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OPTIMIZATION OF FINANCIAL PORTFOLIOS USING MONTE CARLO SIMULATIONS AND PYTHON

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ABSTRACT

This study simulates portfolio construction using 10 stocks from the Dow Jones index, as well as from the stock exchanges of Mexico, Japan, and Colombia, applying Monte Carlo simulations to generate various weight combinations. The analysis calculates three key metrics: expected return, volatility, and Sharpe ratio. Historical closing prices of the selected stocks from 2014 to 2024 are used, which are standardized and scaled for easier comparison. After performing 1000 simulations, the portfolio with the highest Sharpe ratio from the market is identified as the most efficient. The results are visualized in an efficient frontier graph, highlighting the optimal portfolio, enabling investors to select the best risk-return combination.

Keywords: Monte Carlo, portfolios, Sharpe ratio.

1.0 INTRODUCTION

Portfolio optimization is a fundamental pillar in financial decision-making, as it enables investors to maximize expected returns while managing the risks inherent in investments (Mendonça, Ferreira, Cardoso & Martins, 2020). In this context, Monte Carlo simulation has established itself as a powerful tool for evaluating different combinations of assets, providing a robust approach to portfolio optimization across diverse capital markets (Gunjan & Bhattacharyya, 2023).

This study aims to simulate the construction of investment portfolios using 10 representative stocks from the Dow Jones index, as well as from the stock exchanges of Mexico, Japan, and

Colombia. Through Monte Carlo simulations, different combinations of portfolio weights are generated, and three key metrics are calculated: expected return, volatility, and the Sharpe ratio. The objective is to identify the most efficient portfolio, that is, the one that maximizes risk-adjusted return (Pankunni & Kumar, 2020).

The process begins with the collection of historical closing prices of the selected stocks from 2014 to 2024. These data are cleaned and standardized to allow for accurate comparisons among the different stocks. Subsequently, 1,000 simulations are performed to generate random combinations of weights, ensuring that their sum equals 1. The results are presented in both tabular and graphical form, highlighting the efficient frontier, which facilitates the identification of the optimal portfolio.

This analysis underscores the effectiveness of Monte Carlo simulations in portfolio optimization and in evaluating investment opportunities based on their return and risk characteristics.

1.1 General Objective

To apply Monte Carlo simulations to the construction of investment portfolios using 10 representative stocks from the Dow Jones index and the stock exchanges of Mexico, Japan, and Colombia, calculating risk-adjusted performance metrics in order to identify the most efficient portfolio.

1.2 Specific Objectives

The first objective is to obtain the historical closing prices of the 10 selected stocks from the Dow Jones index and the stock exchanges of Mexico, Japan, and Colombia for the period from 2014 to 2024.

The second objective is to clean the data by removing null or incorrect values, replacing them with the most recently available price to ensure the consistency of the analysis.

The third objective is to scale the closing prices to standardize the stocks so that all begin with a value of 1, allowing for accurate comparisons of the percentage variations of each stock.

The fourth objective is to generate 1,000 Monte Carlo simulations to calculate the expected return, volatility, and Sharpe ratio of each portfolio, and to select the most efficient one based on the highest Sharpe ratio.

2.0 THEORETICAL FRAMEWORK

Portfolio optimization is one of the most relevant disciplines within the field of finance, particularly in relation to investment management in capital markets. This process not only forms the foundation for an efficient allocation of resources, but also has the fundamental objective of identifying the most profitable and well-balanced combinations of assets in order to maximize expected returns while properly managing the risks inherent in the investment environment (Vo, Pham, Pham, Truong, & Nguyen, 2019). In simple terms, portfolio optimization seeks to enable investors to achieve an appropriate balance between return and risk. This process requires meticulous analysis, supported by a series of key variables such as expected return, volatility, and risk-adjusted performance (Ma, Han, & Wang, 2021).

