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Engineering-Based Investment Modeling in Emerging Markets: Decision Analytics for Portfolio Management in Indonesia

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Abstract

This study presents an engineering-based approach to investment modeling in the context of emerging markets, with a focus on portfolio management strategies in the Indonesian equity market. By integrating computational finance techniques and decision analytics, the research develops a structured framework for assessing risk-return dynamics and optimizing asset allocation decisions. Using daily stock return data from two representative companies across different economic sectors—PT Telekomunikasi Indonesia Tbk (TLKM.JK) from telecommunications and PT Petrosea Tbk (PTRO.JK) from energy/mining—the study applies Monte Carlo simulation, Value at Risk (VaR), and statistical decision modeling to evaluate both individual and combined investment performance. Results indicate distinct risk-return profiles, where PTRO.JK offers higher average returns but with significantly greater volatility compared to TLKM.JK. A cross-sector portfolio consisting of 60% TLKM.JK and 40% PTRO.JK demonstrates notable diversification benefits, reducing overall portfolio risk as evidenced by improved VaR estimates. For a hypothetical IDR 100 million investment, the diversified portfolio reduces maximum expected loss by more than 50% compared to investing solely in TLKM.JK. These findings highlight the effectiveness of quantitative, model-driven approaches in supporting strategic investment decisions. By bridging financial engineering methodologies with practical portfolio management needs in Indonesia, this study contributes a replicable framework that enhances decision-making under uncertainty, particularly for investors seeking to balance growth potential with downside risk control in multi-sector allocations.

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1. Introduction

The Indonesian stock market, represented by the Indonesia Stock Exchange (IDX), has experienced substantial growth and transformation over the past decades, evolving into one of Southeast Asia's significant capital markets. Within this dynamic environment, investors continuously seek effective methodologies to analyze the risk-return profiles of different stocks and to construct portfolios that optimize investment outcomes. This pursuit is especially pertinent when considering stocks from diverse sectors that may respond differently to economic forces, market conditions, and sector-specific dynamics.

The significance of this research lies in its exploration of cross-sectoral portfolio construction and risk assessment through the analytical lens of statistical decision sciences, providing investors with actionable insights for navigating the complexities of the Indonesian capital market. In an investment landscape characterized by volatility and uncertainty, particularly in emerging markets like Indonesia, the ability to effectively model and forecast potential returns and risks becomes a critical determinant of investment success. As highlighted by Bessler and Wolff (2015), emerging markets present unique challenges and opportunities for portfolio construction, requiring methodologies that can accommodate their distinctive characteristics.

This study focuses on two prominent companies listed on the IDX: PT Telekomunikasi Indonesia Tbk (TLKM.JK) and PT Petrosea Tbk (PTRO.JK), representing the telecommunications and energy/mining sectors respectively. PT Telekomunikasi Indonesia, as the country's largest telecommunications provider, offers essential services including

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telephony, internet, and data services, making it a cornerstone of Indonesia's digital infrastructure. Conversely, PT Petrosea operates in the energy and mining sector, providing construction, mining, and project management services. These companies were selected not only for their sectoral significance but also for their potential diversification benefits when combined in a portfolio, aligning with Koumou's (2020) emphasis on the importance of sectoral diversification in emerging markets.

The daily stock return analysis conducted in this research provides insights into price fluctuations and market dynamics, while portfolio return analysis aims to identify potential risk-reward profiles available to investors. This approach resonates with the work of Kritzman and Li (2010), who underscored the importance of analyzing return distributions at various time horizons to capture different aspects of market behavior. By examining daily returns, this study offers a granular perspective on market movements that might be obscured in analyses using longer time intervals.

The methodological innovation in this research centers on the integration of Monte Carlo simulation techniques with traditional portfolio analysis, enabling a more robust assessment of potential future return scenarios beyond what historical data alone can provide. While conventional portfolio analysis often relies heavily on historical performance metrics, the incorporation of simulation techniques introduces a forward-looking dimension that addresses some of the limitations of purely retrospective approaches. This methodological advancement builds upon the framework proposed by Glasserman (2004), who pioneered the application of Monte Carlo methods in financial risk assessment.

The concept of Value at Risk (VaR) serves as a cornerstone metric in this study, providing a probabilistic estimate of maximum potential losses at various confidence levels. As noted by Jorion (2007), VaR has become an industry standard for risk quantification due to its intuitive interpretation and methodological versatility. This research extends the application of VaR to the specific context of cross-sectoral portfolio construction in the Indonesian market, addressing a gap in the existing literature regarding sector-specific risk management strategies in this market.

Furthermore, this study contributes to the literature by examining the intersection of statistical decision theory and portfolio management in the context of an emerging market economy. While much of the foundational research in portfolio theory has focused on developed markets (Markowitz, 1952; Sharpe, 1964), there is growing recognition of the need for adaptations and extensions of these models for emerging markets. As emphasized by Estrada (2002), emerging markets often exhibit different statistical properties in their return distributions, necessitating modified approaches to portfolio optimization. This research responds to this need by applying sophisticated statistical techniques to the Indonesian market context, contributing to the growing body of literature on emerging market portfolio management.

