



## Research Article

# Optimal Portfolio Selection Under Catastrophic Events Using Monte Carlo Simulation

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## Abstract

The global stock market is a critical mechanism for the allocation of scarce financial resources to productive economic activities. However, investors continuously face the dual challenge of minimising risk while simultaneously maximising returns. This tension becomes particularly acute during catastrophic events such as pandemics, which can severely disrupt market stability and undermine conventional investment strategies. The COVID-19 pandemic, for instance, caused significant downturns across major stock markets worldwide, highlighting the vulnerability of concentrated investment portfolios and reinforcing the importance of sound portfolio diversification strategies. This study applies Markowitz's Modern Portfolio Theory (MPT) to nine selected stocks listed on the United States (US) stock market, spanning sectors including Technology, E-commerce, Energy, Health, Automobile, Transport, and Entertainment. Stock performance is evaluated over two distinct periods: before the pandemic (January 2018 to December 2019) and during the pandemic (January 2020 to December 2021), using data obtained from Yahoo Finance. The expected returns of the selected stocks are estimated using the Capital Asset Pricing Model (CAPM). A diversified portfolio is then formulated, the Sharpe ratio is computed for risk-adjusted performance evaluation, and the efficient frontier is constructed using Monte Carlo simulation implemented in Python. The simulation generates 2,000 portfolio scenarios to identify the optimal risky portfolio. The results demonstrate that a well-diversified portfolio can yield superior risk-adjusted returns, with the optimal portfolio achieving a Sharpe ratio of 1.21 at a return of 27.02% and a standard deviation of 22.36%. These findings underscore the effectiveness of MPT and Monte Carlo simulation as practical tools for optimal portfolio selection, particularly in the context of catastrophic market events.

## Keywords

Stock Market, Asset Allocation, Diversification, Optimal Risky Portfolio, Capital Asset Pricing Model

## 1. Introduction

The COVID-19 pandemic undoubtedly shook even the well-grounded economic giant such as the US. Many stocks experienced a downturn amid rising investor fear of a possible global economic crash. The stock market is an essential component of the economy, where most of the world's capital is exchanged. It is crucial for attracting and directing distributed

liquidity and savings along optimal paths, ensuring the adequate allocation of scarce financial resources to the most profitable activities and projects. Certainly, a lessened decline in the growth of the stock market has a significant impact on the economy. However, it is unwise for an investor to keep re-

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sources in such a risky market, coupled with the economic recession due to COVID-19. Investment in an economy experiencing a pandemic requires experience and careful analysis of trends and information.

Powerful machine learning and time series techniques such as the auto-regressive integrated moving average (ARIMA) model [1-3], support vector machine (SVM) [4, 5], multi-layer perceptron (MLP) [6-9] and many other deep learning models are available for the prediction of future stock prices, not all information variables can be incorporated in such techniques, particularly in the event of the pandemic where government and company decisions are based on the spread and control of the virus. One investment strategy that has stood the test of all time is diversification with hedges on risk by allocation of available investment funds into a pool of performing stocks satisfying a condition of negative correlation in returns.

Henry Markowitz developed a mathematical approach, popularly known as the modern portfolio theory (MPT), which can quantitatively measure the risk and return of an investment as well as the risk - return trade-offs, capable of guiding an investor against losing their entire investment. Markowitz's model is in fact, a 'natural wisdom' from the popular adage, 'don't put all your eggs in one basket'. In his book 'The Early History of Portfolio Theory: 1600 - 1960', Markowitz admits that diversification of investment has been a long, well-established practice since the 19th century, before he published his paper on portfolio selection in 1952, which won the Nobel Prize in Economics. However, what was lacking prior to 1952 was an adequate theory of investment that could detail the significance of diversification when risks are correlated, distinguish between efficient and inefficient portfolios, and analyse risk-return trade-offs on the portfolio as a whole [10]. Portfolio theory has since then been studied and improved for asset pricing and diversification since its introduction in 1952. James Tobin, a renowned economist, in his essay, 'Liquidity Preference as Behaviour Toward Risk' derived the 'Efficient Frontier' and 'Capital Market Line' concepts based on Markowitz's work [11]. He concluded that investment portfolios will differ only in their relative proportions of stocks. William Sharpe, John Lintner, and Jan Mossin independently formulated the Capital Asset Pricing Model (CAPM) based on earlier works of Markowitz and Tobin. This groundbreaking model has since provided an evolutionary benchmark in the theory of capital markets equilibrium, offering a better way for investors to value securities as a function of systematic risk [12]. [13] discovered an intriguing relationship between the Markowitz model and the Sharpe model in a comparative analysis of the two models. Analysis of the predicted index portfolio and standard deviations revealed that Sharpe's model replicates and even sometimes produces increasingly better results as more indexes are added. [14] examined whether the CAPM is valid to forecast the behaviour of individual stocks and their returns, as well as its validity in the portfolio with stocks listed

in the Malaysian market using the Ordinary Least Squares (OLS) unbiased estimator, autocorrelation, and heteroscedasticity tests. The study shows that CAPM can be used as a proxy to estimate stock return and diversify the portfolio to reduce unsystematic risk for policy execution, profit, and wealth maximization. The right application of Markowitz portfolio diversification could build up investors' confidence towards investment decisions to generate and allocate resources for economic growth. [15] studied problems under stochastic and integer constraints and proposed an algorithm for estimating the exact solution of their problem. The approach proved to be effective compared to the state-of-the-art Mixed-Integer Nonlinear Programming (MINLP) solvers. For up to 200 assets, the algorithm is able to solve the optimality problem in a reasonable amount of time. [16] researched a novel approach to solve the Markowitz optimization problem for large portfolios to estimate the optimal portfolio. The study considered unconstrained regression representation of the mean-variance optimization problem coupled with high-dimensional sparse regression methods.

