Risk and Return Management: An Integrative Approach to Portfolio Optimization Using the Markowitz Model, and Monte Carlo Simulation

School of Computing,
Dublin City University, Dublin

Saket Agarwal
22263038
saket.agarwal3@mail.dcu.ie

Raj Vibhute
22261276
raj.vibhute2@mail.dcu.ie

I. Abstract

This paper gives a thorough investigation that focuses on data analysis methods for rating the top stock market performers. Utilise the Capital Asset Pricing Model (CAPM) and Markowitz Portfolio Theory to optimise portfolios based on risk and return. To evaluate portfolio performance and risk-adjusted returns, we use the Sortino Index and the Sharpe Ratio. We make use Monte Carlo simulations to forecast stock prices and evaluate the risk of investments. Additionally, simulations of option prices are run to predict option prices for risk assessment. The study offers useful information for managing risks, optimising portfolios, and making informed stock market investments. We provide a useful method for creating effective portfolios that strikes a compromise between return maximisation and risk management.

Keywords: Data Analysis, Markowitz Portfolio Theory, Capital Asset Pricing Model, Sharpe Ratio, Sortino Index, Portfolio Optimization, Monte Carlo Simulations, Efficient Frontier, Option Pricing.

II. Introduction

In the financial literature, it is well known that investors seek to maximise the return on their investments while minimising the associated risk as much as possible.

An effective investment plan balances risk and reward in a portfolio. A popular technique for tailoring portfolios to an investor's risk and return objectives is the Markowitz model. Additionally, by simulating a variety of potential outcomes in intricate financial settings, Monte Carlo simulation is a one method to efficiently controls risk and reward. The integrated strategy of employing Markowitz models and Monte Carlo simulations provides a comprehensive framework for managing risk and return in portfolios. It combines the benefits of both approaches, giving investors the information they need to make wise selections. Monte Carlo simulations examine how various risk factors affect portfolio performance, giving important insights into how it will behave in various market contexts.

In conclusion, This project aims to delve into to manage risk and returns using the Markowitz Model and Monte Carlo simulation, assisting investors in creating well-informed portfolios to achieve their objectives. A ten-year dataset of S&P stock data is used in the study to analyse long-term trends, spot patterns, and optimise portfolios. To reduce losses and improve overall performance, it is essential to build optimised portfolios that consider daily stock movement, price changes, and rebalancing procedures.

III. Related Work

Fundamentally, Three significant considerations must be addressed while investing in the stock market: stock selection, trading timing, and price forecasting. To maximise returns, investors must concentrate on establishing the best trading period, forecasting stock trends or prices, and selecting potential stocks. Van-Dai Ta et al. [1] present a machine-learning technique for optimising portfolios and predicting stock prices in quantitative trading. The study emphasises the benefits of machine learning in quantitative trading over traditional algorithmic trading. They forecast stock movements using both linear regression and support vector regression models, and they discover that linear regression performs better. The accuracy of predictions increases when technical indicators are included in the dataset. Despite disparities between prediction modelling and real-world trading, their trading method outperforms the S&P 500 ETF-SPY.

Sen et al. [2] take on the problematic issue of anticipating future stock prices and developing optimised portfolios based on their predictions. The top five stocks from nine different industrial sectors on the Indian stock market from January 2016 to December 2020 are the focus of their study's historical price time series analysis. They create portfolios for each industry and create a better long-and-short-term memory (LSTM) model for predicting stock prices. They compare each portfolio's actual and projected returns and risks after five months, demonstrating the LSTM model's excellent accuracy in predicting successful outcomes. They use the LSTM model to predict stocks with high precision, in contrast to the earlier work [1]. CHOU et al. [3] provide the trend ratio, a unique investment technique that varies from the Sharpe ratio, by accurately evaluating portfolio risk by examining the trend line. Short selling and certificates of deposit are used to increase investment earnings and diversify risks. To maximise stock combinations, the global quantum-inspired tabu search method with a quantum NOT-gate (GNQTS) is used, and a sliding window methodology is used to reduce overfitting. The experimental results demonstrate the efficacy of long and short-selling investments, demonstrating that the proposed method outperforms the Sharpe ratio.

Safiudeen et al. [4] aim to present a complete overview of asset allocation and portfolio design literature, integrating theoretical and practical views similar to studies [1][2] and [3]. They believe portfolio management is the best way to attain this goal. The Efficient Markets Hypothesis, which assumes market efficiency based on publicly available information, and behavioural finance, which emphasises irrational behaviour of retail traders leading to market inefficiencies, are investigated as opposing paradigms for analysing asset allocation and security selection. According to experts, fundamental and technical research can help identify price movements in the market and find profitable trading chances. The portfolio management process is divided into four stages: portfolio planning, portfolio creation, portfolio review, and asset allocation. These procedures assist an investor in determining their risk tolerance, risk-taking ability, the ideal weighting of each investment in the portfolio, and an acceptable predicted return based on current market conditions. Unlike earlier research [1][2][3], Safiudeen et al. [4]

include these four phases to provide a holistic portfolio management method.