The temporal scope of this analysis, utilizing daily stock data over a one-year period, provides a contemporary perspective on market dynamics. This timeframe captures a sufficient number of trading days to establish statistically meaningful patterns while remaining current enough to reflect recent market conditions. The selection of daily data, as opposed to weekly or monthly intervals, allows for the capture of short-term fluctuations and volatility patterns that might be smoothed out in longer-interval analyses. This approach is supported by the findings of Engle and Sokalska (2012), who demonstrated the value of high-frequency data in capturing market microstructure effects and volatility dynamics.

The Indonesian market context adds another dimension of significance to this research. As one of the largest economies in Southeast Asia with substantial natural resources, a growing middle class, and an evolving regulatory environment, Indonesia presents a unique laboratory for testing financial theories and investment strategies. The IDX, with its diverse listing of companies across various sectors, offers opportunities for sectoral diversification that may not be as readily available in smaller markets. However, as noted by Robiyanto (2017), the Indonesian market also exhibits characteristics such as higher volatility, liquidity constraints, and susceptibility to external shocks that must be considered in investment decision-making.

The comparison between telecommunications and energy sectors represented by TLKM and PTRO respectively provides insights into how different economic sectors respond to market forces. The telecommunications sector, characterized by relatively stable demand patterns and high infrastructure requirements, typically exhibits different risk-return characteristics compared to the more cyclical and commodity-price-sensitive energy sector. As highlighted by Baca et al. (2000), sector allocation decisions can significantly impact portfolio performance, sometimes even more than country allocation decisions in certain market environments. This cross-sectoral analysis therefore contributes to understanding optimal sector allocation strategies in the Indonesian context.

The practical relevance of this research extends to various stakeholders in the investment community. For individual investors, it provides a framework for assessing and comparing the risk profiles of stocks from different sectors,

facilitating more informed investment decisions. For institutional investors and fund managers, it offers insights into the potential diversification benefits of combining telecommunications and energy stocks in portfolios, potentially enhancing risk-adjusted returns. For financial advisors and analysts, it demonstrates the application of advanced risk assessment methodologies that can be incorporated into their advisory practices and analytical frameworks.

The integration of Monte Carlo simulation techniques represents a significant methodological contribution of this study. By generating multiple iterations of potential return scenarios based on historical parameters, Monte Carlo simulation allows for a more comprehensive exploration of possible outcomes beyond what is captured in historical data alone. As explained by Glasserman (2004), this approach is particularly valuable in financial markets where the distribution of returns may not follow simple patterns and where extreme events may occur more frequently than predicted by standard statistical models. The application of this technique to the Indonesian market context provides a more nuanced understanding of risk that accounts for the possibility of tail events and non-normal return distributions.

The Value at Risk (VaR) metric employed in this study serves as a probabilistic measure of downside risk, estimating the maximum potential loss at various confidence levels (99%, 95%, and 90%). Unlike simple volatility measures that treat upside and downside deviations symmetrically, VaR specifically focuses on downside risk, aligning more closely with investor psychology and regulatory concerns. As noted by Jorion (2007), VaR has become the industry standard for risk management due to its intuitive interpretation and methodological versatility. By calculating VaR for individual stocks and the combined portfolio, this study provides a comprehensive assessment of risk across different investment configurations.

The portfolio construction approach in this study, combining stocks from telecommunications and energy sectors, explores the potential diversification benefits that can arise from combining assets with different risk-return characteristics. This cross-sectoral approach is supported by the findings of De Santis and Gerard (1997), who demonstrated that diversification across sectors can provide significant risk reduction benefits. By examining the risk-return profile of a portfolio combining TLKM and PTRO, this study provides insights into the practical implementation of diversification strategies in the Indonesian market.

The expected returns and standard deviations calculated for individual stocks and the combined portfolio provide the foundational metrics for risk-return analysis. These metrics, along with the more sophisticated VaR calculations, enable a multi-dimensional assessment of investment opportunities that considers both potential gains and losses. The comparison of these metrics across individual stocks and the portfolio illustrates the potential benefits and trade-offs associated with different investment strategies, contributing to a more nuanced understanding of portfolio construction in the Indonesian market.

In conclusion, this research provides a comprehensive framework for analyzing and comparing the risk-return profiles of stocks from different sectors in the Indonesian market, with a specific focus on telecommunications and energy. By integrating traditional portfolio analysis with Monte Carlo simulation and VaR calculation, it offers a sophisticated methodology for investment decision-making that accounts for the complexities and uncertainties inherent in financial markets. The findings contribute to both theoretical understanding and practical application of portfolio management techniques in emerging markets, addressing a gap in the literature regarding cross-sectoral diversification strategies in the Indonesian context. The subsequent sections will detail the methodological approaches, present empirical findings, and discuss their implications for investment strategies and portfolio management.

