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MODELING RISK-BASED STOCK PORTFOLIO: EVIDENCE FROM LONG TIME SERIES

Malik Cahyadin[1]*, Luthfi Aradhana Riesendra[2], Tamat Sarmidi[3]
[1]malikcahyadin_feb@staff.uns.ac.id, [2]luthfiaradhana22@gmail.com,
[3]tamat@ukm.edu.my
[1,2]Universitas Sebelas Maret, Indonesia
[3]Universiti Kebangsaan Malaysia, Malaysia
*corresponding author

Abstract

The judicious selection of a stock portfolio necessitates a meticulous and precise analysis of risk and return levels. Therefore, this study employs a simulation model to generate a practical and optimally diversified stock portfolio by considering risk level. Secondary data were employed on 952 Indonesian stocks and 4 global ETFs across four stages cover historical data, liquidity, risk-return performance, and fundamental indicators during 1st March 2007– 1st March 2025. Sharpe Ratio Maximization (SR Max) and Risk Parity (RP) methods were utilized. The findings reveal that during all daily data SR Max exhibited a Compound Annual Growth Rate (CAGR) of 16.15%, a volatility of 17.39%, and a drawdown of -39.11%. Meanwhile, RP recorded CAGR of 12.81%, a volatility of 13.24%, and a drawdown of -32.98%. By considering risk analysis, SR Max is appropriate for investors who accept high levels of risk in pursuit of significant growth opportunities. Conversely, RP is better suited to investors who prioritise stability and are willing to accept lower returns. Furthermore, the implication stimulates investors able to formulate a more rational and sustainable asset allocation strategies. In addition, the financial authority should pay more attention on the financial market stability.

Keywords: Stock Portfolio; Risk Parity; Sharpe Ratio; Investor Decision Making.

Abstrak

Pemilihan portofolio saham memerlukan analisis tingkat risiko dan imbal hasil yang tepat dan akurat. Oleh sebab itu, studi ini mensimulasi portofolio saham yang praktis dan terdiversifikasi optimal berbasis risiko. Data sekunder digunakan terhadap 952 saham dan 4 ETF global melalui empat tahap terdiri atas kelengkapan data historis, likuiditas, kinerja risiko-return, dan indikator fundamental selama 1 Maret 2007–1 Maret 2025. Metode Sharpe Ratio Maximization (SR Max) dan Risk Parity (RP) digunakan. Temuan studi mengungkap bahwa selama periode keseluruhan data harian SR Max mencatat CAGR sebesar 16,15%, volatilitas sebesar 17,39% dan drawdown sebesar -39,11%. Sementara itu, RP mencatat CAGR sebesar 12,81%, volatilitas sebesar 13,24% dan drawdown sebesar -32,98%. Dengan mempertimbangkan analisis risiko, SR Max adalah tepat untuk investor yang mampu menghadapi risiko tinggi dengan mengejar peluang pertumbuhan. Sebaliknya, RP lebih sesuai bagi investor yang mengutamakan stabilitas dan menerima imbal hasil rendah. Selanjutnya, implikasi kebijakan mendorong investor mampu memformulasikan strategi rasional dan alokasi aset berkelanjutan. Selain itu, otoritas keuangan harus memberi perhatian lebih terhadap stabilitas pasar keuangan.

Kata Kunci: *Portofolio Saham; Risk Parity; Sharpe Ratio; Pembuatan Keputusan Investor.*

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INTRODUCTION

In Indonesia, while the financial inclusion index has reached 85.10% in 2022, the level of financial literacy remains at 49.68% (OJK, 2022). The discrepancy between access and comprehension has grave ramifications, including individuals becoming ensnared in illicit online loans, speculative instruments, and online gambling, as well as the inability to manage investment portfolios in a sustainable manner. Confronted with these challenges, novice investors find themselves ill-equipped to navigate the complexities of portfolio risk management strategies due to their limited financial resources and understanding of financial concepts. Drawing from the author's personal experience, inquiries such as "how to initiate investment safely?" "How to manage assets to avoid loss?" and "what investment instruments should I acquire?" frequently emerge from friends, colleagues, and family members. This condition underscores the necessity for a pragmatic framework that can assist novices in constructing a data-driven and pragmatic portfolio.

Ayub et al. (2015) investigated risk-based portfolio optimization for 100 listed-companies of Karachi Stock Exchange during 2000-2010. They found several factors determined the portfolio optimization cover portfolio size and portfolio sorting procedure. In addition, downside risk framework perform is better than Markowitz mean–variance framework. Disruption contributes on portfolio market risk. For example, Kamali et al. (2024) examined the portfolio optimization by considering minor losses and certain opportunities in the Securities and Exchange Organization of Iran from February 26, 2020 until March 4, 2023. They argued that several factors affected portfolio optimization such as open price, high price, low price, last price, trading volume, number of trading volumes, the value of trading volumes, and dollar price change. Sharp's ratio shows that putting 75% of assets in the first fund and 25% in the second, in case of a pandemic, or 25% in the first and 75% in the second in case of currency risk, leads to the highest profitability.

In certain instances, the emphasis placed on returns in stock portfolio optimization predictions can overshadow the consideration of price volatility risk, thereby overlooking the intricate interplay of multiple spillover effects among a portfolio of stocks (Ma et al., 2024). Consequently, a risk- and return-based stock portfolio in the CSI 100 of Chinese stocks was simulated. The heterogeneous graph attention network (HGA-MT) method was applied in this study. The findings illustrate that the minimum yield rate is 11.09%, the gain is 8.29%, the internal rate of return (IRR) of SP is 11.24%, and the IRR of MDD is 14.42%. A further finding from a comparison of major developed stock markets with the BRICS Stock Market during September 29, 1997–October 14, 2013, revealed significant variability in the time-varying conditional correlations between these markets during upturn and downturn periods (Mensi et al., 2017). Additionally, (Mensi et al., 2025) examined the correlation between the stock markets of China, Europe, Japan, the UK, and the US, and so-called "safe-haven assets" namely, gold, Bitcoin, and green bonds. It was explained that there is a considerable tail risk in portfolio management. Gold, Bitcoin, and green bonds have the potential to serve as safe havens for international equities.

The present study posits five inquiries. Initially, the question must be posed:

How should assets be filtered based on risk and fundamentals? Secondly, the determination of portfolio weights using the SR Max and Risk Parity approaches is imperative. Thirdly, it is imperative to ascertain the realistic minimum capital. A fourth inquiry pertains to the comparison of its performance with that of the IHSG and LQ45. The fifth inquiry pertains to the degree of resilience exhibited by the portfolio when confronted with extreme risks. These inquiries direct us to the overarching objective of the study, which is to develop a risk-based stock portfolio model in Indonesia. This endeavor utilizes a long time series, encompassing daily data from the period spanning from March 2007 to March 2025. Moreover, this study makes several contributions to the extant literature. First, this study utilizes a risk-based stock portfolio simulation, employing a variety of approaches over an extensive time series. Secondly, the results of the simulation model express robust stock portfolio findings. Thirdly, investors can utilize these simulation findings to determine which stocks to purchase. Fifthly, the capacity of the stock exchange authority to enhance stock trading governance is a potential catalyst for ensuring the long-term stability of the financial sector. The methodologies employed in this study are designed to assess the efficacy of portfolio strategies grounded in historical data and simulation models (Fabozzi, 2011).

This study proposes a novel perspective on the existing literature in several ways. First, it employs a long series of Indonesian stock portfolio by considering international stock market (S&P 500 and Gold commodity). Second, SR Ratio Maximization and Risk Parity Approaches were utilized by considering several steps of simulations. In addition, the originality pays more attention on lower risk and stable return of stock porfolios in Indonesia using SR Ratio Maximization and Risk Parity for a long series.

The extant literature on stock portfolio modeling in Indonesia has historically centered on the evaluation of classical models, such as the mean-variance model or the single index model. However, there has been limited exploration of domestic stocks and the ideal data assumptions that are characteristic of more recent models. Nugraha et al. (2024) and Yusup (2022) examined the efficacy of portfolio optimization models within the Indonesian market. However, these studies have not incorporated a multi-stage selection process, minimum capital estimation, or stress testing based on long-term economic scenarios. Furthermore, these studies have not considered the application of asset filtering-based portfolio strategies, risk simulations, and the affordability of initial capital for retail investors. The multi-asset portfolio approach, which incorporates a combination of domestic stocks, hedging instruments such as gold, and global ETFs (e.g., SPY), is seldom implemented in a practical manner by novice investors in Indonesia. Indeed, the diversification of asset portfolios is imperative in reducing correlation and enhancing portfolio stability (Malkiel and Ellis, 2021). A review of extant literature reveals a paucity of explicit discussion regarding the comparison of portfolio performance against domestic benchmarks, such as the IHSG and LQ45. This benchmark is widely regarded as the primary reference point for Indonesian retail investors in evaluating the relative performance of an investment strategy. This study addresses this knowledge gap by directly testing the relative superiority of two portfolio models against the market index. The models are evaluated in terms of return, drawdown, and risk ratio, in the context of a real and fluctuating domestic economy.