In the development of portfolio optimization, measuring, evaluating, and adjusting the characteristics of the assets that compose the portfolio is essential (Saunders, Cornett, & Erhemjamts, 2021). To carry out this type of optimization, analysts and financial managers employ a variety of specialized methodologies and tools that allow them to model and assess portfolio behavior under diverse market scenarios. These tools, far from being merely technical instruments, are crucial for sound investment decision-making, as they facilitate the identification of the best asset combinations that not only maximize returns but also prudently manage the risks involved (Xiang & Borjigin, 2024). Within this framework, it is necessary to examine the fundamental concepts that underpin portfolio optimization, highlighting tools such as Monte Carlo simulation and the use of the Python programming language, which provide a significant advantage in analytical efficiency and results visualization.

Portfolio optimization constitutes a complex technical process that essentially seeks to identify the asset allocation that best balances expected return with associated risk (Gutiérrez, Pagnoncelli, Valladão & Cifuentes, 2019). This balance is crucial for investors to make financially viable decisions over time. In particular, portfolio optimization is closely related to modern portfolio theory developed by economist Harry Markowitz in the mid-20th century (Oyedeko, Kolawole, Samson, & Voloshyna, 2023). In his approach, Markowitz introduced the concept of diversification as a means to mitigate portfolio risk, proposing that an investor can reduce total portfolio volatility by combining assets whose returns have low or even negative correlation (Hunjra, Hanif, Mehmood & Nguyen, 2021).

Diversification is based on the premise that asset returns do not always move in the same direction. For example, if one asset experiences a negative return during a given period, other assets in the portfolio may not be affected in the same way or may even generate positive returns, thereby mitigating overall portfolio risk. Thus, Markowitz's approach establishes that the key to constructing an efficient portfolio lies in selecting and combining assets in such a way that expected returns are maximized for a given level of risk, thereby optimizing the relationship between the two (Wu, Chen, Chen, & Jeon, 2020).

In practical terms, portfolio optimization involves determining the asset mix that maximizes expected return for a specific level of risk. This selection process requires an appropriate allocation of weights to each asset within the portfolio, taking into account their individual characteristics and their interrelationships within the portfolio. Therefore, the correct combination of assets is based not only on their historical performance but also on the correlation among assets and their behavior under different market scenarios (Abensur & de Carvalho, 2022).

Expected return is undoubtedly one of the most important metrics in investment decision-making, as it provides an estimate of the anticipated average return of an asset or portfolio over a given period. In the context of portfolio theory, expected return is calculated by considering the historical returns of the assets in the portfolio, weighted according to their proportion in the total portfolio. This calculation allows investors to anticipate potential gains per unit of investment, assuming that market conditions remain similar to those observed in the past (Rahman & Gan, 2020).

In a simplified model, the expected return of a portfolio composed of multiple assets is calculated by summing the weighted returns of each asset. For example, if a portfolio consists of two assets, its expected return is estimated as a weighted combination of the individual returns of each asset, multiplied by their respective weights within the portfolio. This calculation is key to determining the overall performance of the portfolio and, ultimately, to making informed asset allocation decisions (Plyakha, Uppal & Vilkov, 2021).

Risk, understood as uncertainty regarding future returns, is another essential concept in portfolio management. In finance, risk is commonly associated with volatility, which measures the dispersion of returns around their mean. Volatility indicates the degree of variability that the returns of an asset or portfolio may experience over time. The higher the volatility, the greater the risk, as future returns become more uncertain. In this sense, investors must consider both expected return and the associated risk when making asset allocation decisions (Huang, Schlag, Shaliastovich & Thimme, 2019).

In portfolio optimization, risk management is a fundamental component, as investors seek to achieve a balance between expected return and the level of risk they are willing to assume. To reduce risk, investors employ various strategies, with diversification being one of the most effective. Diversification involves combining assets with different risk profiles to mitigate total portfolio risk. By including assets whose returns exhibit low or negative correlation, it is possible to reduce portfolio volatility and, consequently, overall risk. Thus, the active management of correlations among assets within the portfolio is a crucial aspect of optimization (Koumou, 2020).