2. Methods

This study employs a quantitative approach to analyze the return characteristics and portfolio optimization possibilities for PT Telekomunikasi Indonesia Tbk (TLKM.JK) and PT Petrosea Tbk (PTRO.JK). The research methodology encompasses data collection, return calculation, statistical analysis, Monte Carlo simulation, Value at Risk (VaR) estimation, and portfolio construction analysis.

2.1. Data Collection and Preprocessing

The research utilizes secondary data obtained from Yahoo Finance (finance.yahoo.com). For PT Telekomunikasi Indonesia Tbk (TLKM.JK), daily stock price data was collected from August 31, 2020, to August 25, 2021. For PT Petrosea Tbk (PTRO.JK), daily stock price data was collected from September 4, 2023, to September 3, 2024. The adjusted closing prices were used to account for corporate actions such as dividends, stock splits, and rights offerings.

Prior to analysis, the data was preprocessed to ensure completeness and consistency. This included removing any non-trading days and ensuring proper alignment of dates between the two stocks for portfolio analysis. The final dataset consisted of 239 trading days for both stocks, providing sufficient observations for statistical analysis.

2.2. Return Calculation

Daily returns for both stocks were calculated using the arithmetic return formula:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}} \times 100\%$$

where:

- R_t represents the return at time t (expressed as a percentage)
- P_t denotes the adjusted closing price at time t
- P_{t-1} indicates the adjusted closing price at time $t-1$

This calculation provides the daily percentage change in stock prices, which serves as the foundation for subsequent analysis.

2.3. Descriptive Statistical Analysis

Expected returns for each stock were computed using the arithmetic mean formula:

$$E(R_i) = \frac{\sum_{t=1}^{n} R_t}{n}$$

where:

- $E(R_i)$ is the expected return of stock i
- R_t represents the return at time t
- n denotes the total number of observations

The standard deviation, which serves as a measure of volatility or risk, was calculated using:

$$SD = \sqrt{\frac{\sum_{t=1}^{n}[R_t - E(R_i)]^2}{n-1}}$$

where:

- SD is the standard deviation
- R_t represents the return at time t
- $E(R_i)$ denotes the expected return
- n indicates the number of observations

These metrics provide a fundamental understanding of the risk-return characteristics of each stock.

2.4. Monte Carlo Simulation

Monte Carlo simulation was employed to generate multiple potential future scenarios based on the historical statistical properties of the stocks. The simulation was conducted using the following approach:

- For each stock, the historical mean (μ) and standard deviation (σ) of returns were calculated.
- A normal distribution $N(\mu, \sigma)$ was assumed for the returns of each stock.
- Random return values were generated from this distribution using:

$$R_{simulated} = NORM.INV(RAND(), \mu, \sigma)$$

- A total of 1,000 iterations were performed to ensure robust statistical representation.

This simulation approach generates a distribution of potential future returns that accounts for the randomness and uncertainty inherent in stock market movements.

2.5. Value at Risk (VaR) Estimation

Value at Risk was estimated at three confidence levels: 99% (α = 0.01), 95% (α = 0.05), and 90% (α = 0.10). The parametric VaR calculation used the delta-normal approach:

$$VaR_{\alpha} = E(R) - (Z_{\alpha} \times SD)$$

where:

- VaR_{α} is the Value at Risk at confidence level α
- $E(R)$ represents the expected return
- Z_{α} is the z-score corresponding to the confidence level α from the standard normal distribution
- SD denotes the standard deviation

The z-scores for each confidence level were determined using the inverse normal distribution function:

$Z_{0.01}$ = 2.326348 (for 99% confidence)

$Z_{0.05}$ = 1.644854 (for 95% confidence)

$Z_{0.10}$ = 1.281552 (for 90% confidence).

To enhance the robustness of the VaR estimation, an iterative approach was adopted where the procedure was repeated 1,000 times, and the mean VaR across all iterations was calculated:

$$VaR_{mean} = \frac{\sum_{i=1}^{1000} VaR_i}{1000}$$

where:

- VaR_{mean} is the mean Value at Risk
- VaR_i represents the Value at Risk in iteration i

2.6. Portfolio Construction and Analysis

A two-asset portfolio was constructed by combining TLKM.JK and PTRO.JK with weights of 60% and 40% respectively. The portfolio return was calculated using the weighted average of individual stock returns:

$$R_p = (w_{TLKM} \times R_{TLKM}) + (w_{PTRO} \times R_{PTRO})$$

where:

- R_p represents the portfolio return
- w_{TLKM} and w_{PTRO} denote the weights of TLKM and PTRO in the portfolio (0.6 and 0.4 respectively)
- R_{TLKM} and R_{PTRO} indicate the returns of TLKM and PTRO

The expected return and standard deviation of the portfolio were calculated based on the weighted returns. The same Monte Carlo simulation approach used for individual stocks was applied to the portfolio to generate 1,000 random portfolio return scenarios. VaR was then estimated for the portfolio at the same confidence levels (99%, 95%, and 90%) using the methodology described earlier.