The findings of this study illuminate several salient points. Initially, three domestic stocks have been identified as offering consistent risk-based portfolio and relatively stable returns cover BBCA, SMSM, and INDF. Secondly, the minimum investment capital required for an optimal portfolio that is financially viable for aggressive investors is approximately IDR 8.75 million (SR Max approach). Meanwhile, conservative investors require IDR 10.27 million (RP approach), with a tracking error of 0.01%.

LITERATURE REVIEW

Risk Diversification and Portfolio

Modern portfolio management constitutes the foundation of long-term investment strategies, particularly in the context of market uncertainty management through asset diversification. Markowitz (1952) introduced the concept of the "efficient frontier," a quantitative framework that allows investors to optimize asset composition by combining expected returns and portfolio risk. The efficacy of diversification is contingent upon the possession of low or negative correlation among assets in a given portfolio. Suppression of portfolio volatility without a concomitant reduction in potential returns is indicative of effective diversification. The principle of diversification assumes particular significance for novice investors due to their limited information and conservative risk preferences. The utilization of indicators such as the return on equity (ROE) ratio, the price-to-book value (PBV), and profit growth is also recommended to assess the fundamental strength of a company (Bodie et al., 2014).

The amalgamation of domestic stocks, gold as a safe haven instrument, and global ETFs such as the S&P 500 (multi-asset diversification) play a significant contribution in mitigating systemic and geographic risks. Baur & McDermott (2016) demonstrated a negative correlation between gold and the global equity market. Similarly, Malkiel & Ellis (2021) asserted the significance of multi-asset and geographic diversification in constructing a long-term portfolio. Furthermore, investors are obliged to undertake a thorough examination of historical risk performance, encompassing portfolio such as drawdown and volatility. This analytical process facilitates the identification and exclusion of assets that exhibit an excessively speculative character. Assets with controlled volatility have been demonstrated to exhibit enhanced stability, particularly in contexts where market efficiency is compromised.

This current study emphasizes on the Indonesian stock porfolio using SR Ratio Maximization and Risk Parity approaches for a long series. This means that it provides a better procedur for stock portfolio risk-based simulation. In addition, this current study selects several lower risk and stable return of stock portfolios in Indonesia.

Risk Assessment and Portfolio Resilience

The management of extreme risk in contemporary investment portfolios necessitates not only the utilization of volatility measures but also the implementation of a simulation approach that incorporates non-normal loss distributions. One widely used method is Value at Risk (VaR), a quantitative measure that estimates the maximum possible loss at a given confidence level. According to Glasserman (2003) and Jorion (2007), Value at Risk (VaR) is a standard tool for measuring downside risk, especially when combined with Monte Carlo simulations to mimic thousands of possibilities.

The comprehension of the concept of Value at Risk enables novice investors to discern the potential for adverse outcomes in their portfolios. However, they are also capable of making more rational and informed investment decisions in the face of market uncertainty. Therefore, the concept of VaR will be utilized for assessing the lower risk of stock portfolio in this study.

Sharpe Ratio and Risk Parity

Two quantitative approaches that are widely used in portfolio weighting are Sharpe Ratio Maximization and Risk Parity. The Sharpe ratio, a measure of the relationship between excess return and total risk, was first introduced by Sharpe (1966). This model is frequently employed by aggressive investors, as it aims to optimize the efficiency of returns relative to the level of risk. The advantage of this model is predicated on its simple formula. However, the model is sensitive to the estimation of expected returns, which can result in extreme weight allocations if the projections are inaccurate.

Qu et al. (2023) study demonstrated that, under stable market conditions, the Sharpe model exhibited superior performance in comparison to established benchmarks, such as the S&P 500. However, Dong (2022) observed that its performance exhibited a decline in instances of market turbulence, given its failure to account for asymmetric risk distribution and its reliance on drawdown as a metric for risk assessment. Conversely, Risk Parity endeavors to equalize the risk contribution between assets based on volatility and correlation, independent of projected returns. Qian's (2004) theory was founded on the concept of risk budgeting, a notion that would subsequently garner widespread adoption from prominent global asset managers, including Bridgewater Associates. This approach is regarded as more stable and suitable for conservative investors. It demonstrates a greater degree of resistance to market uncertainty.

In Indonesia, Kurniawan et al. (2020) demonstrated that the Risk Parity approach yielded a higher Sharpe Ratio compared to the conventional strategy and offered investors protection from market downturns in over 77% of the simulations. These findings substantiate the pertinence of this approach for retail investors in emerging markets. A critical examination of these two strategies reveals notable distinctions. Specifically, Sharpe's strategy demonstrates a propensity to pursue growth in stable market conditions, while Risk Parity exhibits a higher degree of adaptability and stability in volatile market settings. Investors are able to select an approach that aligns with their risk profile and investment horizon.

In particular, the current study uses Sharpe Ratio and Risk Parity for a long series of Indonesian stock portfolio. The condition means that the current study provide a better step and understanding of a lower risk and stable return of several stock portfolios in Indonesia for a long series.

Hypothesis Development

In developing countries, the efficacy of asset allocation through diversification is curtailed by the significant interdependence among domestic financial instruments and markets. As demonstrated by Bessler et al. (2017), the integration of global assets has been shown to enhance the risk-return profile. This finding aligns with the conclusions of Almeida et al (2023), who posited that diversification through assets such as gold and global exchange-traded funds (ETFs) enhances portfolio stability. Additionally, Paolella et al. (2024) observe that risk parity is sustained despite a propensity for a fat-tailed return distribution.

Deng et al. (2013) posited that the standard Sharpe Ratio (SR Max) is often ineffective in capturing tail risk. Consequently, a methodology referred to as Risk Parity (RP) was developed to distribute risk evenly across assets. As Maillard et al. (2009) have described, risk parity portfolios exhibit greater stability in comparison to mean-variance portfolios, due to the former's independence from estimates of expected returns. Furthermore, Anderson et al. (2011) found that risk parity tends to outperform during crisis periods, although the long-term potential returns tend to be lower than the SR Max approach.

Furthermore, the present study employs the SR Max and RP models to assess an Indonesian stock portfolio, while incorporating global stock market data. This is due to the fact that prior research has exclusively concentrated on developed markets or a solitary optimization method. Therefore, the following hypothesis is formulated:

H0: There is no difference in the risk and return levels of stock portfolios based on SR Maximization and Risk Parity.

H1: There is a difference in the risk and return levels of stock portfolios based on SR Maximization and Risk Parity.

RESEARCH METHODOLOGY

Data and Variables

The present study utilizes secondary data to develop simulation models for stock portfolios. It utilizes a long daily data during 2007: March 1-2025: March 1 from the IDX website, **API** *Yahoo Finance* **(yfinance),** and Exchange Traded Funds (ETFs) global. The main data is stock return. Additionally, the present study encompasses four distinct economic phases: the global financial crisis (GFC), the post-GFC era, the period of the pandemic caused by the severe acute respiratory syndrome (SARS-CoV-2) virus, and the post-pandemic era. The selection of this period aims to evaluate the resilience of the portfolio to the dynamics of the long-term economic cycle (Damodaran, 2012).

The total stocks were amount to 952. In addition, the stock portfolio analysis also considering 4 exchange-traded funds (ETFs). The risk-based stock filtering process is carried out through four stages. The first stage is the assessment of the completeness of monthly historical data from 2007: March 1 to 2025: March 1. The second stage is the assessment of liquidity, defined as the average daily transaction value > IDR 1 billion. The third stage is the performance evaluation based on historical returns, drawdowns, and volatility. The fourth stage is the fundamental selection using financial ratio indicators. The selection of these variables aligns with established best practices in portfolio management, which advocate for a combination of quantitative and fundamental analysis to achieve long-term stability (Malkiel & Ellis, 2021; Palepu & Healy, 2012). Morover, the stocks were utilized to construct two risk-based portfolios under Sharpe Ratio Maximization (SR Max) and Risk Parity (RP) methods. The optimization process was executed using the Python programming language and the PuLP Solver library (Ben-Tal et al., 2012). This approach was undertaken in the context of specific technical constraints, including a maximum weight allocation of 30% for each asset and the prohibition of leverage.

The present study also utilizes computational algorithms and financial analysis to determine the minimum investment capital necessary to replicate the optimized portfolio. The calculation of the minimum capital considers the most recent stock market price, the smallest trading lot unit (for domestic stocks), and fractional or full units (for global ETFs). The stock portfolio optimization process employs the Mixed-Integer Linear Programming (MILP) approach (Loge, 2023).

The performance of the stock portfolio is evaluated by means of key metrics of investment performance. The following metrics are employed: CAGR, annual volatility, Sharpe ratio, and maximum drawdown (Sortino and Meer, 1991). Furthermore, the analysis of significant risk utilizes the Value at Risk (VaR) method, Monte Carlo Simulation with 100,000 iterations and a 99% confidence level. This approach is predicated on probabilistic distribution modeling and random simulation (Glasserman, 2003; and Jorion, 2007).

Furthermore, the performance of stock portfolio is also evaluated in relation to two domestic market indices, namely: IHSG and LQ45. These indices are utilized as standard passive benchmarks due to their representation of retail stock market exposure in Indonesia and their extensive adoption as benchmarks by local market participants (Yusup, 2022). The evaluation was examined to provide the relative superiority of filtering and risk optimization strategies for investors in Indonesia.