It was revealed that, under mild sparsity assumptions, the model asymptotically achieves mean-variance efficiency and effectively controls the risk. Rather than assessing portfolio efficiency, [17] focused on the quantification of the effects of diversity on the Lithuanian Exchange Market using daily stock prices from 2009 to 2010. With the construction of portfolios of various sizes to achieve the non-systematic risk elimination effect, they compared the diversification effects of naïve and weighted stock portfolios. The effect of diversification is measured in terms of the percentage of diversifiable risk elimination and is proportional to the number of companies in the portfolio. The findings revealed a significant difference in the diversification impact of naïve and differentially weighted portfolios when they consist of a smaller number of stocks.

This research studies the performance of selected stocks listed on the US market in the areas of Technology, E-commerce, Energy, Health, Automobile, Transport, and Entertainment before and during the COVID-19 pandemic using the returns and the CAPM. Following Markowitz's modern portfolio theory, a portfolio is formulated, and the optimal portfolio is selected using Monte Carlo simulations.

## 2. Modern Portfolio Theory

Most equity investors, rather than putting all their funds into one company's stock, hold stock in a number of companies. The mean-variance portfolio theory assumes that investment decisions are based primarily on risk and return, and that investors are willing to accept higher risk in exchange for higher expected return.

### 2.1. The Case of N Securities

Suppose there are  $N_i, i = 1, \dots, n$  securities available to an

investor. Suppose further that a proportion  $x_i$  is invested in security  $S_i$ .  $x_i$  is a fraction of the total sum to be invested and can assume any value along the real line subject to the constraint that  $\sum_i x_i = 1$ . The return on the portfolio is  $R_p = \sum_i x_i R_i$ , where  $R_p$  is the return on security  $S_i$ . The expected return on the portfolio is

$$E = E[R_p] = \sum_i x_i E_i \quad (1)$$

Where  $E_i$  is the expected return on security  $S_i$ . The variance of the portfolio is

$$V = \text{var}[R_p] = \sum_j \sum_i x_i x_j C_{ij} \quad (2)$$

Where  $C_{ij}$  is the covariance of the returns on securities.

## 2.2. Portfolio Optimisation Problem

For the available  $N$  securities, the aim is to choose  $x_i$  to minimise variance (the statistical measure for risk)  $V$  subject to the constraints:  $\sum_i x_i = 1$  and  $E = E_p$ . The goal is to minimise the portfolio variance,  $V$  subject to the two constraints  $\sum_i x_i = 1$  and  $E = E_p$ . The Lagrangian function for minimisation is

$$L = \sum_i \sum_j C_{ij} x_i x_j - \lambda \left( \sum_i E_i x_i - E_p \right) - \mu \left( \sum_i x_i - 1 \right) \quad (3)$$

where  $\lambda$  and  $\mu$  are the Lagrangian multipliers in this case. We are trying to minimize the variance  $V$  subject to the expected return and 'all money invested' constraints.

Setting the partial derivatives of  $L$  with respect to all the  $x_i$  and  $\lambda$  and  $\mu$  equal to zero minimizes  $V$  with

$$\begin{aligned} 2 \sum_j C_{ij} x_j - \lambda E_i - \mu &= 0 \\ \sum_i x_i E_i &= E_p \\ \sum_i x_i &= 1 \end{aligned} \quad (4)$$

The top half of this curve, i.e., above the point of global minimum variance, is the efficient frontier.

## 3. Capital Asset Pricing Model

CAPM extends the concepts of the portfolio theory in an attempt to characterize the entire investment market on some extra assumptions regarding the market. CAPM gives the relationship between risk and return in the security market as a whole, assuming that investors act in accordance with mean-variance portfolio theory and the market is in equilibrium [18]. In the case of two securities  $A$ , a portfolio of risky assets  $A$  and  $B$ , a portfolio of just one risk-free asset  $r$ ,  $x_A$  can be expressed in terms of  $E_p$  as:

$$x_A = \frac{E_p - E_B}{E_A - E_B} \quad (5)$$

with a portfolio variance expressed as

$$V_p = x_A^2 V_A + x_B^2 V_B + 2x_A x_B C_{AB} \quad (6)$$

Here  $V_B = 0$  and  $C_{AB} = 0$  since portfolio  $B$  is risk-free. The variance simplifies to

$$V_p = x_A^2 \sigma_A^2 = \left( \frac{E_p - E_B}{E_A - E_B} \right)^2 \sigma_A^2 \quad (7)$$

This is a straight line in  $(E_p, \sigma_p)$  space. The efficient frontier with a risk-free asset is parabolic in  $(E, \sigma)$  space. The straight line above in the expected return standard deviation space is a degenerate case of a hyperbola. The assumption is that a rational investor would hold a combination of the risk-free asset and  $M$ , the portfolio of risky assets at the point where the straight line of the risk-free return touches the original efficient frontier. The straight line denoting the new efficient frontier is called the Capital Market Line (CML) and has the equation:

$$E_p - r = \frac{(E_M - r) \sigma_p}{\sigma_M} \quad (8)$$

Where  $E_p$  is the expected return of any portfolio on the efficient frontier.  $\sigma_p$  is the standard deviation of the return on the portfolio.  $E_M$  is the expected return on the market portfolio.  $\sigma_M$  is the standard deviation of the return on the market portfolio.