Castro et al. [6] present an optimisation methodology for analysing portfolios of investment projects with genuine options in a separate study. In contrast to the traditional approach focused on mean-variance analysis using the Sharpe ratio, the methodology tries to maximise the Omega performance indicator by taking into account all moments of the portfolio's return distribution or net present values (NPVs). This approach provides a complete portfolio performance evaluation using Omega as an objective function. A Monte Carlo simulation example shows how optimising the Omega measure results in a better risk-return ratio.

To improve investor economic growth, Javier Fernández-Rendón et al. [5] present a more realistic approach to portfolio selection. They give an integer variable-based portfolio selection model that addresses the difficulties associated with applying solutions in practice due to asset indivisibility. The model offers practical solutions for the mixed-integer nonlinear programming issue using a genetic algorithm, boosting practicality and improving portfolio optimisation strategies. The study employs large datasets from 2000 to 2019, including various elements and methodologies to provide a complete understanding of portfolio optimisation and prediction.

IV. **Data Integration**

During the study gathered historical data for the S&P 500 index companies from 2008 to 2018 from Yahoo Finance. We then combined the individual files for each organisation to produce a comprehensive data set so that it can be used more quickly in research. The fact that this integration made it possible to explore and analyse more data has produced a uniform picture of past results for most businesses over the period under consideration.

Following the consolidation of data, the focus has been reduced to the top 50 performing companies in the S&P 500 index. We focused on researching organisations that performed remarkably throughout a specific period to choose the best-performing ones. The final dataset, which serves as the foundation for our analysis and investigation in this study, contains historical data for these top 50 organisations from 2008 to 2018. This dataset will allow us to explore several facets of the financial and

market patterns that these organisations demonstrated during the given time frame.

V. **Exploratory Data Analysis**

Exploratory data analysis, is a crucial stage in comprehending and drawing conclusions from a dataset. In this section, we conducted exploratory data analysis (EDA) on a dataset with 136,687 rows and eight columns. The names of columns shall be Date, Open, High, Low, Closed, Adj Close, Volume and Name. In order to identify any data pertaining issues while showing details such as null values, types and column names, we have performed an evaluation of the dataset's size and form. To comprehend the distribution of the data and its central tendencies, summary statistics such as count, mean, standard deviation, minimum, quartiles, and maximum values were computed for each column. We then looked at the data's first and last few rows in order to get a better idea of its structure, as well as any potential quality or formatting issues.

To understand the different representations of the dataset during the EDA phase, we took note of each distinct value in the 'Name' column. We also determined the percentage of missing data for each column, highlighting regions needing additional research or imputation methods. We also made temporal analysis simpler by altering the "Date" column's datetime format and extracting the year for time-based analysis or grouping based on annual trends. This in-depth dataset analysis lays the groundwork for future research and potential revelations.

In order to highlight performance trends for that period, we performed additional analysis by filtering the data from 2008 to 2013 and computing average values for each year and company. Based on the average high value and paying particular attention to companies with steadily rising stock values, the top 10 performing companies were chosen. We produced a bar chart for 2008 to 2013, highlighting changes and patterns in the stock prices of these top 10 firms using the "Open" and "Close" columns.
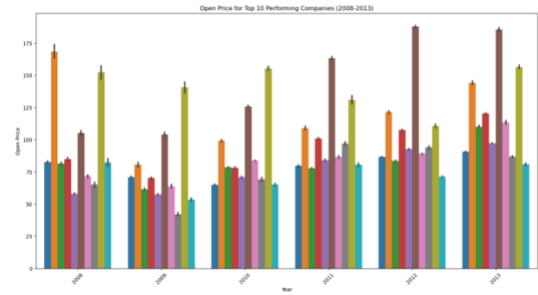

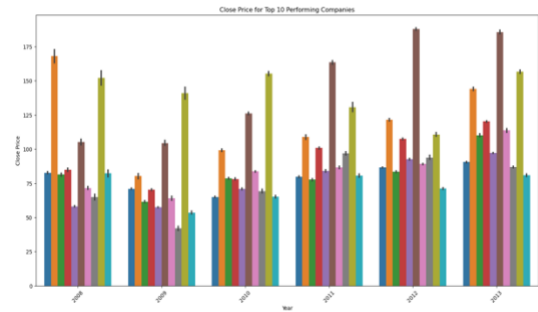Fig 1. Open Price for Top 10 Performing Companies (2008 – 2013)

Fig 2. Close Price for Top 10 Performing Companies (2008 – 2013)

Additionally, a bar chart for the "Volume" Column was made, which aids in highlighting any significant changes in their trading activity.
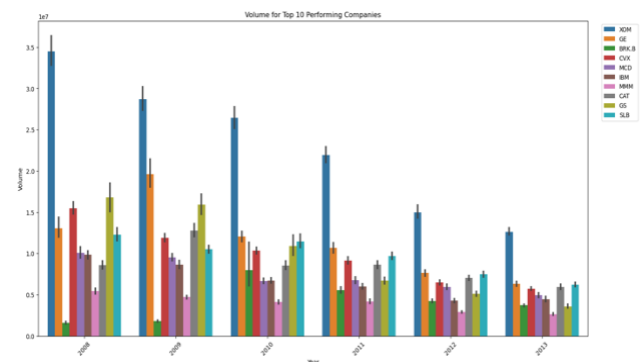