This study employed several stages of data distribution analysis. Initially, the stock return data was represented through a histogram to evaluate the normality of the data. Secondly, the Jarque-Bera (JB) test was applied to evaluate the normality of the data distribution. Thirdly, the Augmented Dickey-Fuller (ADF) test was selected for investigating the stationarity of the time series data.

Risk-Based Stock Portfolio Models

Sharpe Ratio Maximization

The Sharpe Ratio Maximization model is a financial model that aims to determine the combination of assets in a portfolio that provides the highest return relative to its total risk. The primary indicator in this model is the Sharpe Ratio, defined as the ratio of the portfolio's excess return to its volatility Elton et al. 2014; Sharpe, 1966). Furthermore, the Sharpe Ratio is utilized in a variety of performance evaluation models and serves as the primary benchmark for asset allocation strategies. According to Bodie et al. (2014), this ratio offers significant insights into the efficiency of investment portfolios. It is important to note that the magnitude of the value directly corresponds to the amounts of returns received per unit of risk undertaken. The formula for the Sharpe ratio is as follows (see Khokhlov, 2011; Sharpe, 1966):

$$Sharpe\ Ratio = \frac{Rp-Rf}{\sigma p} \text{ .... (1)}$$

Rp is expected return, Rf equals risk-free-rate, and σp represents standard deviation.

The objective function (negation of Sharpe Ratio) can be written as follows (Qu and Zhang, 2023):

$$min \ - \frac{Rp - Rf}{\sigma p} \text{........ (2)}$$

Equation (2) has constraints as follows (Khokhlov, 2011; and Qu & Zhang, 2023):

$$\sum_{i=1}^{n} \omega i = 1 \text{ .... (3)}$$

Total portfolio alocation = 1 (100%), under a weighted value of asset is $0 \leq \omega i \ b_{¡}$ (the maximum level = 30% per asset).

Risk Parity Model

Risk Parity (RP) is a portfolio allocation technique that endeavors to distribute risk uniformly across assets in a portfolio, as opposed to basing this distribution on market capitalization or anticipated returns. The efficacy of this model has been demonstrated by its capacity to generate more stable portfolios in volatile market conditions (Maillard et al. 2009; Qian, 2004). The following equation is employed to represent the RP (Qian, 2004):

$$RCi = RCj, for\ all\ of\ i, j \text{........ (4)}$$

$RCi = RCj$ is risk contribution of asset i.

Total portfolio risk can be drawn as follows (Markowitz, 1952):

$$\sigma p = \sqrt{\omega^T \sum \omega} \text{ .... (5)}$$

The contribution for each asset can be formulated as follows (Maillard et al., 2009; and Qian, 2005):

$$RCi = \omega i \, . \left(\frac{\partial \sigma_p}{\partial \omega_i}\right) = \ \omega i \ (\sum \omega) i / \sigma p \quad \text{........ (5)}$$

Mixed-Integer Linear Programming

Mixed-integer linear programming (MILP) is an optimization method used to solve the problem of optimal resource allocation with linear constraints, where some of the decision variables must be integers. In the context of portfolio management, MILP is employed to ascertain the minimum requisite investment to attain the optimized portfolio weights, taking into account practical constraints such as stock lot size, asset fractionality, and minimum allocation per asset (Cornuejols & Tutuncu, 2006; and Mansini et al., 2015).

The equation of MILP can be written as follows (Cornuejols & Tutuncu, 2007):

$$min\ V \ - \sum_{i=1}^{n} Pi\ Qi \text{ .... (6)}$$

V is total value of investment, Pi equals price of financial asset i and Qi represents total unit of financial asset i.

The following assumptions were applied in the MILP analysis:

1. The portfolio weights approximate the optimal SR Max and RP weights with a maximum tracking error of ±0.01%.
2. The technical limit for domestic stock lots is a multiple of 100 stocks.
3. Investors have the option to purchase Global ETFs in whole or partial units.

4. Portfolio stock weights are non-negative, with a maximum allocation of 30% per stock in the portfolio.

Stock Portofolio Simulation

a. Benchmarking Portfolio Performance

1) Compound Annual Growth Return (CAGR)

The Compound Annual Growth Rate (CAGR) is a metric frequently utilized to assess the average annual growth of a stock portfolio over an investment period. It is regarded as being neutral to short-term volatility because it incorporates the effects of annual compounding. This formula is comprehensively delineated in the financial literature as a tool for evaluating the long-term performance of investments (Bodie et al., 2014). The compound annual growth rate (CAGR) is as follows Qian, 2004:

$$CAGR = (\frac{Vf}{Vi})^{\frac{1}{n}} - 1 \text{ …….. } (7)$$

Vf is final value of portfolio, Vi is initial value of portfolio, dan n equals year of investment.

2) Maximum Drawdown

Maximum Drawdown (MDD) is a metric that quantifies the maximum peak-to-trough decline in the value of a stock portfolio during a specified time period. The term MDD is employed to denote the maximum risk of loss that investors may encounter within a specific price decline cycle. The MDD equation is as follows (Jorion, 2007):

$$MDD = \frac{max}{t \in [0,T]} \left(\frac{Peak_t - Trough_t}{Peak_t}\right) \text{ …….. } (8)$$

3) Alpha and Beta

Alpha and Beta are two primary indicators employed to evaluate the performance and risk characteristics of a portfolio or financial asset (Grinold and Kahn, 1999). Alpha is defined as the excess return on a portfolio's performance that cannot be attributed to general market movements. Concurrently, Beta quantifies the portfolio's responsiveness to market or benchmark fluctuations. Beta values are a quantitative metric that assist investors in comprehending the extent of systematic risk exposure inherent in a stock portfolio. The Alpha equation is as follows (Grinold and Kahn, 1999):

$$\alpha = Rp - \hat{R}p \text{ …….. } (9)$$

Rp is actual return of portfolio and $\hat{R}p$ equals expected return by considering a risk model.

Furthermore, Equation of Beta can be illustrated as follows (Grinold and Kahn, 1999):

$$\beta = \frac{Cov(Rp,Rm)}{Var(Rm)} \text{ …….. } (10)$$

Rp is return of portfolio and Rm represents return of market benchmark.

4) Treynor Ratio

The Treynor ratio employs the concept of systematic risk (Beta), defined as the market risk that is not susceptible to diversification. This method finds application in well-diversified portfolios, where the unique risk (unsystematic risk) is considered to have been eliminated. The Treynor ratio equation is as follows (Treynor, 2007):

$$Treynor\ Ratio = \frac{Rp - Rf}{\beta p} \text{ .... (11)}$$

Rp is expected return, Rf is risk-free-rate, and βp equals Beta of stock portfolio.

5) Sortino Ratio

The Sortino ratio is a financial metric that is particularly concerned with downside risk, defined as the risk of a decline in investment value below the minimum acceptable return level. This method incorporates the negative deviation of the portfolio. The Sortino ratio equation is as follows (Sortino and Meer, 1991):

$$Sortino\ Ratio = \frac{Rp - Rmar}{\sigma d} \text{ .... (12)}$$

Rp is return of portfolio, $Rmar$ equals a minimum of acceptable return, and σd is downside deviation.

b. Monte Carlo Simulation

The Monte Carlo simulation is a statistical technique used to estimate the outcome of a complex process in which uncertainty is a significant factor. This technique is particularly beneficial in calculating VaR, especially in cases where the return distribution deviates from normality or when the portfolio structure is intricate.

The Monte Carlo Simulation method is characterized by a set of general steps, the first of which involves the estimation of the asset return distribution (e.g., log-normal returns). Subsequently, the simulation will generate hundreds or thousands of random return paths based on that distribution. The portfolio return for each simulation must be calculated, and the VaR must be determined based on the X percentile (e.g., 5%) of the simulated return distribution.

The Monte Carlo method has gained widespread popularity due to its ability to manage intricate portfolio structures, inter-asset correlations, and non-normal return distributions. As Antonelli et al. (2002) demonstrated, Monte Carlo methods yield more precise Value-at-Risk (VaR) estimates than conventional parametric approaches, particularly in extreme market settings. This approach has established itself as a leading method in the field of modern risk modeling.

c. Value at Risk (VaR)

Value at Risk (VaR) is a statistical metric that quantifies the maximum potential loss of a portfolio over a specified time period with a certain level of confidence. VaR is a widely utilized metric in the domain of financial risk management, serving a critical role in determining risk tolerance limits and capital allocation strategies. The VaR equation is as follows (Jorion, 2007):

$$VaR = z \cdot \sigma \cdot t \text{ .... (13)}$$

z is Z value under a certain significant level, σ equals standard deviation of portfolio, while t represents a time horizon (usually in days).

RESULT AND DISCUSSIONS

Risk-Based Portfolio Filtering

The initial step in establishing a practical, risk-based portfolio for novice investors is through a multi-layered asset selection process. The present study employs a multi-layered screening approach, encompassing four distinct stages, to assess a total of 951 domestic stocks listed on the Indonesia Stock Exchange (IDX), along with four global ETFs. The selection of parameters at each stage is informed by the most recent financial literature, thereby ensuring academic validity and relevance to retail market conditions.