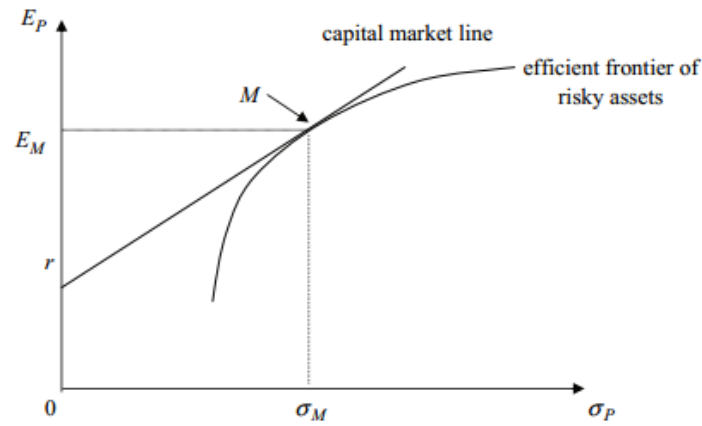


Figure 1. The Efficient Frontier with Risk-free Asset.

### 3.1. The Security Market Line

Another possible way to relate the expected return on any asset to the return on the market is the equation.

$$E_i - r = \beta_i (E_M - r) \quad (9)$$

where  $E_i$  is the expected return on security  $i$ ,  $r$  is the return on the risk-free asset,  $E_M$  is the expected return on the market portfolio,  $\beta_i$  is the beta factor of security  $i$  defined as  $\text{cov}(R_i, R_M) / V_M$  [19]. Equation (9) can equally be expressed as:

$$E_i = r + \beta_i (E_M - r) \quad (10)$$

indicates that the expected return on any asset is equal to the risk-free rate plus a risk premium. This is a straight-line equation in the  $(E, \beta)$  space called the Security Market Line (SML). This line shows that the expected return on an asset is linearly related to its systematic risk as measured by beta.

### 3.2. The Sharpe Ratio

The Sharpe ratio, developed by William F. Sharpe [12], is a widely used measure of risk-adjusted portfolio performance. It quantifies the excess return earned per unit of total risk (standard deviation) and is defined as:

$$S = \frac{E_p - r}{\sigma_p} \quad (11)$$

where  $E_p$  is the expected portfolio return,  $r$  is the risk-free rate, and  $\sigma_p$  is the standard deviation of the portfolio return.

A higher Sharpe ratio indicates a more favourable risk-adjusted return. In the context of portfolio optimisation using

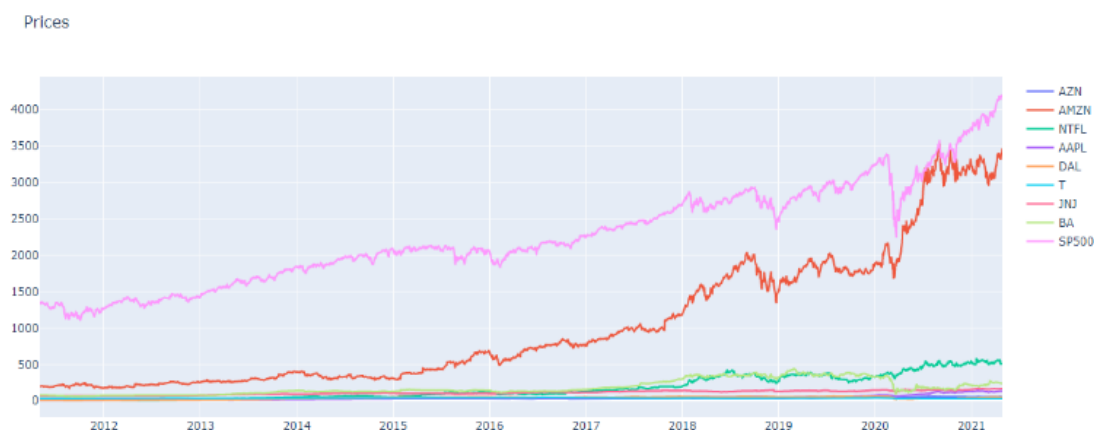
Monte Carlo simulation, the Sharpe ratio serves as the primary criterion for selecting the optimal risky portfolio from among the many feasible portfolios on the efficient frontier. The portfolio with the maximum Sharpe ratio represents the best possible trade-off between risk and return, and is referred to as the tangency portfolio or the optimal risky portfolio. In this study, a zero risk-free interest rate is assumed in the computation of the Sharpe ratio.