Monte Carlo simulation is one of the most widely used tools for modeling uncertainty in portfolio optimization. This mathematical technique allows for the generation of a large number of possible scenarios based on random variables, helping to simulate portfolio behavior under various market conditions (Zhang, 2021). Through Monte Carlo simulation, thousands of simulations of potential future portfolio returns can be conducted, taking into account the probability distributions of the assets involved.

This technique is particularly useful when historical data are insufficient to predict future asset behavior, as it enables the evaluation of a wide range of possible outcomes and provides a more robust view of the risks and returns associated with the portfolio (Zheng, Yu, Wang & Tao, 2019). Through Monte Carlo simulation, analysts can identify the most efficient portfolio for different risk levels, thereby facilitating informed decision-making.

The selection of asset combinations within a portfolio is a central aspect of optimization (Sarwar, Shahbaz, Anwar & Tiwari, 2019). Diversifying a portfolio across different types of assets, such as stocks, bonds, and other financial instruments, is a key strategy for reducing overall risk. However, asset selection is based not only on expected returns but also on the correlation among assets. Assets whose returns exhibit low or negative correlation are particularly valuable for portfolio optimization, as they help reduce volatility and overall risk.

Risk-adjusted performance is another fundamental criterion for evaluating whether a portfolio is generating adequate returns relative to the risk assumed. One of the most commonly used metrics to measure risk-adjusted performance is the Sharpe ratio, which compares a portfolio's excess return to its volatility (Raza & Ye, 2025). This ratio indicates how well a portfolio compensates for the risk taken. A high Sharpe ratio suggests that the portfolio is generating strong returns per unit of risk, making it an efficient option for investors.

Volatility is the primary measure of risk in portfolio optimization. It represents the dispersion of returns around the mean, and investors seek to minimize it in order to reduce uncertainty regarding future portfolio performance (Li & Webster, 2023). Although there may be an inverse relationship between risk and return, reducing risk is generally expected to decrease expected return. The challenge lies in finding an appropriate balance between return and risk, and portfolio optimization plays a crucial role in achieving this objective.

The use of tools such as Python has revolutionized portfolio optimization by providing an accessible and powerful platform for implementing complex mathematical models. Python offers specialized libraries such as NumPy, Pandas, Matplotlib, and SciPy, which enable analysts and investors to perform Monte Carlo simulations, calculate metrics such as the Sharpe ratio and the efficient frontier, and conduct statistical analyses efficiently. This ability to automate and simplify the optimization process allows analysts to experiment with different asset combinations, evaluate their associated returns and risks, and make more informed and accurate decisions (Nystrup, Lindström & Madsen, 2020; Perrin & Roncalli, 2020).

Consequently, portfolio optimization is an essential component of investment management. Techniques such as Monte Carlo simulation and risk-adjusted performance analysis provide investors with effective tools to maximize returns while managing associated risks. Supported by Python, analysts can execute these models more efficiently and accurately, enabling them to make informed decisions and optimize performance in financial markets.

3.0 METHODOLOGY

The process established to carry out this research in order to achieve the proposed objective was developed in the following four stages:

Historical Data Collection: Historical closing prices were downloaded for 10 selected stocks from the Dow Jones index and the stock exchanges of Mexico, Japan, and Colombia, covering the period from 2014 to 2024.

Data Cleaning: A data cleaning process was conducted to remove null or incorrect values. Erroneous or missing values were replaced with the most recently available price, ensuring the consistency and quality of the data used in the analysis.

Price Scaling: The closing prices of each stock were scaled to standardize them. This process allowed all stocks to start with a value of 1, facilitating accurate comparisons of the percentage variations among the selected stocks.

Monte Carlo Simulations: A total of 1,000 Monte Carlo simulations were generated to calculate the expected return, volatility, and Sharpe ratio of each portfolio resulting from different asset combinations, using a 4.5% risk-free rate based on U.S. Treasury bonds. Subsequently, the most efficient portfolio was selected according to the highest Sharpe ratio, enabling the identification of the optimal portfolio for decision-making.

The characteristics with which this research was designed are presented below (Table 1).