Portfolio filtering is executed based on the completeness of historical data. The assets that are considered for inclusion in the study are limited to those for which complete daily closing price data is available from March 2007 to March 2025. This is imperative to ensure the integrity of the long-term time-series analysis and to facilitate the testing of the portfolio's consistency against the dynamics of the four major economic phases. In this inaugural stage, 308 domestic stocks and 4 global ETFs were selected, thereby bringing the total number of assets under consideration to 312. According to Bodie et al. (2014) and Gujarati & Porter (2009), the utilization of comprehensive historical data constitutes a basic statistical validity in long-term empirical studies.

The subsequent phase entails liquidity screening, which entails the establishment of a minimum limit of the average daily transaction value of IDR 1 billion for domestic stocks. The purpose of this threshold is to prevent the entry of small liquidity stocks that have a high market impact risk and potential price manipulation. At this stage, the number of stocks that meet the liquidity criteria is significantly reduced from 308 stocks to 94 stocks and 4 US ETF. Amihud and Mendelson seminal 1986 study posited that low-liquidity stocks exhibit elevated risk premiums.

The third stage of the process entails the screening of historical risk and return performance. In this stage, assets are evaluated based on quantitative indicators such as Compound Annual Growth Rate (CAGR) must be above 7%, annual volatility, and maximum drawdown (deviation ±5–10% from the benchmark) in five specified economic phases. For a financial asset to successfully pass the filtration stage, it is imperative that all criteria are met and their uniformity is thoroughly evaluated.

The findings indicate that no individual stock consistently outperformed during all five periods. This condition underscores the imperative for diversification. However, several global and domestic stocks demonstrated high performance, achieving a rating of 4 out of 5, including BBCA.JK (Bank Central Asia), ETF QQQ, SPY, VTI, and GLD. Furthermore, SMSM, INDF, and MYOR demonstrated a score of 3 out of 5, suggesting that they possess fundamental qualities that are satisfactory. Conversely, the majority of other financial assets received a rating of 1 out of 5.

The approach delineated in Table 1 aligns with the principle of risk-adjusted return, which stipulates the inclusion of assets that demonstrate consistent competitive performance in comparison to established benchmarks, such as IHSG and LQ45. According to Sortino & Meer (1991), a more relevant approach for conservative investors than simply projecting expected returns is asset selection based on downside risk and return consistency.

Table 1. Filtering Liquidity of Stocks Portfolio

QQQ	PTRO.JK	KKGI.JK	NISP.JK	MYOR.JK
GLD	APIC.JK	SONA.JK	PNLF.JK	AUTO.JK
VTI	TSPC.JK	KARW.JK	PNBN.JK	BBNI.JK*
SPY	INDF.JK*	PSAB.JK	SSIA.JK	KIJA.JK
BNLI.JK	AKRA.JK*	BBCA.JK*	INPC.JK	PGAS.JK*
TIRA.JK	UNTR.JK*	BMRI.JK*	JIHD.JK	LSIP.JK
TRUS.JK	PTBA.JK*	BNGA.JK	DOID.JK	SMDR.JK
PANR.JK	CMNP.JK	SMSM.JK	ANTM.JK*	GJTL.JK
ITMA.JK	JPFA.JK*	MTDL.JK	MAPI.JK*	MEDC.JK*
RAJA.JK	DKFT.JK	ISAT.JK*	BKSL.JK	KPIG.JK
IMAS.JK	PYFA.JK	AGRO.JK	LPPF.JK	UNVR.JK*
WAPO.JK	INDX.JK	MLBI.JK	DILD.JK	GGRM.JK
ASII.JK*	AIMS.JK	HMSP.JK	MPPA.JK	INTP.JK
BBRI.JK*	MAIN.JK	KLBF.JK*	CNKO.JK	BDMN.JK
CPRO.JK	TLKM.JK*	LPKR.JK	MAYA.JK	INCO.JK*
BFIN.JK	CPIN.JK*	EXCL.JK*	ENRG.JK	BVIC.JK
ULTJ.JK	ARNA.JK	PWON.JK	SMGR.JK*	ADHI.JK
SCMA.JK	TKIM.JK	CTRA.JK*	AALI.JK	BMTR.JK
TINS.JK	INKP.JK*	SMRA.JK*	RALS.JK	
MLPL.JK	BRPT.JK*	BCAP.JK	BBKP.JK	* = LQ45

The fourth stage is fundamental evaluation. The evaluation is conducted using financial ratio analysis, which reflects profitability, efficiency, capital structure, and market valuation. The following ratios are used: return on equity (ROE), earnings per share (EPS), growth, net profit margin (NPM), operational efficiency (OPEX/revenue), debt-to-equity ratio (DER) as a marker of financial leverage, price-to-earnings ratio (PER) and price-to-book value ratio (PBV) as valuation indicators, and dividend policies such as dividend per share (DPS) and dividend payout ratio (DPR). The findings indicate that the majority of domestic stocks meet the established criteria, with the exception of MYOR.

The exchange-traded fund (ETF) is determined by several factors, including historical return performance, risk consistency, and the structure and scope of the index it represents. The exchange-traded fund (ETF) selected for the portfolio are SPY, which provides the primary exposure to diversified global equities, and GLD, which functions as a hedge asset that enhances portfolio resilience in extreme market conditions. According to Palepu & Healy (2012) and White (2003), these indicators are most often employed in the long-term investment feasibility analysis. Their utilization is primarily attributed to their capacity to reflect operational efficiency, profitability, and fair valuation. Stocks with volatile financial performances are eliminated.

The culmination of this selection process yielded five prominent assets: The analysis will include BBCA, INDF, and SMSM as dominant domestic stocks, and two global ETFs, namely SPY (S&P 500) and GLD (gold-based), as a representation of international diversification and hedging instruments. This composition illustrates a multi-asset portfolio that is fundamentally strong and has proven to be stable in volatile market conditions.

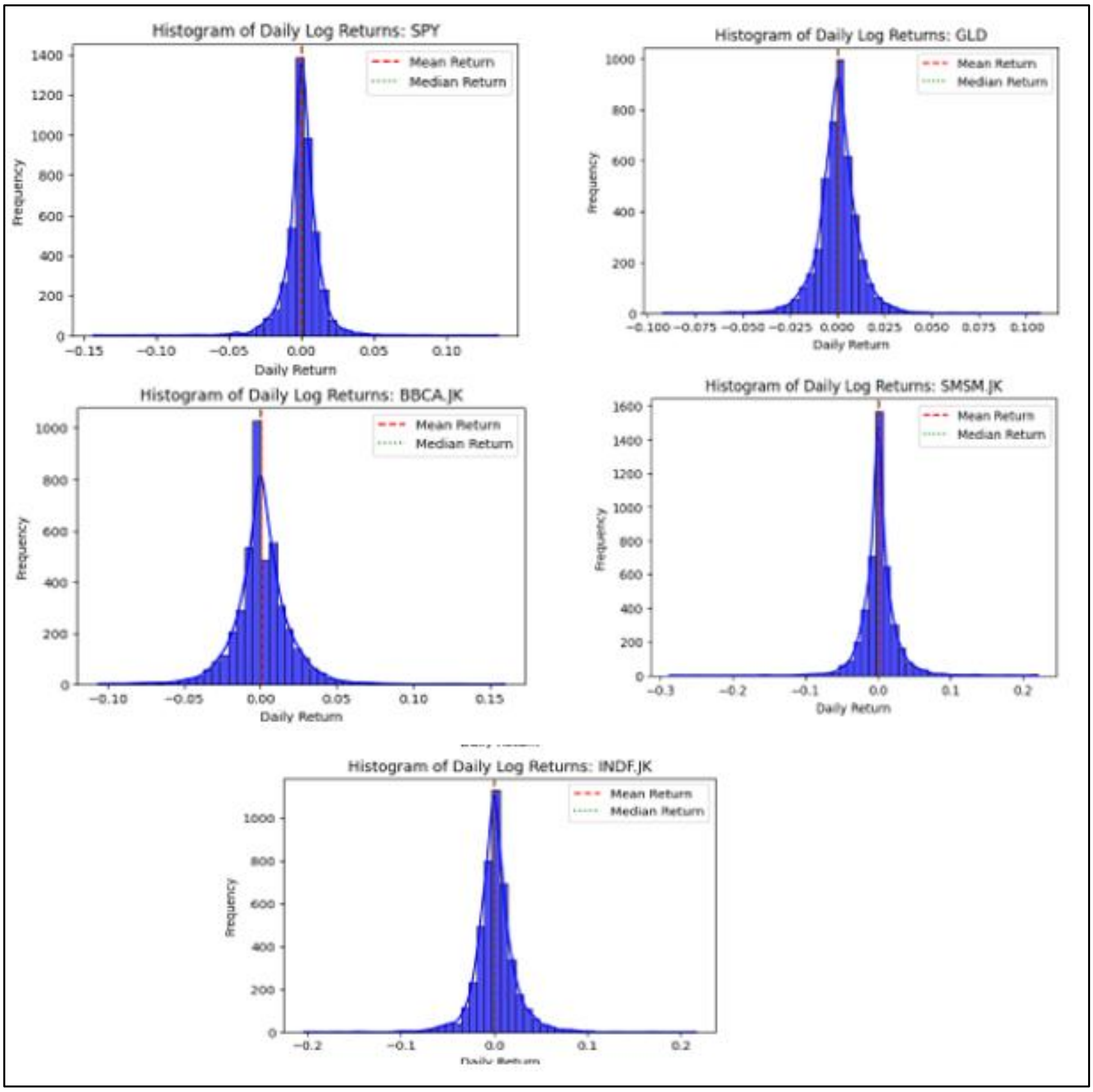

Figure 1. Histogram of Stock Portfolio

Sharpe Ratio Maximization and Risk Parity

The Sharpe Ratio Maximization model is a financial risk management model that aims to maximize the efficiency of risk to return using the Sharpe Ratio indicator. The Sharpe Ratio is the ratio between excess return and portfolio volatility. The optimization process is executed through the utilization of the Sequential Least Squares Quadratic Programming (SLSQP) algorithm, with constraints including a maximum weight of 30% per asset and a cumulative weight of 100%. The optimization results indicate an aggressive allocation with the following composition: The assets under consideration are as follows: BBCA (30%), SMSM (30%), SPY (22.8%), GLD (16.2%), and INDF (1%). The model generates an annual expected return of 16.28%, accompanied by a volatility of 17.14%, yielding a Sharpe Ratio of 0.5417.

