surge to 7.6 billion liters, reflecting a noteworthy 20% year-on-year increase. This consumption is achieved through a blending rate of 28.5% in diesel, affirming the significant impact of the B30 program on bolstering domestic CPO usage.

Portfolio optimization is a crucial concept in finance, offering a methodical approach for investors to maximize profits while minimizing risks. Its significance lies in creating a well-balanced investment portfolio that aligns with an investor's goals and limitations. This involves using advanced mathematical and statistical tools to strategically allocate assets, leveraging historical data and market trends to identify high-return opportunities. Diversifying investments across various asset classes, like stocks, bonds, commodities, and real estate, safeguards against poor individual asset performance, enhancing potential returns while reducing overall risk.

Risk management is a vital aspect of portfolio optimization, aiming to reduce overall risk exposure while maintaining an acceptable level of return. Achieving this involves diversifying investments across various asset classes and sectors, safeguarding against market events or economic changes that could harm a single investment. Portfolio optimization models also consider asset correlations, assessing how they move together or apart. This is crucial for identifying assets with low or negative correlations, which effectively lower the portfolio's overall risk. Portfolio optimization revolves around the efficient frontier concept, representing the optimal portfolios offering the best-expected return for a given risk level. Using mathematical techniques like mean-variance analysis and modern portfolio theory, investors can pinpoint the portfolio allocation on this efficient frontier. This allocation ensures the highest possible return while considering risk tolerance and constraints.

Portfolio optimization is a valuable tool that helps investors strike a balance between maximizing returns and minimizing risk. This involves using advanced techniques to create portfolios that effectively manage risk while aiming for higher profits. Diversification across different assets and considering their correlations are key strategies to enhance returns and reduce susceptibility to market downturns. This study focuses on optimizing the portfolio of CPO stocks using a novel approach. This approach combines adjusted risk ranking, linear programming, and ANOVA (Analysis of Variance) to improve portfolio performance. The first step involves adjusted risk ranking, which goes beyond traditional risk measures to provide a more comprehensive evaluation of each asset's risk. This ensures a thorough assessment of their suitability for the portfolio.

The second step employs linear programming to achieve optimal asset allocation. By treating portfolio optimization as a linear programming problem, this method identifies the best combination of assets that maximizes returns while adhering to specific constraints. This approach enhances portfolio performance by effectively managing risk within set boundaries. The research seeks to answer specific questions: (1) How can the CPO stocks portfolio be optimized using adjusted risk ranking, linear programming, and ANOVA? (2) What are the resulting portfolio's performance and risk characteristics? (3) To what extent do these methods contribute to effective portfolio optimization for CPO stocks? By addressing these questions, the study sheds light on the methodology's application and outcomes in optimizing portfolios, specifically for CPO stocks from 2016 to 2022. All in All, the research employs ANOVA to analyze differences between asset groups within the CPO portfolio. The study employs ANOVA tests to detect notable differences in returns or risks among different asset categories. These discoveries offer valuable guidance for enhancing portfolio composition and performance by favoring the most promising asset categories. This research holds substantial significance in the realms of portfolio optimization and risk management. It seeks to contribute significantly to current knowledge by applying adjusted risk ranking, linear programming, and ANOVA techniques to optimize the Crude Palm Oil (CPO) stocks portfolio. The study aims to offer fresh insights and actionable implications for making investment decisions.

A significant contribution of this study lies in the innovative use of adjusted risk ranking, facilitating the ranking and prioritization of stocks based on their performance relative to risk. This method recognizes the diverse risk levels associated with different stocks, empowering investors to select stocks with ideal risk-return profiles for their portfolios. By focusing on risk-adjusted rankings instead of mere raw returns, investors can make more enlightened choices, ultimately enhancing portfolio performance. Moreover, the integration of linear programming techniques for portfolio optimization offers a methodical and quantitative approach to determining the best allocation of assets. Factoring in diverse considerations like diversification, risk tolerance, and return objectives, this research aims to produce portfolios that maximize returns while curbing risk. The outcomes of this study have far-reaching benefits, particularly for investors, fund managers, and financial institutions striving to construct efficient and diversified portfolios.