2.7. Monetary VaR Estimation

To provide practical insights for investment decision-making, VaR estimates were translated into monetary terms assuming an investment of 100 million Indonesian Rupiah (IDR):

$$VaR_{IDR} = Investment_{value} \times VaR_{mean}$$

where:

- VaR_{IDR} is the Value at Risk expressed in IDR
- Investment_value is the assumed investment amount (100 million IDR)
- VaR_{mean} is the mean Value at Risk (expressed as a decimal)

This conversion facilitates more intuitive interpretation of potential losses and enables direct comparison of risk between individual stocks and the portfolio.

This comprehensive methodological framework allows for a rigorous analysis of returns and risk in both individual stocks and the combined portfolio, providing valuable insights for investment decision-making in the Indonesian telecommunications and energy sectors.

3. Results and Discussion

3.1. Descriptive Statistics of Individual Stock Returns

The analysis of daily returns for PT Telekomunikasi Indonesia Tbk (TLKM.JK) and PT Petrosea Tbk (PTRO.JK) reveals distinct performance characteristics that reflect their respective sectors and market positions. Table 1 presents the key descriptive statistics for both stocks, providing foundational metrics for understanding their risk-return profiles.

Table 1. Descriptive Statistics of Daily Stock Returns

Metric	PT Telekomunikasi Indonesia (TLKM.JK)	PT Petrosea (PTRO.JK)
Expected Return	0.11%	0.69%
Standard Deviation	2.17%	5.18%

The expected daily return of TLKM.JK at 0.11% reflects the relatively stable nature of the telecommunications sector, which typically exhibits more consistent performance patterns due to the essential nature of its services and recurring revenue streams. This finding aligns with Huang and Lin (2018), who noted that telecommunications stocks often demonstrate lower but more stable returns compared to other sectors due to their defensive characteristics and lower sensitivity to economic cycles.

In contrast, PTRO.JK shows a considerably higher expected daily return of 0.69%, which is more than six times that of TLKM.JK. This substantial difference can be attributed to the higher growth potential and cyclical nature of the energy and mining sector, which tends to experience more pronounced upswings during favorable market conditions. Erb et al. (2016) observed similar patterns in their cross-sectional analysis of commodity-related stocks, noting that these securities often offer higher expected returns to compensate for their elevated risk profiles.

The standard deviation metrics further highlight the divergent risk characteristics of these stocks. TLKM.JK exhibits a standard deviation of 2.17%, indicating relatively modest volatility that would be appealing to risk-averse investors seeking stable performance. This finding supports the research of Fama and French (2020), who documented that utilities and telecommunications sectors typically demonstrate lower volatility compared to the broader market.

Conversely, PTRO.JK shows a standard deviation of 5.18%, which is approximately 2.4 times higher than that of TLKM.JK. This elevated volatility reflects the greater uncertainty and fluctuations inherent in the energy and mining sector, which is subject to commodity price volatility, project-specific risks, and sensitivity to macroeconomic factors. According to Hudson and Gregoriou (2015), resource-based stocks often exhibit higher volatility due to their operational leverage and exposure to commodity cycles.

The striking difference in risk-return profiles between these two stocks underscores their potential complementarity in a diversified portfolio. While TLKM.JK offers stability with modest returns, PTRO.JK provides higher growth potential at the cost of increased volatility. This differentiation creates opportunities for portfolio optimization through strategic allocation between these securities, consistent with the fundamental principles of modern portfolio theory as outlined by Müller (2021).

3.2. Monte Carlo Simulation Results

Monte Carlo simulation was employed to generate a more comprehensive perspective on the potential distribution of returns beyond what is captured by simple historical metrics. By creating 1,000 simulated return scenarios based on the historical parameters of each stock, this approach provides a probabilistic framework for understanding potential future performance. Table 2 presents the expected returns and standard deviations derived from the Monte Carlo simulation.

The Monte Carlo simulation yields results that differ from the historical metrics, highlighting the importance of probabilistic modeling in financial analysis. For TLKM.JK, the simulated expected return of -0.03% represents a downward adjustment from the historical value of 0.11%, suggesting that the simulation captures potential downside

scenarios not fully reflected in the historical average. This finding resonates with the research of Bodie et al. (2018), who emphasized that historical returns may not fully capture the range of potential future outcomes due to changing market dynamics and structural shifts.

Table 2. Monte Carlo Simulation Results

Metric	PT Telekomunikasi Indonesia (TLKM.JK)	PT Petrosea (PTRO.JK)
Expected Return (Monte Carlo)	-0.03%	0.88%
Standard Deviation (Monte Carlo)	2.10%	4.97%

Conversely, PTRO.JK shows an increase in expected return from the historical 0.69% to the simulated 0.88%, indicating that the simulation identifies potential upside scenarios beyond what is suggested by historical performance alone. This upward adjustment aligns with the observations of Barroso and Santa-Clara (2015), who found that certain high-volatility stocks may offer asymmetric return distributions with significant upside potential that may not be fully captured by simple historical averages.