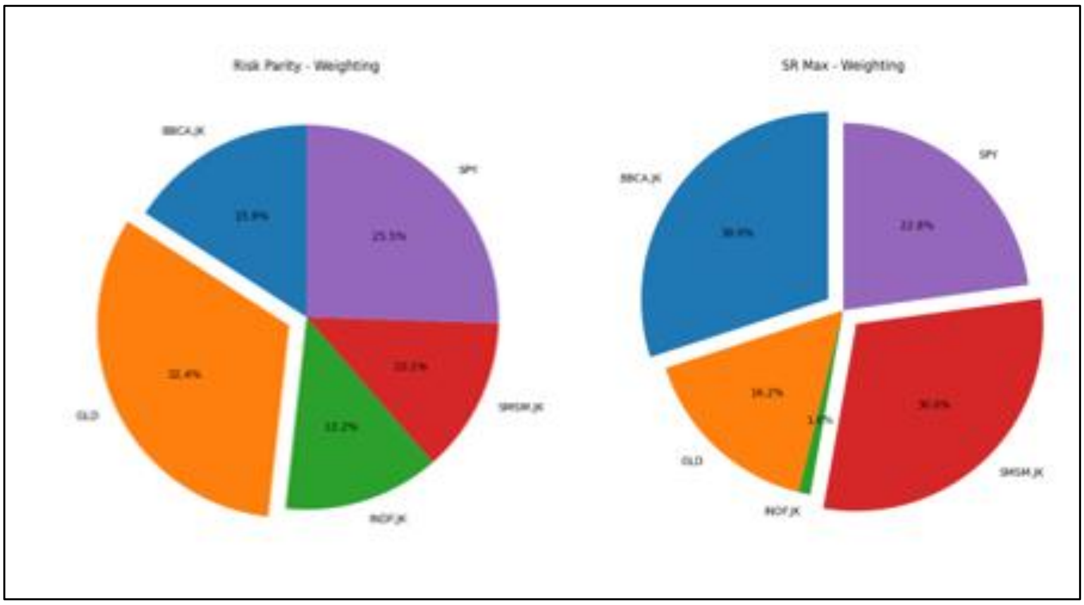

Figure 2. SR Max and RP Weighting

The Risk Parity model is predicated on the principle of allocating portfolio risk equally among assets based on their respective contributions to volatility. The optimization results indicate a more balanced weighting: The top five holdings are as follows: GLD (32.4%), SPY (25.5%), BBCA (15.9%), SMSM (13.2%), and INDF (13%). The model's primary objective is to achieve stability, with an anticipated return of 13.13%, a volatility of 13.24%, and a Sharpe Ratio of 0.4633.

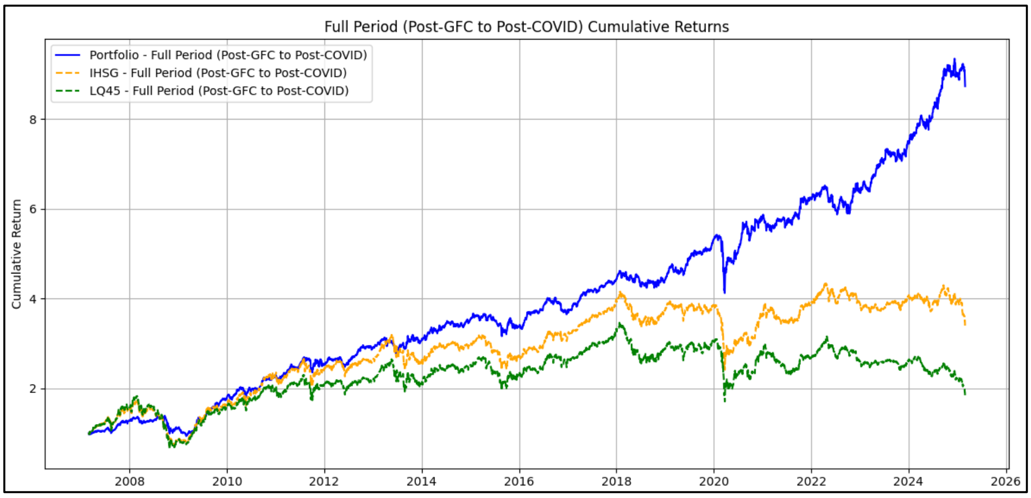

Figure 3. SR Max Visualization of Stock Portfolio

The two aforementioned portfolio calculation models demonstrate complementary approaches. The Sharpe ratio is a metric that is particularly well-suited for investors who prioritize achieving the highest possible returns. Conversely, Risk Parity is well-suited for novice investors who prioritize portfolio stability and symmetric risk diversification.

Minimum Levels of Investment for Selecting Stock Portofolio

The current study determines the minimum capital required to replicate a real portfolio by novice investors. This calculation is contingent upon the technical limitations of the market, wherein domestic stock transactions are executed in lots of 100 shares. Concurrently, global ETFs are available in full or fractional units, as dictated by the platform.

To address these limitations, the Mixed-Integer Linear Programming (MILP) optimization method is employed. The objective of optimization is to minimize the total initial capital while maintaining the tracking error to the optimal weight below ±0.01%. The integration of integer variables, which are employed in the context of domestic stocks, with continuous variables, which are utilized in the context of ETFs, enables the precise realization of a portfolio. This is achieved by determining the number of lots and real units. Pursuant to the prevailing market price at the inception of the investment period, the realization of the SR Max Portfolio is contingent upon a minimum capital of IDR 8,757,282. However, it should be noted that the Risk Parity Portfolio has a minimum capital requirement of IDR 10,270,371.

Table 2. Distribution of Minimum Investment for Selecting Stocks Portfolio

	SR Max			Risk Parity		
	Lot/Unit	Value	Weighting	Lot/Unit	Value	Weighting
BBCA.JK	74	2.627.000	30,00%	46	1.633.000	15,90%
GLD	2,126	1.413.425	16,14%	4,997	3.322.191	32,35%
INDF.JK	1	90.200	1,03%	15	1.353.000	13,17%
SMSM.JK	973	2.627.100	30,00%	498	1.344.600	13,09%
SPY	1,999	1.999.556	22,83%	2,617	2.617.579	25,49%

As illustrated in the above table, the calculation results are estimations of the minimum capital required, considering the optimal weight and the initial investment price conditions. However, this optimization method is characterized by its flexibility and adaptability. Investors with capital above the minimum value can rerun the MILP algorithm to produce a lot or unit configuration that matches the actual amount of funds, without altering the direction of the strategy. Conversely, if investors possess a limited amount of capital, they can still construct a portfolio with a compromise on weight accuracy, provided they understand the potential deviation of performance and re-simulate the risk and return. This approach offers novice investors the opportunity to adjust their initial capital to align with their financial capabilities, while adhering to the fundamental principles of an efficient and measurable risk-based portfolio.

Simulating and Benchmarking of Stock Portfolio

The stock portfolio during the study period (2007:1 March–2025:1 March) was subjected to a long-term performance evaluation using Sharpe Ratio Maximization (SR Max) and Risk Parity (RP). The stock portfolio was subjected to a comprehensive evaluation that encompassed four distinct economic phases: the global financial crisis (GFC), the ensuing recovery period, the pre-pandemic era, the pandemic period, and the post-pandemic era. This analysis was conducted with the objective of assessing the portfolio's performance in the context of prevailing market dynamics. The study's findings are elucidated in Table 3.