## 4. Results

The US economy generally received some shocks from the pandemic waves. To ascertain the impact of covid-19 on the stock market, we study the returns of some selected popular - Apple (AAPL), Microsoft (MSFT), Google (GOOGL), Amazon (AMZN), Alibaba (BABA), Sea Limited (SE), Exxon Mobil (XOM), NextEra Energy (NEE), Shell (SHEL), Walt Disney Company (DIS), Netflix (NFLX), Facebook/Meta (FB), Ford Motor (F), Tesla (TSLA), Toyota Motor (TM), United Health Group Incorporated (UNH), AbbVie Inc. (ABBV), Abbott Laboratories (ABT), Boeing (BA), Delta Airlines (DAL) and American Airlines Group (AAL) stocks in various areas of the economic - Technology, E-commerce, Energy, Health, Automobile, Transport and Entertainment. The table gives the average returns of these stocks before the pandemic, from January 2018 to December 2019, and during the pandemic, from January 2020 to December 2021.

### 4.1. Model Construction, Analysis and Results

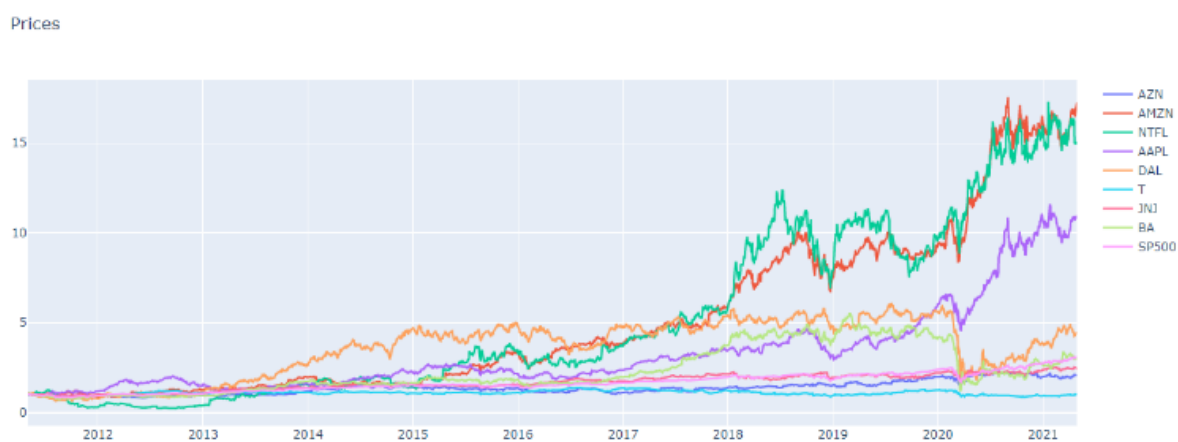
Closing prices of AstraZeneca (AZN), Johnson & Johnson (JNJ), Apple (AAPL), AT&T (T), Netflix (NTFX), Amazon (AMZN), Boeing (BA), Standard and Poor's (S&P500), and Delta Airlines Inc. (DAL) data from May 2011 to April 2021 were obtained from Yahoo Finance. Figure 2 shows the daily price variation of the stocks.



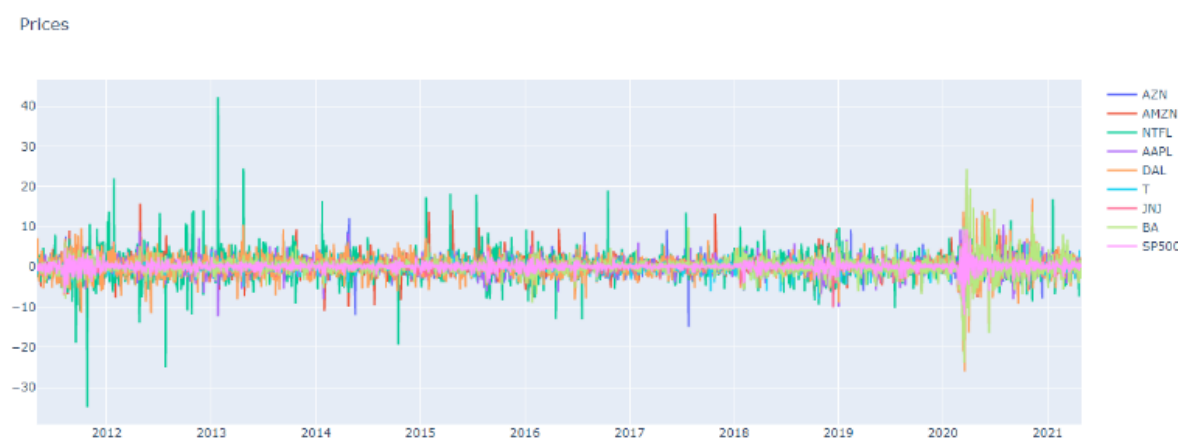
**Figure 2.** Closing Price of Stocks.

For a comparative movement in stock prices over the period, the data are scaled as shown in Figure 3. It is observed that Netflix and Amazon were the leading stocks between 2019 and 2020, with the former outperforming the latter on average. However, between 2020 and 2021, Amazon performed better than Netflix. This could be as a result of the COVID-19 lockdown, businesses and individuals resorted to online purchases

and delivering services of Amazon. Delta Airlines experienced a significant drop between 2020 and 2021, also as a result of the COVID-19 lockdown and travel restrictions. Daily returns of the various stocks are displayed in Figure 4. Figure 5 shows the pairwise correlation among the stock returns.



**Figure 3.** Normalized Closing Price of Stocks.



**Figure 4.** Daily Return of Stocks.



Figure 5. Correlation of Stock Returns.