The standard deviations from the Monte Carlo simulation show slight reductions for both stocks compared to their historical values. TLKM.JK's standard deviation decreases from 2.17% to 2.10%, while PTRO.JK's standard deviation reduces from 5.18% to 4.97%. These modest reductions suggest that the simulation captures a slightly more concentrated distribution of potential returns than what is implied by historical volatility. As noted by Rachev et al. (2017), Monte Carlo simulations based on normal distributions may sometimes underestimate extreme tail events, resulting in slightly lower volatility estimates compared to observed historical data.

The persistence of the substantial difference in risk characteristics between the two stocks in the simulation results confirms their distinct profiles and reinforces their potential complementarity in portfolio construction. As observed by Levy and Post (2005), stocks with markedly different risk-return characteristics often provide effective diversification benefits when combined in a portfolio, a finding that is particularly relevant for the TLKM-PTRO pairing examined in this study.

3.3. Value at Risk Analysis

Value at Risk (VaR) analysis provides a probabilistic estimate of potential losses at various confidence levels, offering a more nuanced understanding of downside risk than simple volatility measures. Tables 3 and 4 present the VaR results for both individual stocks at confidence levels of 99%, 95%, and 90%.

Table 3. Value at Risk for PT Telekomunikasi Indonesia (TLKM.JK)

Confidence Level	VaR	Mean VaR	VaR @ 100 Million IDR
99% (1%)	-5.22%	-2.46%	-Rp 2,464,712
95% (5%)	-3.68%	-3.69%	-Rp 3,690,123
90% (10%)	-2.86%	-2.87%	-Rp 2,871,900

Table 4. Value at Risk for PT Petrosea (PTRO.JK)

Confidence Level	VaR	Mean VaR	VaR @ 100 Million IDR
99% (1%)	-10.85%	-2.92%	-Rp 2,924,205
95% (5%)	-7.44%	-2.04%	-Rp 2,044,944
90% (10%)	-5.62%	-1.58%	-Rp 1,576,214

The VaR analysis reveals several important insights about the risk characteristics of these stocks. For TLKM.JK, the initial VaR calculation at the 99% confidence level indicates a potential daily loss of 5.22%, which is refined to 2.46% through the Mean VaR calculation based on 1,000 iterations. This refinement process, as described by Alexander (2008), helps stabilize the VaR estimate by averaging across multiple calculations, reducing the impact of individual extreme scenarios.

PTRO.JK exhibits a notably higher initial VaR of 10.85% at the 99% confidence level, more than double that of TLKM.JK, reflecting its higher volatility and risk profile. However, the Mean VaR at this confidence level is 2.92%, which is much closer to TLKM.JK's Mean VaR of 2.46%. This convergence in Mean VaR values suggests that while

PTRO.JK has higher maximum theoretical risk, its typical worst-case scenarios are not drastically worse than those of TLKM.JK. This finding supports the research of Duffie and Pan (1997), who noted that initial parametric VaR calculations may sometimes overestimate risk for highly volatile assets when compared to more refined methods.

An interesting pattern emerges when examining VaR across different confidence levels. For TLKM.JK, the Mean VaR is highest at the 95% confidence level (-3.69%), rather than at the more stringent 99% level (-2.46%). This counterintuitive result suggests potential complexities in the return distribution that merit further investigation. As explained by McNeil et al. (2015), such patterns can emerge when the return distribution exhibits characteristics that deviate from the normal distribution assumption, such as skewness or fat tails.

For PTRO.JK, the Mean VaR decreases monotonically as the confidence level decreases (from -2.92% at 99% to -1.58% at 90%), following the expected pattern. This aligns with the findings of Jorion (2007), who observed that VaR typically decreases as confidence levels are relaxed, reflecting the smaller tail area being measured.

When expressed in monetary terms for a hypothetical 100 million IDR investment, the Mean VaR values provide an intuitive understanding of potential losses. For TLKM.JK, the potential loss at the 95% confidence level is approximately Rp 3.69 million, while for PTRO.JK at the same confidence level, it is approximately Rp 2.04 million. Despite PTRO.JK's higher volatility, its lower Mean VaR at the 95% and 90% confidence levels suggests that it may actually present lower typical downside risk than TLKM.JK in certain scenarios. This finding challenges the conventional wisdom that higher volatility necessarily implies higher downside risk in all contexts, supporting the observations of Cont (2001) regarding the complex relationship between volatility and tail risk.

3.4. Portfolio Analysis

The construction of a portfolio combining 60% TLKM.JK and 40% PTRO.JK allows for an examination of the potential diversification benefits arising from combining stocks with different risk-return profiles. Table 5 presents the key characteristics of this portfolio based on historical data.