Table 3. Results of Stocks Portfolio Simulation

	Total Return	CAGR	Volatility	MaxD	Sharpe
IHSG	230.08%	6.86%	19.54%	-58.70%	0.01
LQ45	78.91%	3.28%	23.75%	-64.32%	-0.14
Max SR	1379.33%	16.15%	17.39%	-39.11%	0.53
Risk Parity	774.87%	12.81%	13.24%	-32.98%	0.46

The simulation results indicate that the SR Max portfolio offers the most aggressive performance, with a cumulative total return of 1379.33%, a CAGR of 16.15%, and a Sharpe Ratio of 0.53. Conversely, the RP portfolio has yielded a return of 774.87%, exhibiting a compound annual growth rate (CAGR) of 12.81% and a Sharpe Ratio of 0.46. These findings suggest that a more moderate and stable strategy may be preferable. For illustrative purposes, the JCI was examined, and it was found to have a CAGR of 6.86%. The LQ45 exhibited a lower CAGR of 3.28%, and its Sharpe Ratio was determined to be 0.01 and -0.14, respectively.

In terms of risk, the RP strategy demonstrates a stability advantage, exhibiting an annual volatility of 13.24% and a maximum drawdown of -32.98%. It has been demonstrated that the condition under consideration is more defensive than SR Max, which has a volatility of 17.39% and a drawdown of -39.11%. It is noteworthy that both approaches demonstrated a substantially higher degree of resilience to market pressures when compared to IHSG (-58.70%) and LQ45 (-64.32%), which experienced a substantial decline in value during the crisis period. With respect to return contribution, the SR Max portfolio is influenced by SMSM (41.93%). Conversely, the RP model exhibits a more equitable distribution of contributions, particularly from GLD (26.96%), SPY (22.78%), and BBCA (20.18%).

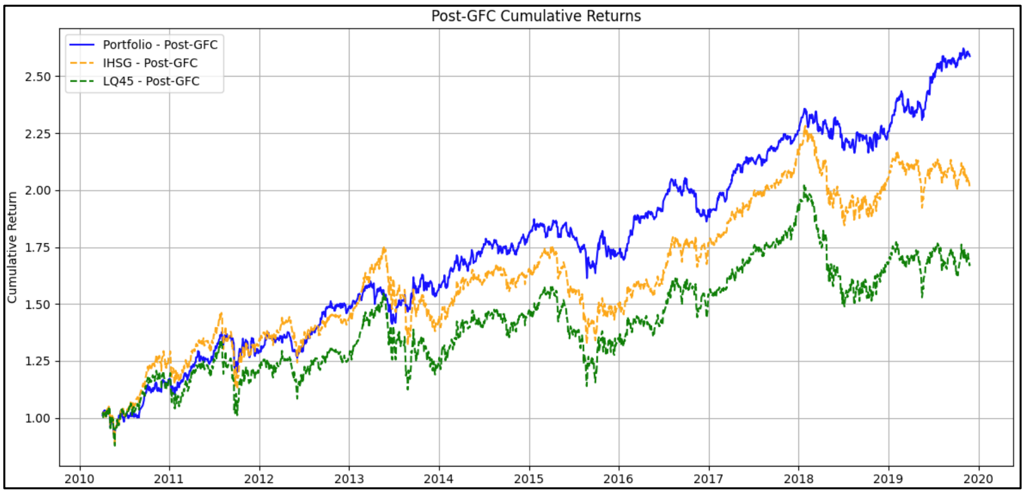

Figure 4. SR Max of Stock Portfolio Simulation

The extant literature also posits that, while Sharpe Ratio Maximization is theoretically optimal, it tends to rely on estimates of expected future returns that are difficult to predict with accuracy. Conversely, the Risk Parity approach does not necessitate the estimation of returns and prioritizes the analysis of risk structure, facilitating consistent execution in practical settings. This methodology has been demonstrated to yield competitive outcomes over an extended timeframe (Shah and Parikh, 2019). Besides, Horn & Oehler, (2024) considered ESG rating on stock portfolio in several developed countries during 2014-2019.

During the Global Financial Crisis (GFC) period of 2007–2010, financial markets experienced extreme stress, marked by the collapse of the subprime mortgage market in the US, the bankruptcy of large institutions such as Lehman Brothers, and a significant decline in global stock markets. A detailed exposition of the outcomes of the stock portfolio simulation during the Global Financial Crisis (GFC) period is provided in Table 4.

Table 4. Result of Stock Portfolio Simulation during GFC

	Total Return	CAGR	Volatility	MaxD	Sharpe
IHSG	80.10%	21.01%	29.99%	-58.70%	0.47
LQ45	69.36%	18.62%	35.02%	-64.32%	0.34
***Max* SR**	139.58%	32.73%	25.94%	-39.11%	0.92
Risk Parity	96.31%	24.43%	19.67%	-32.98%	0.85

The findings derived from the simulation suggest that the SR Max portfolio yielded a total return of 139.58%, accompanied by a Compound Annual Growth Rate (CAGR) of 32.73%, a volatility of 25.94%, and a Sharpe Ratio of 0.92. Concurrently, the RP portfolio yielded a return of 96.31%, exhibiting a compound annual growth rate (CAGR) of 24.43%, a volatility of 19.67%, and a Sharpe Ratio of 0.85.

For the sake of comparison, IHSG and LQ45 recorded Compound Annual Growth Rates (CAGRs) of 21.01% and 18.62%, respectively, with extreme drawdowns of -58.70% and -64.32%. In this particular case, research has demonstrated that RP exhibits a comparatively diminished drawdown percentage of -32.98%, in contrast to the -39.11% exhibited by SR Max, which was found to demonstrate the capacity to sustain a relatively moderate level of drawdown. With respect to asset contribution, SR Max demonstrates a clear predominance from SMSM (58.20%) and BBCA (34.50%), suggesting a significant reliance on two prominent domestic stocks. Conversely, RP employs a more egalitarian approach to the distribution of contributions. BBCA (32.06%), INDF (23.26%), and GLD (20.41%).

This finding aligns with the notion that Risk Parity-based strategies possess a structural advantage in the management of downside risk, particularly during systemic crises. This approach is characterized by its independence from estimates of future returns and the balancing of risk contributions across assets. Consequently, this method yields a more stable portfolio when confronted with concurrent drawdowns across asset classes (Qian, 2011).

The period following the global financial crisis (GFC) of 2008 (2010–2019) signifies a phase of relatively stable global economic recovery (see Table 5). During this period, global monetary policy was characterized by its accommodative nature, interest rates remained low, and market sentiment underwent a gradual recovery.

This environment offered significant opportunities for asset price growth, particularly in the global technology and financial sectors. Furthermore, the Sharpe Ratio Maximization (SR Max) approach demonstrated a clear advantage in terms of returns. The SR Max portfolio yielded a total return of 251.81%, accompanied by a Compound Annual Growth Rate (CAGR) of 13.93% and a Sharpe Ratio of 0.49. In contrast, the Risk Parity (RP) approach yielded a total return of 155.83%, a Compound Annual Growth Rate (CAGR) of 10.23%, and a Sharpe Ratio of 0.32. The findings demonstrated that both outcomes exhibited substantial superiority over the established benchmarks, IHSG (CAGR of 7.30%, and SR of 0.05) and LQ45 (CAGR of 5.26%, and SR of -0.06). These findings corroborate the efficacy of the quantitative approach in capitalizing on favorable market trends.

Table 5. Result of Stock Portfolio Simulation in Post-GFC

	Total Return	***CAGR***	***Volatility***	***MaxD***	***Sharpe***
IHSG	97.31%	7.30%	16.57%	-24.65%	0.05
LQ45	63.92%	5.26%	20.25%	-27.63%	-0.06
***Max* SR**	251.81%	13.93%	14.39%	-17.40%	0.49
Risk Parity	155.83%	10.23%	11.02%	-13.83%	0.32

In terms of risk, SR Max demonstrated an annual volatility of 14.39%, accompanied by a maximum drawdown of -17.40%. Concurrently, RP exhibited a volatility of 11.02% and a drawdown of -13.83%. The strategy of distributing risk contributions in a balanced manner should be carried out as emphasized by (Anderson et al., 2011). With respect to the return contributions of assets, the SR Max portfolio once again demonstrates a reliance on leading domestic stocks, including BBCA (42.44%) and SMSM (34.05%). In contrast, the distribution of returns on RP tends to exhibit greater evenness, with the following composition: SPY (30.44%), BBCA (28.64%), GLD (17.90%), SMSM (13.83%), and INDF (9.18%). This condition can indicate superior structural stability over an extended period.

The literature also makes note of the fact that in market conditions characterized by an increasing stock performance trend, the SR Max strategy, which pursues the return-to-risk ratio, can effectively capture alpha from leading stocks, especially if the expected return estimation is based on strong historical data (Clarke et al., 2011). Conversely, RP has been regarded as a dependable strategy for long-term investors, as it emphasizes stability and the consistent accumulation of returns.

The period of the global pandemic known as "Coronavirus Disease 2019 (2019–2022)" was characterized by widespread disruption to economic activity, as evidenced by the implementation of lockdowns, the interruption of supply chains, and the profound sense of uncertainty among investors, leading to significant fluctuations in asset prices across various categories. In this context, the objective of this study is to evaluate the performance of the SR Max and RP portfolios in comparison to the domestic market benchmarks, IHSG and LQ45.