Figure 6 displays the risk/return of the stocks. As seen in the graph, stocks that generate high returns also bear high risk in most cases.

## 4.2. Expected Return

First, the performance of the selected stocks against the market (S&P500) is evaluated using the Capital Asset Pricing Model (CAPM). This offers an idea of the effect of each of the stocks on the portfolio to be constructed. The SML is fitted to each stock and market with an assumed zero risk-free interest rate, following Equation (10). Table 1 gives the alpha, beta, and expected return of all the stocks based on the CAPM.

A beta value greater than one implies the stock will increase the risk of the portfolio when included. For a Beta value less than one, the asset will reduce the risk of the portfolio when added. The results show that Boeing has the highest expected return of 17.3%, but is also the most volatile stock of about 35% more volatile than the market. An investor seeking to profit from the high profits that Boeing offers must also be prepared to bear this risk of 35%. This means that an investor seeking to profit from the high profits that Boeing offers must also be prepared to bear the risk of 35%. Delta Air Lines has 15.9% expected return and is about 23% more volatile than the market. Johnson and Johnson (JNJ) is the least risky stock among the selected stocks.

Alpha value generally gives information about how an investor can beat the market, whereas the beta value helps the investor to diversify away the non-systematic risk.

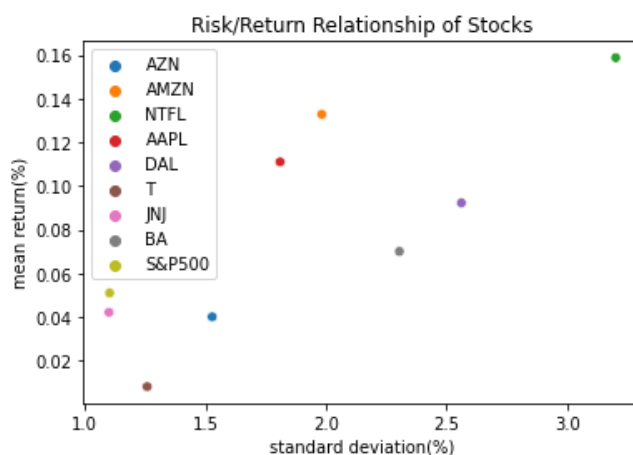


Figure 6. Risk-Return of Stocks.

Table 1. Alpha, Beta and Expected Returns of Stocks based on CAPM.

| Stock | Alpha | Beta | Expected Return (%) |
|-------|-------|------|---------------------|
| AZN   | 0.00  | 0.70 | 8.96                |

| Stock | Alpha | Beta | Expected Return (%) |
|-------|-------|------|---------------------|
| AMZN  | 0.08  | 1.00 | 12.88               |
| NTFL  | 0.11  | 1.05 | 13.47               |
| AAPL  | 0.06  | 1.08 | 13.84               |
| DAL   | 0.03  | 1.24 | 15.90               |
| T     | -0.03 | 0.69 | 8.85                |
| JNJ   | 0.01  | 0.66 | 8.48                |
| BA    | 0.00  | 1.35 | 17.29               |

### 4.3. Portfolio Formulation

Markowitz states in his theory that risk and return are linked together, and therefore, the degree of risk is measured at each scenario. It is also difficult to generate high returns without being exposed to the same level of risk. This is illustrated in Figure 7. By investing solely in one of the eight considered stocks, it is impossible to achieve a return more desirable than the asset itself. In Figure 7, investors would prefer a risk/return relationship situated as far to the upper left of the graph as possible, offering a high return while bearing a low risk; this is impossible due to the fact that a high return almost always comes with high risk. This explains why diversification is necessary.