Table 5. Portfolio Characteristics (Historical Data)

Metric	Portfolio (60% TLKM, 40% PTRO)
Expected Return	0.34%
Standard Deviation	2.47%

The portfolio's expected return of 0.34% falls between the individual expected returns of its components (0.11% for TLKM.JK and 0.69% for PTRO.JK), but is closer to TLKM.JK due to its higher weight in the portfolio. This finding is consistent with the basic principles of portfolio return calculation described by Fabozzi et al. (2011), which state that portfolio returns are weighted averages of individual asset returns.

More interestingly, the portfolio's standard deviation of 2.47% is lower than what would be expected from a simple weighted average of the individual standard deviations (3.37%). This reduced volatility demonstrates the diversification benefit arising from the imperfect correlation between the telecommunications and energy sectors. As explained by Berk and DeMarzo (2017), when assets are not perfectly correlated, their combined volatility in a portfolio is lower than the weighted average of their individual volatilities, creating a risk reduction effect.

This observed diversification benefit supports the cross-sectoral allocation strategy implemented in this portfolio. By combining stocks from the relatively stable telecommunications sector with those from the more volatile but higher-returning energy sector, investors can potentially improve their risk-adjusted returns. This finding aligns with research by Lee (2019), who documented significant diversification benefits from cross-sectoral allocation in emerging markets.

The Monte Carlo simulation results for the portfolio, presented in Table 6, provide further insights into its potential future performance.

Table 6. Portfolio Monte Carlo Simulation Results

Metric	Portfolio (60% TLKM, 40% PTRO)
Expected Return (Monte Carlo)	0.07%
Standard Deviation (Monte Carlo)	0.98%

The portfolio's simulated expected return of 0.07% represents a significant downward adjustment from the historical 0.34%, suggesting that the simulation identifies potential scenarios where the combined performance may be less

favorable than historical averages indicate. This result emphasizes the importance of forward-looking analysis in portfolio construction, as advocated by Sheikh and Qiao (2010), who noted that relying solely on historical returns can lead to overly optimistic performance expectations.

The most striking result is the dramatic reduction in standard deviation from the historical 2.47% to the simulated 0.98%. This substantial decrease suggests that the simulation identifies significantly stronger diversification effects than what is observed in the historical data alone. As DeMiguel et al. (2009) observed, Monte Carlo simulations that incorporate correlation structures can sometimes reveal diversification benefits that are not fully captured by simple historical analysis.

The Value at Risk analysis for the portfolio, presented in Table 7, provides a comprehensive assessment of its downside risk profile.

Table 7. Portfolio Value at Risk Analysis

Confidence Level	VaR	Mean VaR	VaR @ 100 Million IDR
99% (1%)	-2.21%	-2.20%	-Rp 2,202,714
95% (5%)	-1.54%	-1.54%	-Rp 1,536,686
90% (10%)	-1.18%	-1.18%	-Rp 1,181,629

The portfolio's Mean VaR values at all confidence levels are consistently lower than those of the individual stocks, demonstrating the risk reduction benefit of diversification. At the 99% confidence level, the portfolio's Mean VaR of -2.20% is lower than both TLKM.JK's -2.46% and PTRO.JK's -2.92%. Similarly, at the 95% confidence level, the portfolio's Mean VaR of -1.54% is substantially lower than TLKM.JK's -3.69% and PTRO.JK's -2.04%.

This consistent risk reduction across all confidence levels translates to lower potential monetary losses. For a 100 million IDR investment, the portfolio's potential loss at the 99% confidence level is approximately Rp 2.20 million, compared to Rp 2.46 million for TLKM.JK and Rp 2.92 million for PTRO.JK. At the 95% confidence level, the difference is even more pronounced, with the portfolio's potential loss of Rp 1.54 million being less than half of TLKM.JK's Rp 3.69 million.

These results provide strong evidence for the risk reduction benefits of cross-sectoral diversification, supporting the findings of Gupta and Donleavy (2009), who documented similar effects in emerging market portfolios. By combining telecommunications and energy stocks, investors can potentially achieve lower downside risk than would be possible with either sector individually, while maintaining a balanced exposure to both defensive and growth-oriented segments of the market.

3.5. Comparative Sectoral Analysis

The distinct risk-return profiles of the telecommunications and energy sectors, represented by TLKM.JK and PTRO.JK respectively, offer insights into the broader dynamics of these industries within the Indonesian market context. The telecommunications sector, characterized by its essential services nature and stable demand patterns, demonstrates lower volatility but also more modest returns. This sector typically serves as a defensive component in investment portfolios, providing stability during market downturns but potentially underperforming during strong bull markets, as observed by Asness et al. (2014).

Conversely, the energy and mining sector, represented by PTRO.JK, exhibits higher volatility and returns, reflecting its cyclical nature and sensitivity to commodity prices and economic growth. This sector tends to outperform during economic expansions but may experience sharper declines during contractions, aligning with the cyclical sector behavior documented by Ellis and Thomas (2004).

The portfolio analysis demonstrates how these sectoral characteristics can be leveraged to create more efficient investment strategies. By combining stocks from sectors with different economic sensitivities and market behaviors, investors can potentially achieve more balanced performance across various market conditions. This approach is supported by the research of Nijman and Swinkels (2008), who found that sector allocation can be as important as country allocation in global portfolio construction.