Furthermore, this study brings added value to the field by incorporating ANOVA analysis, which enables an assessment of the effectiveness of adjusted risk ranking, linear programming, and ANOVA itself within the context of portfolio optimization. By employing statistical analysis and evaluating the performance and risk attributes of optimized portfolios, this study seeks to shed light on the efficacy of these methodologies. Such insights hold the potential to propel the advancement of portfolio optimization practices and elevate decision-making processes in the finance domain.

In essence, the integration of adjusted risk ranking, linear programming, and ANOVA techniques into portfolio optimization for CPO stocks constitutes a substantial and meaningful contribution to the field. The discoveries and implications stemming from this research can offer invaluable guidance to investors, portfolio managers, and researchers, furnishing a robust framework for constructing investment portfolios that exhibit both strong performance and adept risk management. Through the harmonious application of adjusted risk ranking, linear programming, and ANOVA, this research establishes a comprehensive and methodical approach to optimize the CPO portfolio. This methodological blend facilitates a more nuanced evaluation of asset risks, streamlines the allocation of assets, and facilitates the detection of notable disparities among various asset groups.

In the end, the aim of this research is not only to form a comprehensive and high-performing CPO portfolio by utilizing the collective power of these analytical tools, but also to optimize the Crude Palm Oil (CPO) stock portfolio from 2016 to 2022 in the Jakarta Composite Index by using a customized risk ranking approach, linear programming, and ANOVA analysis

Methods

Portfolio optimization plays a pivotal role in investment management, involving the creation of an ideal asset portfolio that maximizes returns while minimizing risks. This review aims to delve into the existing body of literature on portfolio optimization, adjusted risk ranking, linear programming, and ANOVA, focusing particularly on their application within the context of CRUDE PALM OIL (CPO) stocks. Additionally, this assessment will pinpoint any gaps in the current literature, underscoring the necessity for further exploration in this domain.

The domain of portfolio optimization has given rise to several foundational theories and concepts. One such theory is Modern Portfolio Theory (MPT), formulated by Harry Markowitz during the 1950s. MPT underscores the importance of diversifying assets to attain an optimal trade-off between risk and returns. According to MPT, an investor can mitigate the risk associated with a portfolio by distributing investments across assets exhibiting low or negative correlations. MPT's potency lies in combining assets with varying risk and return profiles, enabling the creation of efficient portfolios that trace the efficient frontier. This frontier delineates the spectrum of portfolios presenting the highest expected returns for given risk levels. Optimal risk-return trade-offs aligned with individual risk preferences can be achieved by selecting portfolios along this efficient frontier. Furthermore, the Capital Market Line, an offshoot of the efficient frontier, encapsulates the risk-return trade-off while incorporating a risk-free asset. Central to MPT is the Mean-Variance Analysis, a pivotal concept that entails optimizing portfolios by factoring in mean returns and the covariance matrix of assets.

Diverse optimization methodologies have been leveraged to forge optimal portfolios. The Markowitz Mean-Variance Model stands as a prevalent strategy, aiming to maximize projected portfolio returns given a risk threshold or minimize portfolio risk at a designated anticipated return. The Sharpe Ratio, gauging surplus return relative to risk, often enters the scene for portfolio ranking. Another prominent contender is the Black-Litterman Model, a framework that assimilates investor viewpoints to fine-tune portfolio weights. These tactics furnish distinct avenues for shaping optimal portfolios rooted in risk and return objectives. Within portfolio optimization, risk ranking takes center stage, unraveling and assessing varied risk facets affiliated with assets. While established risk metrics like standard deviation and beta offer insights into asset volatility and market sensitivity, enhanced risk ranking integrates supplementary risk gauges for refined ranking precision.