Table 1. Research Design

Methodology	Description
Level of Research:	Quantitative and descriptive research. The study focuses on the quantitative analysis of investment portfolios through Monte Carlo simulations, using historical stock data to model return and risk.
Research Purpose:	Pure or basic research. The primary objective is to contribute to academic knowledge by analyzing the return and risk of investment portfolios using Monte Carlo simulation.
Sampling Method:	Deliberate sampling. Ten representative stocks were selected from the markets represented by the Dow Jones index and the stock exchanges of Mexico, Japan, and Colombia, in order to conduct a simulation that covers a variety of assets and scenarios.
Variables Used:	Non-experimental research. Historical closing price data of the selected stocks between 2014 and 2024 were collected to analyze return and risk based on random weights generated in the Monte Carlo simulation.

Source: Prepared by the author.

4.0 RESULTS OBTAINED

In this research project, a Python code (shown in Annex 1) was developed to perform financial portfolio optimization using Monte Carlo simulations and Python, analyzing market portfolios representative of the Dow Jones index and the stock exchanges of Mexico, Japan, and Colombia. The results revealed a wide variety of portfolios with different levels of return and volatility.

The most efficient portfolio, with the highest Sharpe ratio, corresponded to the portfolio representative of the Dow Jones Index, with an annualized return of 33.44% and a volatility of 22.54%, which, based on a 4.5% risk-free rate, resulted in a Sharpe ratio of 1.28. This portfolio optimized the risk–return relationship, highlighting the usefulness of Monte Carlo simulations for exploring different asset combinations. The use of Python facilitated data collection, scenario simulation, and the analysis of key metrics, providing a valuable tool for informed decision-making in portfolio optimization. The main results and their interpretations are presented below.

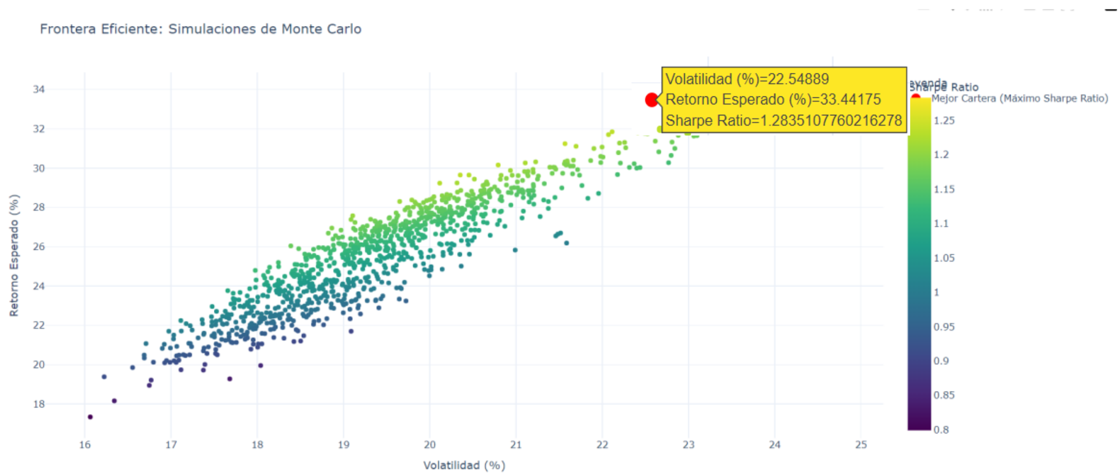
4.1 Identification of the Optimal Portfolio: Representative of the Dow Jones Index

Figure 1 illustrates the efficient frontier of the portfolio resulting from Monte Carlo simulations applied to a set of 10 stocks representative of the Dow Jones index: Apple, Nvidia, Microsoft, Amazon, Walmart, JPMorgan Chase, Visa, UnitedHealth Group, Home Depot, and Procter & Gamble.

Through 1,000 simulations, random weight combinations were generated for each stock, calculating the expected return, volatility, and Sharpe ratio of each portfolio. The objective was to identify the portfolio with the best risk-adjusted performance, determined by the highest Sharpe ratio, using a 4.5% risk-free rate.