Table 6. Result of Stock Portfolio Simulation during COVID-19 Pandemic

	Total Return	CAGR	Volatility	MaxD	Sharpe
IHSG	3.32%	1.58%	21.24%	-37.47%	-0.20
LQ45	-8.99%	-4.43%	28.52%	-44.86%	-0.38
***Max* SR**	23.87%	10.85%	19.24%	-28.49%	0.22
Risk Parity	22.74%	10.36%	15.06%	-23.98%	0.25

As illustrated in Table 6, the portfolio strategy focused on Sharpe Ratio Maximization (SR Max) exhibited a compound annual growth rate (CAGR) of 10.85%, a total return of 23.87%, and a Sharpe Ratio of 0.22. Concurrently, Risk Parity (RP) exhibited a Compound Annual Growth Rate (CAGR) of 10.36%, a total return of 22.74%, and a Sharpe Ratio of 0.25. The performance of the stock portfolio simulation has a tendency to outperform the IHSG (CAGR of 1.58% and SR of -0.20) and LQ45 (CAGR of -4.43% and SR of -0.38).

With regard to risk, the RP portfolio demonstrates a defensive advantage, exhibiting a volatility of 15.06% and a maximum drawdown of -23.98%. This performance stands in contrast to the more volatile SR Max, which exhibits a volatility of 19.24% and a drawdown of -28.49%, suggesting a potential for higher returns from a less volatile portfolio. These findings substantiate the hypothesis that RP exhibits enhanced resilience to extreme market shocks. The return contribution is indicative of the disparities in characteristics among distinct stock portfolios. Specifically, SR Max is predominantly influenced by assets such as SPY (49.26%) and BBCA (24.86%), indicative of a propensity to allocate capital to high-performing assets. In contrast, the distribution of RP is more uniform, with the primary contributions stemming from SPY (57.85%), GLD (34.81%), and BBCA (13.86%).

The findings demonstrate that RP exhibits a Sharpe Ratio that exceeds that of SR Max, owing to the tendency of SR Max to depend on a limited number of primary driving assets. Concurrently, RP disseminates exposure in a manner that fosters enhanced stability in the face of market turbulence. RP is a method of risk management that aims to distribute risk contributions equally and avoid risk concentration. This approach is intended to enhance the structural resilience of the portfolio (Qian, 2011).

Table 7. Result of Stock Portfolio Simulation during Post-COVID-19 Pandemic

	Total Return	CAGR	Volatility	MaxD	Sharpe
IHSG	-14.67%	-4.90%	12.55%	-23.10%	-0.97
LQ45	-33.03%	-11.94%	14.88%	-42.66%	-1.40
***Max* SR**	38.82%	10.96%	13.74%	-13.56%	0.34
Risk Parity	40.52%	11.39%	10.03%	-9.96%	0.50

In the Post-COVID-19 era, spanning the years 2022 to 2025, the strategic management of a stock portfolio entails a delicate balance between the pursuit of growth opportunities and the implementation of risk management measures (see Table 7 for a detailed breakdown). The simulation results indicate that the Risk Parity (RP) portfolio exhibited the optimal performance during the post-pandemic period. The total return on investment was 40.52%, with a compound annual growth rate (CAGR) of 11.39%, a maximum drawdown of -9.96%, and a Sharpe ratio of 0.50. This model demonstrated the highest degree of stability, exhibiting the lowest volatility (10.03%) in comparison to the other models.

Furthermore, Sharpe Ratio Maximization (SR Max) exhibited robust performance, with a total return of 38.82%, a Compound Annual Growth Rate (CAGR) of 10.96%, and a Sharpe Ratio of 0.34. However, the drawdown rate exhibited a higher magnitude of decline (-13.56%) with an annual volatility of 13.74%. The performance of this stock portfolio exhibited superiority over the domestic benchmark, which was comprised of IHSG, with a Compound Annual Growth Rate (CAGR) of -4.90% and a Sharpe Ratio of -0.97. In contrast, LQ45 demonstrated a more unfavorable performance, with a CAGR of -11.94% and a Sharpe Ratio of -1.40.

With respect to return contribution, the RP portfolio demonstrates a more balanced structure, comprising GLD at 40.48%, SPY at 25.21%, SMSM at 18.97%, and INDF at 9.76%. This condition is indicative of the efficacy of the model in reducing risk concentration. Conversely, SR Max exhibits a greater degree of reliance on SMSM (44.58%) and SPY (23.15%), with substantial support from GLD (20.72%).

The present study lends further credence to the hypothesis that the RP approach is more adaptable to the complex post-pandemic dynamics that have emerged. This hypothesis is supported by the findings that hedging assets such as gold (GLD) and global exposure through SPY are associated with the RP approach. According to Maillard et al. (2009), RP designs that minimize risk concentration offer a competitive advantage during periods of unexpected market stress. Alternatively, Savaei et al. (2024) considered the stock portfolio simulation using risk based on the conditional drawdown-at-risk of hybrid possibilistic and flexible model (CDaR-HPFM) under uncertainty.

Alpha, Beta, Treynor, and Sortino Ratio

In order to expand the dimensions of portfolio performance assessment, this study evaluates four additional risk indicators, namely: Alpha, Beta, Treynor Ratio, and Sortino Ratio. The complementarity of these four indicators to the analysis of return and volatility is addressed. Furthermore, the four indicators offer a more comprehensive perspective on the efficiency of systematic risk and downside risk.

Table 8. Alpha, Beta, Treynor and Sortino Ratio

	Beta vs (IHSG)	**Alpha vs (IHSG)**	**Treynor vs (IHSG)**	**Model vs Sortino (IHSG)**
***Max* SR**	0.4867	0.0004	0.1897	0.7318 vs 0.0165
RP	0.4201	0.0002	0.1442	0.6018 vs 0.0165
	Beta vs (LQ45)	*Alpha* vs (LQ45)	Treynor vs (LQ45)	*Model* vs Sortino (LQ45)
***Max* SR**	0.4045	0.0004	0.2283	0.7318 vs -0.1839
RP	0.3473	0.0003	0.1744	0.6018 vs -0.1839

In consideration of the Beta portfolio, the Sharpe ratio optimization (SR Max) portfolio exhibits moderate market sensitivity, as indicated by betas of 0.4867 (IHSG) and 0.4045 (LQ45). Conversely, the Risk Parity (RP) portfolio adopts a more defensive strategy, exhibiting betas of 0.4201 (IHSG) and 0.3473 (LQ45). The Beta values obtained from this analysis suggest that both portfolios demonstrate a satisfactory level of diversification. Chow et al, (2014) observed that low-beta strategies have the capacity to systematically reduce volatility without compromising long-term returns, particularly in global markets and developing countries.

In regard to alpha, both stock portfolios demonstrate favorable outcomes when measured against domestic benchmarks, such as the IHSG and LQ45 indices. Despite the seemingly negligible figures, this advantage is indicative of the efficacy of asset allocation strategies and cross-geographic diversification, rather than merely the capacity to select individual stocks. This is particularly notable given the inclusion of global instruments such as SPY and GLD in the portfolio. Consequently, the resulting alpha is more appropriately interpreted as the result of the structural efficiency of the portfolio, not active speculation. This finding aligns with Ilmanen's, (2011) proposition that alpha can be generated intrinsically through meticulous risk management and diversification, obviating the necessity of market timing or discerning investment opportunities.

The Treynor ratio, a measure of efficiency in the context of market risk, indicates that SR Max exhibits a higher value compared to RP. Specifically, the Treynor ratio for SR Max is 0.1897 and 0.2283, while for RP it is 0.1442 and 0.1744. However, the Sortino ratio provides a contradictory outcome. A cost-benefit analysis reveals that RP exhibits a relative advantage (0.2679) over SR Max (0.2655) when considering only downside deviation. This condition has been demonstrated to indicate enhanced portfolio resilience to potential losses (Kolbadi & Ahmadinia, 2011; and Sortino & Meer, 1991).

Value at Risk and Monte Carlo

To assess the portfolio's capacity to withstand extreme risk, a Monte Carlo simulation was conducted, employing 100,000 iterations and utilizing the historical distribution of daily returns for each stock over the period from 2007 to 2025. The simulation employs a 10-year time horizon, spanning 2,520 days, and maintains a 99% confidence level. This approach aligns with industry standards and is supported by studies conducted by Glasserman (2003) and Jorion (2007).

The simulation results indicate that, with a 99% confidence level, both portfolios exhibit positive Value at Risk (VaR) values. The SR Max portfolio exhibited a VaR of 35.33%, accompanied by an estimated average return of 162.60%. Concurrently, RP recorded a VaR of 32.53%, accompanied by an estimated average return of 130.51%. This finding suggests that, despite the SR Max strategy's higher potential return, RP offers a more symmetrical and stable return distribution. This condition reflects a balanced risk allocation approach (Antonelli et al., 2002). This approach offers valuable insights for novice investors by demonstrating that, under certain conditions, the potential for significant losses can be mitigated and communicated in a probabilistic format.

Sensitivity Analysis of Value at Risk

In order to comprehend the temporal and confidence level variations in portfolio extreme risk, a sensitivity analysis is conducted on Value at Risk (VaR) values at various investment horizons (63 to 2,520 days) and confidence levels (90%, 95%, and 99%), as illustrated in Table 9. The simulation results demonstrate that Sharpe Ratio Maximization (SR Max) and Risk Parity (RP) manifest non-linear patterns over time, thereby reflecting the intricacies of market return distributions, which do not invariably adhere to straightforward predictive patterns, particularly in the short and medium term. This phenomenon has been discussed in the financial risk literature as an effect of fat tails distribution and volatility clustering (Jorion, 2007).