Value at Risk (VaR) emerges as a popular risk gauge, approximating potential portfolio loss over a defined period with a specific confidence level. VaR quantifies downside risk, signifying the utmost loss an investor might face within a given confidence interval. Conditional Value at Risk (CVaR), aka expected shortfall, extends this narrative by capturing mean loss beyond the VaR threshold. Fusing these tailored risk ranking methodologies into portfolio optimization empowers investors to make judicious choices regarding asset selection and distribution in their portfolios. Linear programming takes the stage as a mathematical optimization tool profoundly employed in portfolio optimization. This technique entails shaping a linear objective function and a gamut of linear constraints to ascertain the optimal distribution of assets. Linear programming models take into account myriad variables, encompassing projected returns, risk metrics, and curbs on portfolio composition (such as sector exposure ceilings or asset-specific allocations). The primary goal of employing linear programming within portfolio optimization is to identify the optimal allocation that either maximizes returns or minimizes risk, all the while honoring the provided limitations. This formulation commonly involves introducing variables that represent the weights assigned to assets in the portfolio. Accompanying these variables are constraints that ensure the summation of weights equals one, reflecting a fully utilized portfolio. Linear programming models serve as efficient and proficient tools to resolve portfolio optimization quandaries. They enable investors to construct portfolios aligned with their risk and return goals while upholding specific constraints.

Analysis of Variance (ANOVA) constitutes a statistical methodology employed to scrutinize distinctions among groups or variables. In the realm of portfolio optimization, ANOVA finds utility in evaluating the performance of distinct portfolios fashioned through diverse optimization techniques or risk ranking strategies. By juxtaposing the average returns and risk metrics of divergent portfolios, ANOVA aids in identifying substantial disparities and determining which approach yields superior outcomes.

ANOVA serves as a valuable tool to unravel performance disparities among diverse portfolio optimization strategies, enabling investors to gauge the efficacy of each method. This analytical approach empowers researchers to pinpoint significant elements influencing portfolio performance and gauge the influence of various variables on the optimization process. This statistical assessment delivers crucial guidance to investors navigating the selection of the most potent portfolio optimization strategy for CRUDE PALM OIL (CPO) stocks. Despite the extensive body of literature encompassing portfolio optimization, adjusted risk ranking, linear programming, and ANOVA, a distinct gap emerges in the current research, particularly when applied to the unique realm of CRUDE PALM OIL (CPO) stocks. These stocks represent the most actively traded and liquid entities within the Indonesian stock market.

The research void becomes evident in the scarcity of studies scrutinizing the utility of adjusted risk ranking methods, notably those integrating advanced risk metrics such as VaR and CVaR, within the optimization of CRUDE PALM OIL (CPO) stock portfolios. These metrics offer a more comprehensive perspective on risk by capturing potential losses beyond specified thresholds or confidence levels. Fathoming the ramifications of these refined risk measures on portfolio optimization specific to CRUDE PALM OIL (CPO) stocks would amplify risk management strategies tailored to this distinct market. To address this, comprehensive studies employing linear programming models and ANOVA are requisite to delve into and juxtapose the efficacy of various portfolio optimization strategies for CRUDE PALM OIL (CPO) stocks. Through the application of linear programming techniques, researchers can conceptualize optimization models infused with constraints and objectives pertinent to CRUDE PALM OIL (CPO) stocks. Subsequently, ANOVA can be harnessed to dissect performance differentials across these strategies. This integrated approach enables both researchers and investors to discern the most efficacious avenue for portfolio optimization.

In summary, while portfolio optimization, adjusted risk ranking, linear programming, and ANOVA have undergone extensive exploration in the broader investment management context, there remains an exigent demand for research that distinctly delves into the optimization of CRUDE PALM OIL (CPO) stock portfolios. Addressing these gaps promises to furnish researchers with vital insights into the effectiveness of diverse portfolio optimization methodologies and equip investors in the Indonesian stock market with informed decision-making tools.

Result

The primary goal of this research is to create a theoretical portfolio that achieves optimal performance based on the latest available historical data. The study aims to carefully select stocks that align with specific risk tolerance levels. This optimization process involves strategically allocating stocks to form an ideal portfolio, which is subsequently statistically evaluated for its performance. In essence, this theoretical portfolio serves as a valuable benchmark for providing investment recommendations in the realm of capital markets.

This study unfolds through distinct stages, with the overarching objective of developing an optimal portfolio. These stages encompass Stock Selection, Portfolio Allocation Optimization, and Portfolio Evaluation. Each stage is characterized by specific details and criteria that guide the research. One commonly employed technique for identifying the most suitable stocks within the LQ-45 index involves utilizing the Index Weighting indicator. This approach facilitates the assessment of volatility, market capitalization, and stock performance within the index. Nevertheless, it's crucial to acknowledge the existence of various alternative methods and strategies for prudent stock selection. The choice of method depends on the investor's preferences and objectives.