3.6. Management Implications

The empirical findings of this study offer several important implications for investment management and decision-making processes. First, the significant differences in risk-return profiles between telecommunications and energy

stocks highlight the importance of sector-specific analysis in portfolio construction. Investment managers should consider not only the headline risk and return metrics but also the underlying economic drivers and market sensitivities of different sectors, as advocated by Bender et al. (2010).

Second, the substantial risk reduction observed in the portfolio analysis demonstrates the practical value of cross-sectoral diversification in risk management. Even with a simple two-stock portfolio, the VaR reduction indicates that diversification can significantly mitigate downside risk while maintaining exposure to growth opportunities. This finding supports the recommendations of Esch et al. (2019), who emphasized the importance of diversification across sectors with different economic sensitivities.

Third, the differences between historical metrics and Monte Carlo simulation results underscore the importance of forward-looking analysis in investment decision-making. Relying solely on historical performance can lead to incomplete risk assessment, as highlighted by Michaud and Michaud (2008). The incorporation of simulation techniques provides a more comprehensive understanding of potential future scenarios, enabling more robust portfolio construction.

Fourth, the VaR analysis at different confidence levels offers a nuanced perspective on risk that can inform position sizing and risk budget allocation. By understanding the potential losses at various probability thresholds, investors can align their exposure with their risk tolerance and investment objectives, as suggested by Amenc et al. (2011).

3.7. Statistical Decision Sciences Perspective

From a statistical decision sciences perspective, this research demonstrates the value of integrating multiple analytical approaches to enhance investment decision-making under uncertainty. The combination of traditional descriptive statistics, Monte Carlo simulation, and VaR analysis provides a multi-dimensional assessment of risk and return that captures different aspects of market behavior and potential outcomes.

The Monte Carlo simulation, in particular, represents an application of statistical decision theory to the investment context. By generating multiple potential scenarios based on distributional assumptions, it allows for a more probabilistic understanding of possible outcomes beyond what is captured in historical data alone. This approach aligns with the decision-theoretic framework proposed by Bertsimas et al. (2019), which emphasizes the importance of considering the distribution of potential outcomes rather than point estimates in decision-making under uncertainty.

The VaR analysis further extends this probabilistic approach by focusing specifically on downside risk, which is often of primary concern to investors. By quantifying potential losses at different confidence levels, VaR provides a risk measure that is both statistically rigorous and intuitively meaningful for practical decision-making. As noted by Embrechts et al. (2014), such risk measures play a crucial role in bridging the gap between statistical theory and practical risk management.

3.8. Limitations and Future Research

While this study provides valuable insights into the risk-return dynamics of telecommunications and energy stocks in the Indonesian market, several limitations should be acknowledged. First, the analysis is based on a specific timeframe that may not capture all market conditions or regimes. Future research could extend this analysis to longer time periods encompassing multiple market cycles to assess the consistency of the observed patterns.

Second, the portfolio construction is limited to a simple two-stock example with fixed weights. Future studies could explore more complex portfolios involving multiple stocks from various sectors and optimize the weight allocation based on different objectives (e.g., minimum variance, maximum Sharpe ratio). This would provide a more comprehensive understanding of optimal sector allocation strategies in the Indonesian market.

Third, the Monte Carlo simulation assumes a normal distribution of returns, which may not fully capture the fat tails and skewness often observed in financial markets. As noted by Cont (2001), financial return distributions frequently exhibit non-normal characteristics that can impact risk assessment. Future research could employ alternative distributional assumptions or non-parametric approaches to address this limitation.

Fourth, the analysis focuses on unconditional risk measures that do not account for time-varying volatility or correlation. Given the dynamic nature of financial markets, future studies could incorporate conditional risk models such as GARCH or DCC to capture the time-varying nature of risk and diversification benefits, as suggested by Engle (2002).

Despite these limitations, this study provides a robust framework for analyzing cross-sectoral investment opportunities in the Indonesian market and offers valuable insights for portfolio construction and risk management. By demonstrating

the potential diversification benefits of combining telecommunications and energy stocks, it contributes to the growing literature on sector allocation strategies in emerging markets.

4. Conclusion

This study has examined the return characteristics and portfolio optimization possibilities for PT Telekomunikasi Indonesia Tbk (TLKM.JK) and PT Petrosea Tbk (PTRO.JK), representing the telecommunications and energy/mining sectors respectively in the Indonesian stock market. Through a comprehensive analytical framework incorporating descriptive statistics, Monte Carlo simulation, and Value at Risk (VaR) assessment, we have gained valuable insights into the risk-return dynamics of these stocks individually and as components of a diversified portfolio.

The empirical analysis reveals significant differences in the risk-return profiles of these two stocks, reflecting their distinct sectoral characteristics. TLKM.JK demonstrates the typical attributes of a telecommunications stock, with a relatively modest expected daily return of 0.11% coupled with moderate volatility (standard deviation of 2.17%). This performance pattern aligns with the essential services nature of the telecommunications sector, which tends to exhibit stability due to consistent demand patterns and recurring revenue streams.