Table 9. Sensitivity Analysis Value at Risk (VaR)

Max SR, Initial Investment: 74,481,839 IDR						
	90%		95%		99%	
Days	Value	%	Value	%	Value	%
63	-5,230,009	-7.02%	-7,601,626	-10.21%	-12.133,444	-16.29%
126	-5,723,474	-7.68%	-9,065,104	-12.17%	-15,323,325	-20.57%
252	-4,463,618	-5.99%	-9,254,779	-12.43%	-17,915,157	-24.05%
756	7,317,069	9.82%	-510,487	-0.69%	-15,713,352	-21.10%
1260	23,469,005	31.51%	12,770,629	17.15%	-7,101,392	-9.53%
2520	68,382,203	91.81%	53,486,117	71.81%	25,906,102	34.78%

Risk Parity, Initial Investment: 213,618,321 IDR						
	90%		95%		99%	
Days	Value	%	Value	%	Value	%
63	-11,043,468	-5.17%	-16,396,128	-7.68%	-25,841,304	-12.10%
126	-11,540,134	-5.40%	-18,926,495	-8.86%	-32,701,985	-15.31%
252	-8,387,709	-3.93%	-18,219,511	-8.53%	-37,887,130	-17.74%
756	20,751,297	9.71%	2,944,150	1.38%	-31,384,332	-14.69%
1260	58,227,038	27.26%	35,190,459	16.47%	-9,306,114	-4.36%
2520	164,296,308	76.91%	132,152,725	61.86%	71,033,670	33.25%

In the SR Max model, the highest risk of loss was documented at the medium horizon, which is 252 days with a VaR value of -24.05%. However, as the investment duration increases, the VaR value undergoes a substantial improvement, reaching 34.78% at the 2,520-day horizon. This finding suggests that, despite SR Max's tendency to exhibit volatility in the short term, it possesses the capacity to generate a positive return probability over an extended timeframe. This condition aligns with the model's emphasis on return efficiency, yet it exhibits heightened vulnerability to short-term market volatility (Ilmanen, 2011).

The Risk Parity portfolio exhibits a more consistent stability in risk distribution. The most adverse VaR scenario transpired at the 252-day horizon, exhibiting a level of -17.74%. However, it underwent a substantial decline, reaching a mere -4.36% at 1,260 days. Additionally, this condition exhibited a favorable progression, achieving a positive level of 33.25% at 2,520 days. This finding indicates that the RP strategy necessitates a more extended period to achieve return stability through risk equalization between assets. This approach aligns with the principle of risk budgeting, which posits that an even distribution of risk contributions can mitigate tail risk over time (Qian, 2004).

The sensitivity analysis indicates that long-term strategies can mitigate extreme risks; however, critical intermediate periods (approximately 126–252 days) persist. This phenomenon exemplifies the tendency for risk fluctuations to widen prior to narrowing. The practical implications for novice investors are as follows: first, an adequate level of understanding of risk dynamics across horizons is necessary; second, investment horizon discipline according to risk profiles must be observed. These findings lend support to the argument that portfolio strategies must be designed not only for efficiency, but also for the resilience of distribution risk in a realistic time trajectory for retail investors (Markowitz, 1952; Meucci, 2005).

Paired t-test and Return Contribution

A paired t-test was employed to assess the disparities in portfolio returns (SR Max and Risk Parity) vis-à-vis two primary benchmarks cover the Jakarta Composite Index (JCI) and the LQ45 index (LQ45) during the period 2007–2025 (see Table 10). The Sharpe Ratio Maximization and Risk Parity portfolios exhibited statistically significantly different return performance compared to the Jakarta Composite Index (JCI) and the LQ45 index. The findings support the hypothesis that quantitative investment strategies that diversify risk can offer substantial benefits in comparison to passive strategies.

Table 10. Result of Paired t-Test

	Stock Market	t-statistics	p-value	Significant (<5%)
SR MAX	IHSG	2.0674	0.0388	Yes
SR MAX	LQ45	2.5461	0.0109	Yes
Risk Parity	IHSG	2.3637	0.0181	Yes
Risk Parity	LQ45	2.8786	0.0040	Yes

The SR Max portfolio demonstrated a cumulative return of 1,379.33%, indicating a compound annual growth rate (CAGR) of 16.15%, a volatility level of 17.39%, a maximum drawdown of -39.11%, and a Sharpe ratio of 0.53. This performance significantly exceeded that of the JCI (230.08% with a CAGR of 6.86% and a SR of 0.01) and the LQ45 (78.91% with a CAGR of 3.28% and a SR of -0.14). Conversely, the Risk Parity portfolio exhibited a more conservative approach, yielding a return of 774.87%, a CAGR of 12.81%, a volatility level of 13.24%, a drawdown of -32.98%, and a Sharpe Ratio of 0.46. These conditions yield superior measurement results in comparison to the benchmark. This finding suggests that SR Max demonstrates a propensity for return aggressiveness, while RP is more pronounced in risk stability.

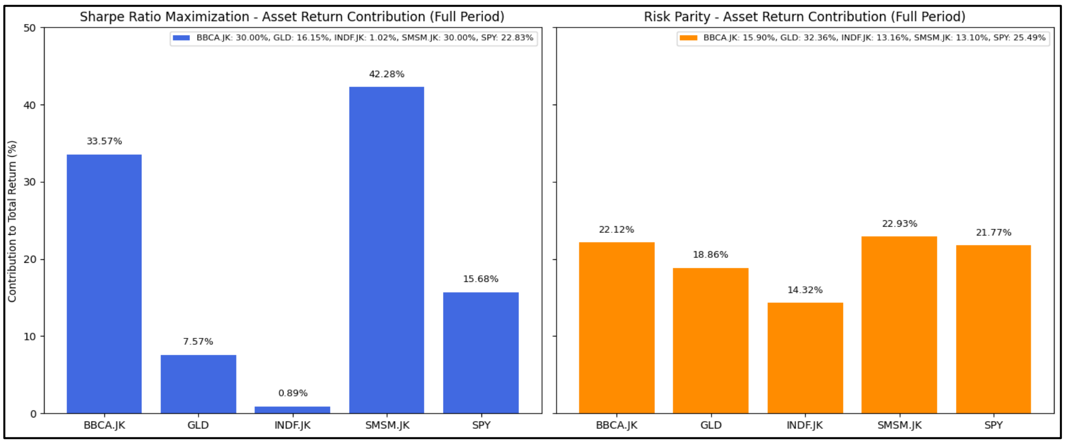

Figure 5. Return Contribution

As illustrated in Figure 5, SR Max demonstrates a tendency to prioritize domestic stocks, particularly those represented by BBCA (33.57%) and SMSM (42.28%). Consequently, the calculation of returns is contingent upon the performance of specific assets. Conversely, Risk Parity allocates contributions more uniformly across a diverse array of exchange-traded funds (ETFs), including GLD (32.36%), SPY (25.49%), BBCA (22.12%), SMSM (22.93%), and INDF (14.32%). This condition lends further support to the argument that RP places significant emphasis on risk balance across assets.

CONCLUSION

The objective of the current study is to utilize a long time series period from March 2007 to March 2025 to simulate a risk-based stock portfolio model. The two primary approaches employed are Sharpe Ratio Maximization and Risk Parity. The findings indicate that SR Max demonstrates notable proficiency in absolute returns, particularly during periods of expansionary markets. However, there is a possibility for relatively high volatility and drawdown. Conversely, Risk Parity has demonstrated a propensity to offer more stable and defensive performance, particularly during periods of crisis and in the aftermath of the post-covid-19 pandemic. It has been demonstrated that both approaches have been shown to exceed the performance of the domestic stock portfolio benchmark, which is comprised of the IHSG and LQ45. Furthermore, both approaches demonstrate consistency in stock portfolio performance simulations, as evidenced by metrics such as the Compound Annual Growth Rate (CAGR), the Sharpe Ratio, and the drawdown. Additionally, a positive return distribution is exhibited through the Value at Risk (VaR) test, which is based on Monte Carlo simulation. The findings from the sensitivity and portfolio risk analysis (Alpha, Beta, Treynor, and Sortino Ratio) further substantiate the attributes inherent in each approach to systematic and asymmetric risk.

This study has several implications. Firstly, the results of risk-based portfolio simulations can be utilized by investors to select stock options that offer stable returns and low risk. Secondly, the development of return and risk of stock portfolios tends to be more sensitive during periods of crisis than during stable periods. Therefore, investors must mitigate risk and diversify stocks. Thirdly, the government can enhance its oversight and governance of the stock exchange to ensure the stability of stock portfolios.

The limitation and further research can be elaborated in several ways. First, the current study employs SR Max and RP methods to simulate stock portfolio maximization. The further research can consider others methods such as stress test and threshold regression. The current study considers US stock market as an international benchmark. The further research can select others countries such as China, Japan, and Europe. Besides, the further research can employ macroeconomic and institutional indicators to provide a better stock portfolio simulation.

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