Index weighting pertains to the methodological framework employed to determine the significance or weight of individual components within an index. Several prevalent approaches to index weighting include:

2) Company Total Assets: This is the most popular method used in many widely followed indexes such as the S&P 500. It assigns weights to index components based on their market capitalization (i.e., the total value of a company's outstanding shares). Larger companies have a higher weight in the index compared to smaller companies. For example, if a company's market cap represents 5% of the total market capitalization of all index components, it would have a 5% weight in the index.

2) Average Day Turnover: financial metric used to measure the average number of shares or contracts traded in a particular asset (such as a stock, commodity, or currency pair) over a specified period, usually a trading day. ADTO is calculated by dividing the total trading volume of the asset over the given period by the number of trading days in that period. ADTO provides insights into the liquidity and trading activity of an asset. It is commonly used by investors, traders, and analysts to assess the level of market interest and participation in a particular security or market. Higher ADTO values generally indicate greater liquidity and interest, making it easier to buy or sell the asset without significantly impacting its price. On the other hand,

lower ADTO values may suggest lower trading activity and potentially higher transaction costs. ADTO is a useful tool for understanding market trends, evaluating the ease of executing trades and assessing the overall trading environment for a given asset

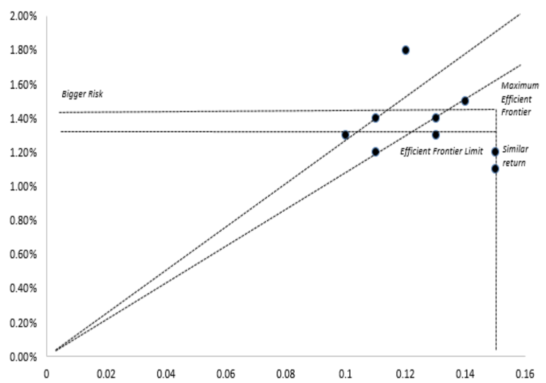
Table 1 LQ-45 Member Weightings 2022

Ticker	Total Assets	AUTO
DSNG IJ	15.36	23.49
SSMS IJ	13.97	14.73
AALI IJ	29.25	7.37
LSIP IJ	12.42	7.33
TAPG IJ	14.53	6.72
STAA IJ	7.01	5.27
MKTR IJ	0.97	5.2
MGRO IJ	2.56	4.62
GZCO IJ	2.05	1.82

Referring to Table 1, it becomes evident that the top-weighted ten stocks in the index exhibit a notable correlation with the segment division. As a result, all these variables remain viable for extended analysis. These particular stocks demonstrate robust and sound fundamental attributes. Consequently, the subsequent phase entails an in-depth examination of the performance of these stocks over the last 60 trading days, spanning from October 7, 2022, to December 30, 2022. The parameter for this performance is the average of gain ($\bar{R_i}$) and measure of risk (σ_i);

Table 2: Best CPO stocks in the last 60 trading days.

Tab 2.



After conducting further filtering, it can be concluded that out of the previous 10 stocks, 4 stocks have been selected. These stocks are AALI, LSIP, TAPG, and STAA, These four stocks will be further analyzed based on rationalization criteria.

According to Elton and Gruber's theory (2002), AALI stock is ranked first due to having the steepest efficiency line angle, followed by AALI, LSIP, TAPG, and STAA. With a deeper analysis, it can be concluded that MGRO stock does not perform better than AALI because the marginal comparison of average returns and relative risks is relatively low. Investors will observe that 〖CV〗-MGRO≈ 〖CV〗_AALI, where the offered returns are relatively similar, but the resulting risks tend to differ, leading investors to choose AALI. Investors tend to select stocks with lower risks and higher profit potential. Therefore, at this stage, I eliminate MGRO and SSMS due to their negative returns.

3.1 Analyzing retail behavior.

The survey was conducted based on the minimum opening balance and recommendations from analysts and market participants from several securities firms. In general, it can be classified as the following table.

Table 4: Minimum opening balance and recommendation for the retail investor

Tab.4.