The visualization of the efficient frontier highlights the relationship between volatility and expected return, emphasizing the optimal portfolio with a return of 33.44%, a volatility of 22.54%, and a Sharpe ratio of 1.28.

Figure 1. Optimal Portfolio Resulting from the Monte Carlo Simulation Applied to the Dow Jones Index



Source: Prepared by the author using Python.

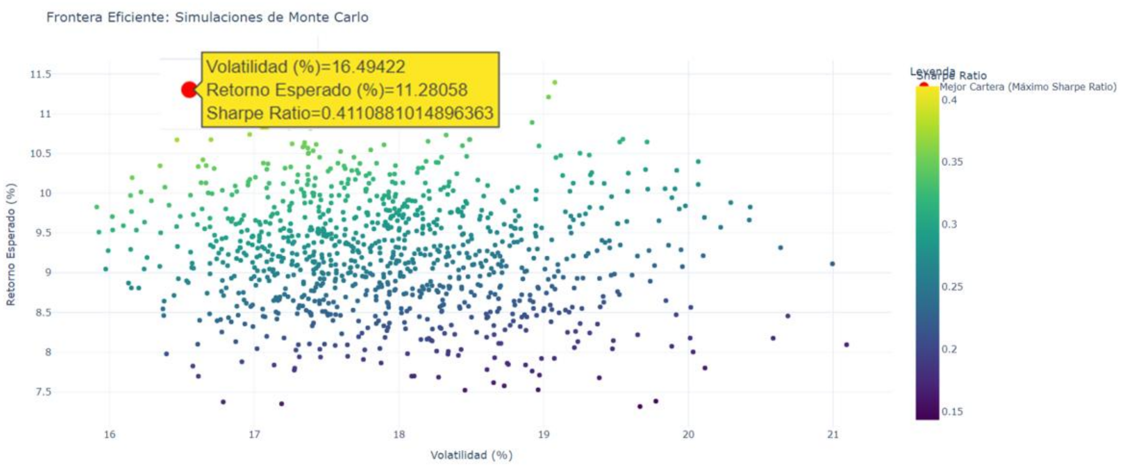
4.2 Optimal Portfolio: Representative of the Mexican Stock Market

Figure 2 illustrates the efficient frontier of the portfolio resulting from Monte Carlo simulations applied to a set of 10 stocks representative of the Mexican stock market: Walmart de México, América Móvil, Grupo México, Fomento Económico Mexicano, Banorte, Cemex, Arca Continental, Inbursa, Grupo Carso, and Grupo Bimbo.

The objective was once again to identify—now for this specific market—the portfolio with the best risk-adjusted return, determined by the highest Sharpe ratio, using a 4.5% risk-free rate.

The visualization of the efficient frontier highlights the optimal portfolio with a return of 11.28%, a volatility of 16.49%, and a Sharpe ratio of 0.41, demonstrating an effective combination of profitability and risk within this market.

Figure 2. Optimal Portfolio Resulting from the Monte Carlo Simulation Applied to the Mexican Stock Market



Source: Prepared by the author using Python.