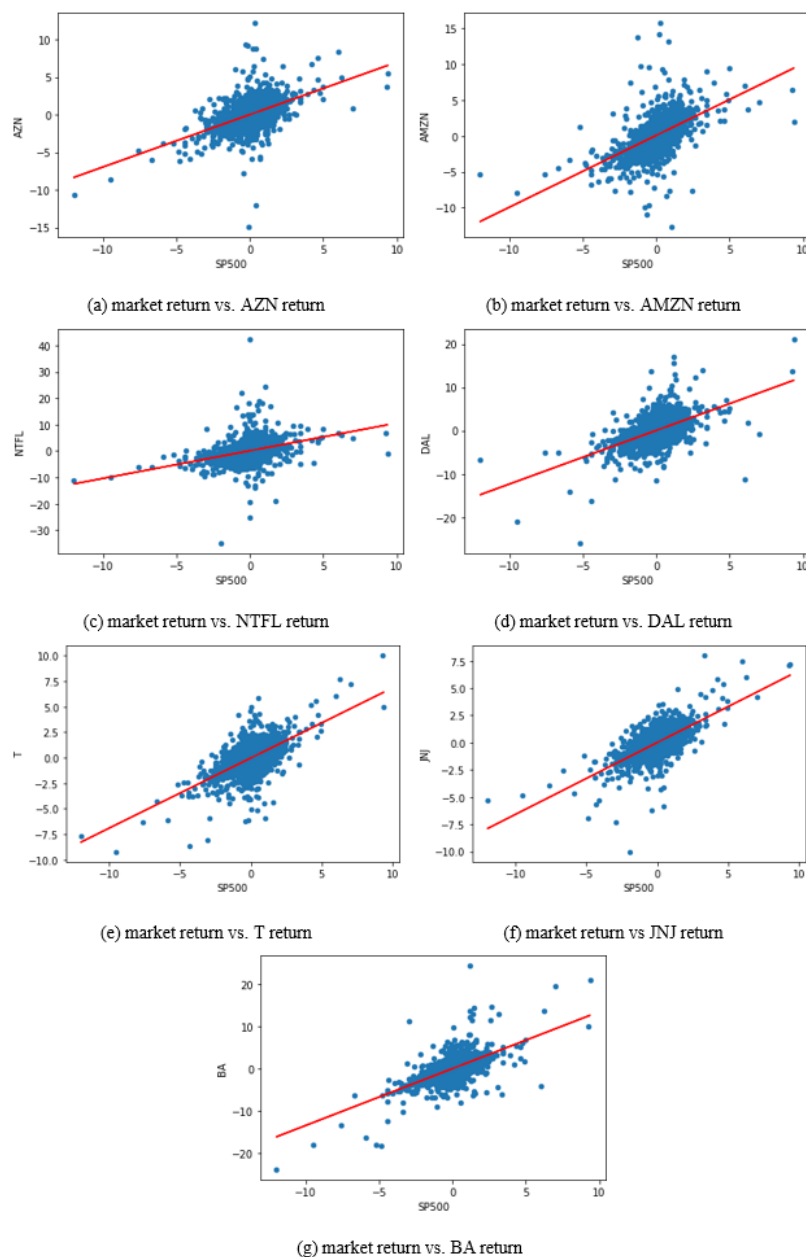


Figure 7. Market Returns vs Stock Returns.

#### 4.4. Portfolio Covariance

Calculating the portfolio covariance is the first step in calculating the portfolio volatility as specified by Equation (2). Covariance determines the relationship between the movements of two stock prices. If two stocks have positive covariance, that

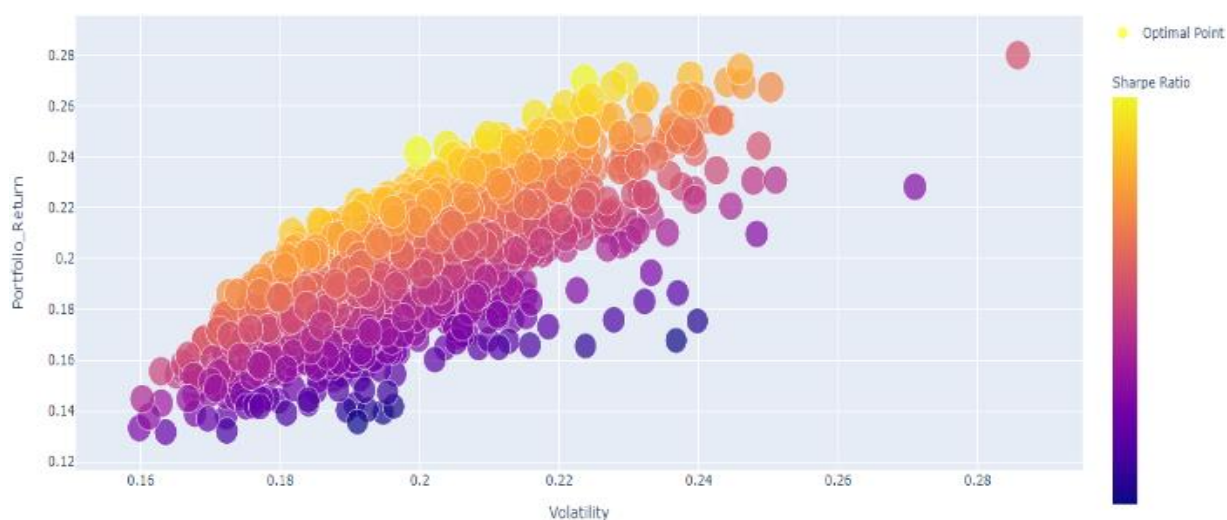
means that their prices move together. Covariance is crucial for asset pairing by selecting stocks with negative covariance values in order to achieve appropriate diversification. However, stock prices are generally positively correlated as shown in Figure 5. Table 2 shows the covariance matrix of the stocks.

**Table 2.** Annualised Covariance Matrix.

| Stock  | AZN   | AMZN  | NTFL  | AAPL  | DAL   | T     | JNJ   | BA    | S&P500 |
|--------|-------|-------|-------|-------|-------|-------|-------|-------|--------|
| AZN    | 0.059 | 0.020 | 0.024 | 0.022 | 0.021 | 0.014 | 0.018 | 0.023 | 0.021  |
| AMZN   |       | 0.100 | 0.067 | 0.041 | 0.029 | 0.014 | 0.017 | 0.031 | 0.031  |
| NTFL   |       |       | 0.258 | 0.039 | 0.037 | 0.012 | 0.016 | 0.034 | 0.032  |
| AAPL   |       |       |       | 0.083 | 0.034 | 0.018 | 0.018 | 0.040 | 0.033  |
| DAL    |       |       |       |       | 0.165 | 0.028 | 0.020 | 0.084 | 0.038  |
| T      |       |       |       |       |       | 0.040 | 0.017 | 0.030 | 0.021  |
| JNJ    |       |       |       |       |       |       | 0.031 | 0.024 | 0.020  |
| BA     |       |       |       |       |       |       |       | 0.134 | 0.041  |
| S&P500 |       |       |       |       |       |       |       |       | 0.031  |

#### 4.5. Efficient Frontier Using Monte Carlo Simulation

After performing 2, 000 simulations using the Monte Carlo method, the efficient frontier is constructed with several scenarios of possible returns and their associated risks. The efficient frontier graph is shown in Figure 8, the weights and Sharpe ratio at each simulation are calculated. The weights generating the lowest standard deviation for the given return are considered the efficient portfolio.