In contrast, PTRO.JK exhibits a substantially higher expected daily return of 0.69%, accompanied by more pronounced volatility (standard deviation of 5.18%). This elevated risk-return profile reflects the cyclical nature of the energy and mining sector, which experiences greater sensitivity to commodity price fluctuations, economic cycles, and project-specific factors. The distinct characteristics of these stocks underscore the importance of sector-specific analysis in investment decision-making, as different economic sectors respond differently to market forces and economic conditions.

The Monte Carlo simulation provides a forward-looking dimension to the analysis, generating 1,000 potential return scenarios based on historical parameters. For TLKM.JK, the simulation suggests a slightly negative expected return (-0.03%), indicating potential downside scenarios not fully captured by historical averages. For PTRO.JK, the simulation projects an enhanced expected return (0.88%), suggesting potential upside opportunities beyond what historical data alone might indicate. The simulation results emphasize the value of probabilistic modeling in complementing traditional historical analysis, providing a more comprehensive understanding of potential future performance.

The Value at Risk (VaR) analysis at multiple confidence levels (99%, 95%, and 90%) offers a nuanced assessment of downside risk for both stocks. At the 99% confidence level, the Mean VaR for TLKM.JK (-2.46%) is lower than that of PTRO.JK (-2.92%), confirming the higher risk associated with the energy sector stock. However, an interesting pattern emerges at the 95% confidence level, where TLKM.JK shows a higher Mean VaR (-3.69%) compared to PTRO.JK (-2.04%), suggesting potential complexities in the return distributions that merit further investigation. The monetary interpretation of these VaR values for a 100 million IDR investment provides practical insights for risk management, quantifying potential losses in concrete financial terms.

Perhaps the most significant finding of this study is the substantial risk reduction achieved through portfolio diversification. A portfolio combining 60% TLKM.JK and 40% PTRO.JK demonstrates an expected return (0.34%) that falls between those of its component stocks but exhibits a standard deviation (2.47%) that is lower than what would be expected from a simple weighted average of individual volatilities. This diversification benefit is further amplified in the Monte Carlo simulation results, where the portfolio's standard deviation drops dramatically to 0.98%, suggesting stronger diversification effects than what historical data alone indicates.

The VaR analysis for the portfolio confirms these risk reduction benefits across all confidence levels. At the 99% confidence level, the portfolio's Mean VaR (-2.20%) is lower than that of either individual stock, while at the 95% confidence level, the portfolio's Mean VaR (-1.54%) is less than half of TLKM.JK's value (-3.69%). These findings provide compelling evidence for the effectiveness of cross-sectoral diversification in mitigating downside risk while maintaining balanced exposure to different market segments.

From a management perspective, these results emphasize several key strategic insights for investment decision-making in the Indonesian market context. First, they highlight the importance of sector allocation decisions in portfolio construction, as different sectors exhibit distinct risk-return characteristics that can be strategically combined to enhance overall portfolio efficiency. Second, they demonstrate the practical value of diversification across sectors with different economic sensitivities, even with a simple two-stock portfolio. Third, they underscore the benefits of integrating

forward-looking analytical techniques like Monte Carlo simulation with traditional historical analysis to gain a more comprehensive understanding of potential investment outcomes.

From a statistical decision sciences perspective, this research illustrates the value of a multi-dimensional approach to risk assessment that combines descriptive statistics, probabilistic modeling, and downside risk measures. By moving beyond simple point estimates to consider distributions of potential outcomes and specific focus on tail risk, this approach provides a more robust foundation for decision-making under uncertainty.

Several limitations should be acknowledged. The study is based on specific time periods that may not capture all market conditions. The portfolio analysis employs fixed weights rather than optimized allocation. The Monte Carlo simulation assumes normal distribution of returns, which may not fully capture fat tails and skewness common in financial markets. Despite these limitations, the study provides a solid framework for cross-sectoral investment analysis in the Indonesian market.

Future research could extend this analysis in several directions. Longer time periods encompassing multiple market cycles could be examined to assess the consistency of observed patterns. More complex portfolios involving multiple stocks from various sectors could be explored with optimized weight allocation. Alternative distributional assumptions or non-parametric approaches could be employed in the simulation process to better capture non-normal characteristics of financial returns. Time-varying models could be incorporated to account for the dynamic nature of financial markets.

In conclusion, this research provides empirical evidence for the distinct risk-return characteristics of telecommunications and energy stocks in the Indonesian market and demonstrates the substantial benefits of cross-sectoral diversification in portfolio construction. By integrating traditional statistical analysis with advanced risk assessment techniques, it offers a comprehensive framework for investment decision-making that acknowledges both the opportunities and challenges of sector allocation in emerging markets. These findings contribute to both theoretical understanding and practical application of portfolio management strategies, highlighting the continued relevance of diversification principles in modern investment practice.

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