Min. Opening Balance (In IDR)	Recommendation
< 20 mio	Beginner
20 - 50 min	Intermediate
> 50 mio	Professional

3) Optimization portfolio.

The criteria used to optimize the portfolio is by measuring the CV's performance. The variables used in the Linear Programming equation are as follows: The variables utilized in the

Linear Programming equation for optimizing the portfolio performance based on a CV are as follows:

S_1 = Lot quantity AALI w_1 = AALI proportion

S_2 = Lot quantity LSIP w_2 = LSIP proportion

S_3 = Lot quantity TAPG w_3 = TAPG proportion

S_4 = Lot quantity STAA w_4 = STAA proportion

ρ_{12} = 0. $\bar{R}_1$ = 0.13%

ρ_{13} = 0.52 $\bar{R}_2$ = 0.13%

ρ_{14} = 0.50 $\bar{R}_3$ = 0.05%

ρ_{23} = 0.31 $\bar{R}_4$ = 0.02%

ρ_{24} = 0.36

ρ_{34} = 0.50

σ_1 = 1.35%

σ_2 = 1.56%

σ_3 = 1.38%

σ_4 = 1.33%

Portfolio equity return valuation:

$$R_{Port} = \sum_{n}^{1} w_i R_i = w_1 R_1 + w_2 R_2 + w_3 R_3 + w_4 R_4$$

Portfolio equity risk valuation:

σ_Port
= √(■(w_(1^2) σ_(1^2) + w_(2^2) σ_(2^2)
+ w_(3^2) σ_(3^(2+)) w_(4^2) σ_(4^2
+ 2) w_(1^2) w_(2^2) σ_1 σ_2 ρ_12
+ 〚2w〛 _1 w_3 σ_1 σ_3 ρ_13@
+ 〚2w〛 _1 w_4 σ_1 σ_4 ρ_14
+ 〚2w〛 _2 w_3 σ_2 σ_3 ρ_23
+ 〚2w〛 _2 w_3 σ_2 σ_3 ρ_23
+ 〚2w〛 _3 w_4 σ_3 σ_4 ρ_34))

Stocks weighting proportion:

$$w_1 = \frac{4940.S_1}{(4940.S_1 + 4963.S_2 + 9225.S_3 + 8550.S_4)}$$

$$w_2 = \frac{4963.S_2}{(4940.S_1+4963.S_2+9225.S_3+8550.S_4)}$$

$$w_3 = \frac{9225.S_3}{(4940.S_1+4963.S_2+9225.S_3+8550.S_4)}$$

$$w_4 = \frac{8550.S_4}{(4940.S_1+4963.S_2+9225.S_3+8550.S_4)}$$

Total proportion in a portfolio

$$w_1 + w_2 + w_3 + w_4 = 1$$

Total portfolio (in value of stocks)

$$(4940.S_1 + 4963.S_2 + 9225.S_3 + 8550.S_4).500 \leq 100\ mil$$

$$(4940.S_1 + 4963.S_2 + 9225.S_3 + 8550.S_4).500 \leq 100\ mil$$

Optimization portfolio version 1.

Objective function: Minimization $CV = \frac{\sigma_{Port}}{R_{Port}}$

Constraint function:

$$w_1 + w_2 + w_3 + w_4 = 1$$

$$w_1 \geq 0$$

$$w_2 \geq 0$$

$$w_3 \geq 0$$

$$w_4 \geq 0$$

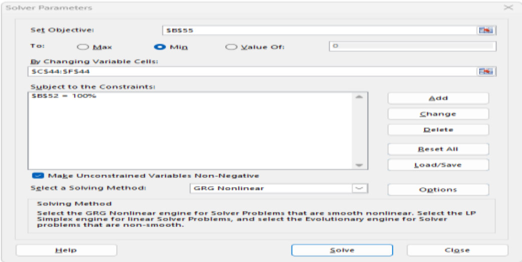


Figure 5. Optimization Portfolio Ver. 1, On Excel solver screen

The result of the Linear Programmingcalculation for portfolio optimization version 1 is as follows:

The result of the Linear Programming calculation for portfolio optimization version 1 is as follows:

Optimization portfolio version 2.