**Figure 8.** Efficient Frontier.

#### 4.6. Selection of Optimal Risky Portfolio

An optimal portfolio offers the investor a higher risk-adjusted

return among all other combinations on the efficient frontier. For a given set of assets, there is only one optimal risky portfolio. This is always located on the upper tangent (efficient frontier) of the

yield curve. In Figure 8, there are several combinations of portfolios on the efficient frontier indicated in yellow, with unique weights of the assets. However, the optimal portfolio is the one highlighted in deep yellow, offering a return of 0.2702% and the associated standard deviation (risk) of 0.2236%. The Sharpe ratio is 1.21, which measures the risk-adjusted performance of the portfolio. No other combination of the assets would generate a higher risk-adjusted return. The statistics of the optimal risky portfolio are shown in Table 3, and the corresponding portfolio weights in Table 4.

**Table 3.** Statistics of Optimal Portfolio.

| Optimal Portfolio | Metric (%) |
|-------------------|------------|
| Return            | 0.2702     |
| Volatility        | 0.2236     |
| Sharpe Ratio      | 1.2120     |

**Table 4.** Portfolio Weights.

| Stock      | AZN  | AMZN | NTFL | AAPL | DAL  | T    | JNJ  | BA   | S&P500 |
|------------|------|------|------|------|------|------|------|------|--------|
| Weight (%) | 0.07 | 0.27 | 0.11 | 0.16 | 0.07 | 0.01 | 0.23 | 0.04 | 0.02   |

## 5. Conclusions

Investors are always looking for the right allocation to diversify their investments in a way that ensures profitability while protecting against losing their entire investment. Markowitz's portfolio theory assures a strategy for achieving these investment goals. As the number of securities available to investors increases, the usual Lagrangian multiplier approach to solving the optimization problem results in a large number of systems of equations, which are cumbersome to handle. Monte Carlo simulations offer a faster and easier approach, ready to handle any number of securities as shown in this work. Relevant decision indexes, such as the Sharpe ratio for several possible scenarios, are also easily estimated.

## Abbreviations

|          |                                           |
|----------|-------------------------------------------|
| MPT      | Modern Portfolio Theory                   |
| CAPM     | Capital Asset Pricing Mode                |
| US       | United States                             |
| SVM      | Support Vector Machine                    |
| ARIMA    | Auto-Regressive Integrated Moving Average |
| MLP      | Multi-layer Perceptron                    |
| CML      | Capital Market Line                       |
| SML      | Security Market Line                      |
| OLS      | Ordinary Least Squares                    |
| MINLP    | Mixed-Integer Nonlinear Programming       |
| S&P500   | Standard and Poor's 500 Index             |
| COVID-19 | Coronavirus Disease-2019                  |
| AMZN     | Amazon                                    |
| BABA     | Alibaba                                   |
| SE       | Sea Limited                               |

|      |                                  |
|------|----------------------------------|
| XOM  | Exxon Mobil                      |
| NEE  | NextEra Energy                   |
| SHEL | Shell                            |
| DIS  | Walt Disney Company              |
| NFLX | Netflix                          |
| FB   | Facebook/Meta                    |
| F    | Ford Motor                       |
| TSLA | Tesla                            |
| TM   | Toyota Motor                     |
| UNH  | United Health Group Incorporated |
| ABBV | AbbVie Inc.                      |
| ABT  | Abbot Laboratories               |
| BA   | Boeing                           |
| DAL  | Delta Airlines                   |
| AAL  | American Airlines Group          |

## Author Contributions

**Daniel Andoh Arhinful:** Conceptualization, Methodology, Resources, Software, Writing – original draft

**Isaac Ampofi:** Data curation, Methodology, Writing – review & editing

**Ebenezer Larbi Asiedu:** Resources, Writing – review & editing

## Data Availability Statement

The data that support the findings of this study can be found at <https://finance.yahoo.com>

## Conflicts of Interest

The authors declare no conflicts of interest.