4.3 Optimal Portfolio: Representative of the Japanese Stock Market

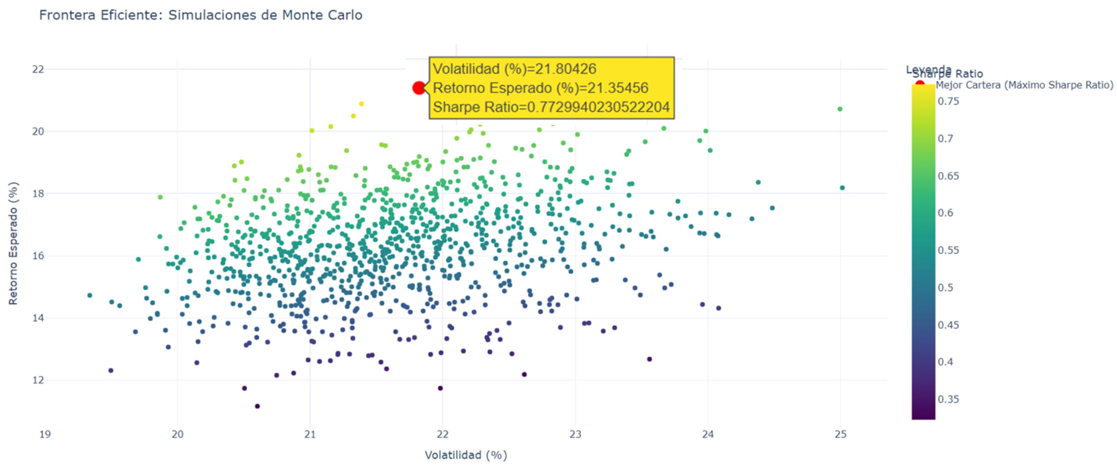
Figure 3 illustrates the efficient frontier of the portfolio resulting from Monte Carlo simulations applied to a set of 10 stocks representative of the Japanese stock market: Toyota Motor Corporation, Sony Group Corporation, SoftBank Group, Mizuho Financial Group, Nintendo Co. Ltd., Panasonic Holdings Corporation, NTT Corporation, Honda Motor Co., Ltd., Takeda Pharmaceutical Company Limited, and Renesas Electronics Corporation.

The objective was once again to identify—now for this market—the portfolio with the best risk-adjusted return, determined by the highest Sharpe ratio, using a 4.5% risk-free rate.

The visualization of the efficient frontier highlights the optimal portfolio with a return of 21.35%, a volatility of 21.80%, and a Sharpe ratio of 0.77, indicating a higher risk-adjusted return compared to the Mexican portfolio.

Although this Japanese portfolio shows a significantly higher return, it also presents greater volatility, suggesting that investors should consider their risk tolerance when selecting among different markets and investment strategies.

Figure 3. Optimal Portfolio Resulting from the Monte Carlo Simulation Applied to the Japanese Stock Market



Source: Prepared by the author using Python.

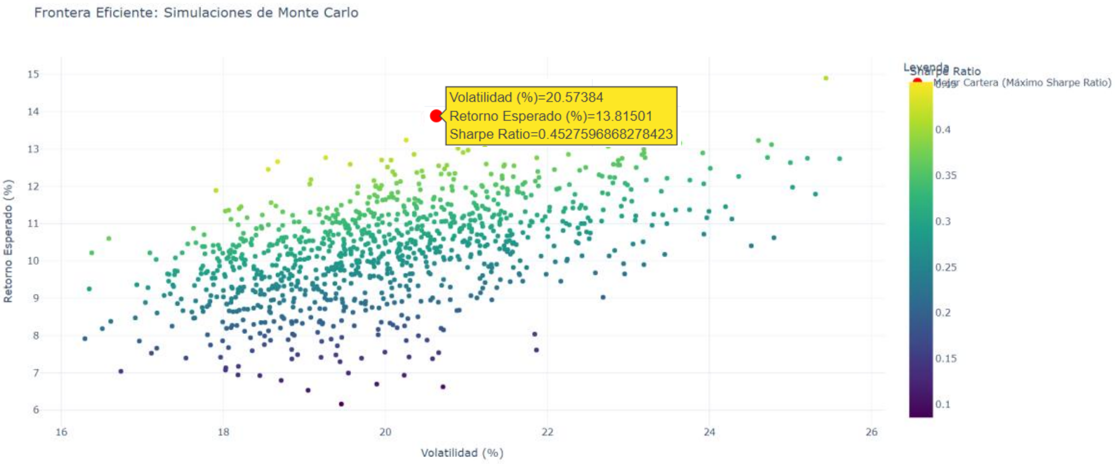
4.4 Optimal Portfolio: Representative of the Colombian Stock Market

Figure 4 illustrates the efficient frontier of the portfolio resulting from Monte Carlo simulations applied to a set of 10 stocks representative of the Colombian stock market: Ecopetrol, Bancolombia, Grupo Energía Bogotá, Grupo de Inversiones Suramericana, Interconexión Eléctrica, Grupo Argos, Cementos Argos, Grupo Aval Acciones y Valores, Banco de Bogotá, Banco Davivienda, and Promigas.