Objective function: Minimization $CV = \frac{\sigma_{Port}}{R_{Port}}$

Constraint function:

$$w_1 + w_2 + w_3 + w_4 = 1$$

$$S_1 \geq 0$$

$$S_2 \geq 0$$

$$S_3 \geq 0$$

$$S_4 \geq 0$$

$$S_1 = \text{int}$$

$$S_2 = \text{int}$$

$$S_3 = \text{int}$$

$$S_4 = \text{int}$$

$$(4940.S_1 + 4963.S_2 + 9225.S_3 + 8550.S_4).500 \leq MAX$$

Table 5: The result of the excel solver calculation

Tab 5.

		STAA	AALI	TAPG	LSIP
	Weights	13%	57%	10%	10%
STAA	27%	0.000177	0.00009	0.000091	0.000059
AALI	26%	0.00009	0.000182	0.000097	0.000059
TAPG	22%	0.000091	0.000097	0.000191	0.000067
LSIP	25%	0.000074	0.000059	0.000067	0.000242

Based on the above image, it indicates optimization without considering the maximum amount of funds. Therefore, the optimal portfolio is achieved with an allocation of 13.3% for STAA, 56.7% for AALI, 9.5% for TAPG, and 10.5% for LSIP. In the next version, the portfolio will be analyzed using the number of lots.

Portfolio Optimization 1 simulation

The next step in the research involves selecting the optimal portfolio (with a CVMin of 5.66) for evaluation using back-testing simulation and ANOVA. The simulation will be conducted using the most recent 60 trading days, starting from October 7, 2022, and ending on December 30, 2022. The portfolio will have a total value of IDR 100,000,000, and its performance will be compared to that of the composite index.

Pic 2. Back-testing portfolio simulation with last 60 days.

Pic 2.After monitoring the trading activities for a period of 60 days, it can be deduced that the portfolio optimization is functioning effectively. The optimization has yielded a positive outcome, with a 6.6% increase in returns (excluding transaction fees), while the index has shown a notable decrease of 2.51%.

Hypothesis testing

$\boldsymbol{H_0} =$ The average profitability of the portfolio is lower or equal to the market's profitability level.

$\boldsymbol{H_1} =$ The average profitability of the portfolio is higher than the market's profitability level.

$\bar{X}_1 = 0.11\%$ $\quad s_1 = 1.11\%$

$n_1 = 60$ $\quad \alpha = 5\%$

$\bar{X}_2 = (0.04\%)$ $\quad s_2 = 0.71\%$ $n_2 = 60$

$$Z_{Uji} = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} = \frac{0.11 - (0.04\%)}{\sqrt{\frac{(1.11\%)^2}{60} + \frac{(0.71\%)^2}{60}}} = 4.1176$$

Z_table=1.645

Statistic Conclusion: The null hypothesis is rejected because the test statistic Z is greater than the critical value Z from the table. Therefore, the alternative hypothesis H1 is accepted, indicating that the average return of the optimal portfolio is higher than the market return.

Conclusion

Answering the research questions above, the aim of this research is to optimize the Crude Palm Oil (CPO) stock portfolio from 2016 to 2022 in the Jakarta Composite Index using a customized risk ranking, linear programming and ANOVA analysis approach, in addition to forming a CPO portfolio. comprehensive and high-performance by leveraging the collective power of existing analytical tools.

The conclusion that can be drawn from this research is that the average return of the optimal portfolio is higher than the market return. However, it is important to note that the research is only conducted up to the fourth stage out of six stages in the complete cycle. If the selected stocks in the portfolio experience a significant decrease in performance during the monitoring phase, those stocks should be removed and the analysis process needs to be repeated from the first stage. This implies that the research requires a continuous cycle of monitoring and maintenance to ensure the portfolio's performance.

During the research period from January 2016 to December 2022, 10 stocks consistently formed the LO-45 index. Based on the Coefficient of Variance (CV) ranking criteria, only 4 stocks were selected for the portfolio optimization process: AALI, TAPG, ADRO, STAA, and LSIP. These stocks were chosen based on their performance and ranking, while the remaining 4 stocks were eliminated as they did not meet the criteria. The optimization process using Linear Programming resulted in a portfolio composition with STAA 27%, AALI 26%, TAPG 22%, and LSIP 25%

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