## References

- [1] Author Ravikumar, S. and Saraf, P. (2020), 'Prediction of stock prices using machine learning (regression, classification) algorithms', 2020 International Conference for Emerging Technology (INCET). IEEE, pp. 1-5.  
<https://doi.org/10.1109/INCET49848.2020.9154061>
- [2] Mondal, P., Shit, L. and Goswami, S., (2014), 'Study of effectiveness of time series modeling (ARIMA) in forecasting stock prices'. International Journal of Computer Science, Engineering and Applications, 4(2), p. 13.  
<https://doi.org/10.5121/ijcsea.2014.4202>
- [3] Reddy, V. K. S. and Sai, K. (2018) 'Stock market prediction using machine learning', International Research Journal of Engineering and Technology (IRJET), 5(10), pp. 1033-1035.
- [4] Leung, C. K. S., MacKinnon, R. K. and Wang, Y. (2014) 'A machine learning approach for stock price prediction', Proceedings of the 18th International Database Engineering & Applications Symposium, pp. 274-277.  
<https://doi.org/10.1145/2628194.2628211>
- [5] Vijh, M., Chandola, D., Tikkiwal, V. A. and Kumar, A. (2020) 'Stock closing price prediction using machine learning techniques', Procedia Computer Science, 167, pp. 599-606.  
<https://doi.org/10.1016/j.procs.2020.03.326>
- [6] Obthong, M., Tantisantiwong, N., Jeamwattananachai, W. and Wills, G. A survey on machine learning for stock price prediction: algorithms and techniques. Proceedings of the 2020 International Conference on Finance, Economics, Management and IT Business, (202) pp. 63-71.  
<https://doi.org/10.5220/0009340700630071>
- [7] Nikou, M., Mansourfar, G. and Bagherzadeh, J. (2019) 'Stock price prediction using deep learning algorithm and its comparison with machine learning algorithms', Intelligent Systems in Accounting, Finance and Management, 26(4), pp. 164-174.  
<https://doi.org/10.1002/isaf.1459>
- [8] Mehtab, S., Sen, J. and Dutta, A. (2020) 'Stock price prediction using machine learning and LSTM-based deep learning models', Symposium on Machine Learning and Metaheuristics Algorithms, and Applications. Singapore: Springer, pp. 88-106.  
[https://doi.org/10.1007/978-981-16-0419-5\\_8](https://doi.org/10.1007/978-981-16-0419-5_8)
- [9] Prasad, V. V., Gumparthi, S., Venkataramana, L. Y., Srinethe, S., Sruthi Sree, R. M. and Nishanthi, K. (2022) 'Prediction of stock prices using statistical and machine learning models: a comparative analysis', The Computer Journal, 65(5), pp. 1338-1351. <https://doi.org/10.1093/comjnl/bxab167>
- [10] Markowitz, H. M. (1999) 'The early history of portfolio theory: 1600-1960', Financial Analysts Journal, 55(4), pp. 5-16.  
<https://doi.org/10.2469/faj.v55.n4.2286>
- [11] Tobin, J. (1958) 'Liquidity preference as behavior towards risk', The Review of Economic Studies, 25(2), pp. 65-86.  
<https://doi.org/10.2307/2296205>
- [12] Sharpe, W. F. (1964) 'Capital asset prices: A theory of market equilibrium under conditions of risk', The Journal of Finance, 19(3), pp. 425-442. <https://doi.org/10.2307/2977928>
- [13] Affleck-Graves, J. and Money, A. (1976) 'A comparison of two portfolio selection models', Investment Analysts Journal, 5(7), pp. 35-40. <https://doi.org/10.1080/10293523.1976.11447265>
- [14] Lee, H.-S., Cheng, F.-F. and Chong, S.-C. (2016) 'Markowitz portfolio theory and capital asset pricing model for Kuala Lumpur stock exchange: A case revisited', International Journal of Economics and Financial Issues, 6(3S).
- [15] Bonami, P. and Lejeune, M. A. (2009) 'An exact solution approach for portfolio optimization problems under stochastic and integer constraints', Operations Research, 57(3), pp. 650-670.
- [16] Ao, M., Li, Y. and Zheng, X. (2017) 'Solving the Markowitz optimization problem for large portfolios. Available at: [http://fmaconferences.org/SanDiego/Papers/MAX-SER\\_MengmengAo.pdf](http://fmaconferences.org/SanDiego/Papers/MAX-SER_MengmengAo.pdf)
- [17] Alekneviciene, V., Alekneviciute, E. and Rinkeviciene, R. (2012) 'Portfolio size and diversification effect in Lithuanian stock exchange market', Engineering Economics, 23(4), pp. 338-347. <https://doi.org/10.5755/j01.ee.23.4.2760>
- [18] Fama, E. F. and French, K. R. (2004) 'The capital asset pricing model: Theory and evidence', Journal of Economic Perspectives, 18(3), pp. 25-46.  
<https://doi.org/10.1257/0895330042162430>
- [19] Perold, A. F. (2004) 'The capital asset pricing model', Journal of Economic Perspectives, 18(3), pp. 3-24.  
<https://doi.org/10.1257/0895330042162359>

## Biography



**Daniel Andoh Arhinful** is a lecturer at the Department of Mathematical Sciences of the University of Mines and Technology (UMaT). He completed his PhD at UMaT in 2025 and his Master of Mathematical Engineering from the University of L'Aquila, Italy, and Brno University of Technology in the Czech Republic. He has an interest in Finance, Dynamical Systems and Chaos Theory, and Mathematical Modelling.



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**Ebenezer Larbi Asiedu** is a Mathematics lecturer at the Department of Mathematical Sciences of UMaT. He holds a PhD and a Master's degree in Mathematics from UMaT. He researches into areas including Disease Modelling, Applied Mathematics, Machine Learning, and Artificial Intelligence.

## Research Field

**Daniel Andoh Arhinful:** Dynamical Systems, Control Systems, Mathematical Epidemiology, Financial Modelling

**Isaac Ampofi:** Financial and Economic Modelling, Financial Derivatives, Machine Learning and Artificial Intelligence

**Ebenezer Larbi Asiedu:** Financial and Economic Modelling, Applied Mathematics, Disease Modelling, Machine Learning and Artificial Intelligence