The objective was once again to identify—now for this market—the portfolio with the best risk-adjusted return, determined by the highest Sharpe ratio, using a 4.5% risk-free rate.

The visualization of the efficient frontier highlights the optimal portfolio with a return of 13.81%, a volatility of 20.57%, and a Sharpe ratio of 0.45. Compared to the Mexican portfolio, which has a return of 11.28%, the Colombian portfolio offers a higher return but with slightly greater volatility (20.57% versus 16.49%). This indicates that, although the Colombian portfolio provides higher profitability, it also carries higher risk, which may be less attractive for investors preferring lower volatility, such as that seen in the Mexican market. However, the risk–return relationship of the Colombian portfolio, given its volatility, is reasonably efficient for those seeking moderate yet relatively stable returns.

Figure 4. Optimal Portfolio Resulting from the Monte Carlo Simulation Applied to the Colombian Stock Market



Source: Prepared by the author using Python.

5.0 CONCLUSION AND DISCUSSION

The results obtained in this research provide a clear perspective on the differences in investment portfolio efficiency when comparing various stock markets, specifically the Dow Jones Index and the stock markets of Mexico, Japan, and Colombia. The optimal portfolio, determined through Monte Carlo simulations, showed that the Dow Jones Index presents the best risk-adjusted performance, with an annualized return of 33.44%, a volatility of 22.54%, and a Sharpe ratio of 1.28. These values indicate that the portfolio composed of Apple, Nvidia, Microsoft, Amazon, Walmart, JPMorgan Chase, Visa, UnitedHealth Group, Home Depot, and Procter & Gamble is significantly more efficient in terms of risk and return compared to the portfolios of Mexico, Japan, and Colombia, whose risk–return relationships were lower, with Sharpe ratios of 0.41, 0.77, and 0.45, respectively.

These results highlight the advantage of developed markets, such as the U.S. represented by the Dow Jones Index, in terms of risk-adjusted return, which may be attributed to factors such as greater economic stability, higher asset diversification, and increased market liquidity. Emerging markets, while offering positive returns, do not reach the same level of efficiency due to higher volatility, lower diversification, and other inherent risks. This finding emphasizes the importance of considering the economic and financial context when selecting investment portfolios, especially in markets with different characteristics.

It is important to note that, although Monte Carlo simulations provide a useful tool for portfolio optimization, this research has certain limitations. First, the data used were limited to historical stock prices and did not consider other macroeconomic, political, or social factors that may influence asset performance. Additionally, while Monte Carlo simulation is robust, it depends on the quality of historical data and assumptions regarding future asset behavior. Unforeseen market fluctuations or unexpected events, such as financial crises or pandemics, could alter the results, suggesting that simulations should be regarded as a complementary tool rather than an exact prediction of the future.

Another limitation is the use of a fixed 4.5% risk-free rate, which may not represent the changing economic conditions of each market. Risk-free rates vary according to each country's monetary policies, and this arbitrary setting could have influenced the selection of optimal portfolios. Furthermore, although 1,000 simulations were conducted, a higher number of simulations could provide even more precise results, especially given the complexity and non-linear behavior of financial markets.

Despite these limitations, the results open the door to future studies that could expand and deepen this analysis. A potential follow-up study could incorporate additional macroeconomic variables, such as interest rates, inflation, or fiscal policies, to assess their impact on portfolio optimization. Additionally, other international stock indices and emerging markets could be analyzed to better understand global dynamics and diversification opportunities. Exploring portfolio optimization with non-traditional assets, such as bonds, real estate, or cryptocurrencies, could also offer a broader approach to risk management within a portfolio.

Finally, it would be valuable to conduct a dynamic analysis simulating changing market conditions, such as interest rate fluctuations or economic crises, to evaluate how portfolios can adapt to unpredictable scenarios. Such studies could significantly contribute to informed decision-making by investors and fund managers in an increasingly globalized and volatile financial environment.

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