Fig 3. Volume for Top 10 Performing Companies (2008 – 2013)

VI. **Methodologies**

In the Methodologies section, we have outlined key strategies and methods used in our investment portfolio optimisation study. The Methodologies section covers a wide range of financial models and measures such as the Markowitz Portfolio Theory, Sharpe Ratio, Sortino Index, Capital Asset Pricing Model (CAPM) and Monte Carlo Simulations. These methodologies have provided important information for building effective portfolios, assessing risk-adjusted performance, making assumptions on projected returns and simulating market scenarios.

• Markowitz Portfolio Theory:

The Markowitz Portfolio Theory, developed by economist Harry Markowitz in 1952, tries to optimise investment portfolios by maximising returns and minimising risk [7]. Diversification is emphasised as a way to reduce total risk. Investors can build portfolios with the optimal return for a particular level of risk by choosing assets with uncorrelated or negatively correlated returns [8].

Markowitz's Portfolio Theory aids in the creation of successful portfolios by identifying top-performing businesses based on historical returns [2]. The notion distributes the budget among numerous businesses, lowering total risk. Monte Carlo simulations are useful for forecasting stock prices and evaluating performance. By examining the trade-offs between risk and return and enabling investors to make logical investment decisions that strive to maximise profits while minimising risk, this approach assists them in making wise judgements [7].

• Sharpe Ratio:

The Sharpe Ratio, named after William F. Sharpe, is a popular financial metric used to evaluate investment performance after considering risk [9]. It calculates the excess return on a portfolio relative to a risk parameter, typically volatility. In this study, the performance of portfolios built using the Markowitz Portfolio Theory is evaluated using the Sharpe Ratio [5]. Finding the best risk-return trade-off among the recently produced portfolios is made easier by computing the Sharpe Ratio for each portfolio.

Investors evaluate and choose portfolios with higher returns and lower volatility using the Sharpe Ratio. The addition of this statistic improves the overall risk-adjusted performance of the investment strategy [9]. Investors can choose portfolios that strike the optimal balance between risk and return by utilising the Sharpe Ratio, which will result in more effective and successful investments.

• Sortino Index:

The Sortino Index is a well-known risk-adjusted performance indicator that evaluates the downside risk of an investment. It concentrates only on the volatility of negative returns, unlike the Sharpe Ratio [9]. The Sortino Index is utilised in this study to assess portfolios built using the Markowitz Portfolio Theory. It aids in the identification of portfolios with greater risk-adjusted returns by penalising significant downside volatility.

For investors who place a high priority on downside risk mitigation, the Sortino Index is quite advantageous. It makes choosing portfolios with superior returns and steady performance throughout market downturns easier [9]. Investors can use the Sortino Index to make educated selections, enhancing negative risk profiles and total risk-adjusted performance. The Sortino Index aids in the improvement of investment strategies for potentially improved outcomes in volatile markets [10].

• Capital Asset Pricing Model (CAPM):

The CAPM is a crucial financial tool that determines the expected return on an asset or portfolio based on systematic risk [11]. The Markowitz mean-variance model was developed to calculate the cost of capital assets. The model assumes a linear relationship between expected return and market risk in a market equilibrium. Three presumptions underlie the CAPM: rational investors; an unhindered, fully operational capital market; and adherence to Markowitz's guidelines for efficient portfolio construction and investment diversification [7].

The CAPM is used in the study to evaluate asset and portfolio performance. For various categories of investors, it offers helpful information by calculating predicted returns. The risk-adjusted discount rate in the CAPM consistently assesses asset attractiveness [9]. This aids investors in developing balanced investment strategies that are in line with their financial objectives, identifying chances to maximise returns depending on their level of risk tolerance, and making informed portfolio allocation decisions.

• Monte-Carlo Simulation:

Monte Carlo simulation is a computer-based method for modelling and analysing complex systems with uncertainty [12]. On the basis of different inputs and probability distributions, it mimics financial assets or portfolios [1][2]. It helps assess potential outcomes and the likelihood of attaining financial goals under various market situations by repeatedly simulating various scenarios and creating random samples [1][2][13]. This approach also evaluates the risks connected to future portfolio returns and investment choices [1].

A crucial instrument in this investment analysis is the Monte Carlo simulation. By taking into account market information, volatility, and correlation, it estimates portfolio success [1][5][6]. It offers insightful information on various investing strategies in erratic markets, assisting investors in making wise choices[2][5]. The simulation supports in risk management and asset allocation for long-term financial goals and assesses the portfolio's resistance to market volatility[1][2][5][6].

VII. Implementation and Results

This section covers the details of how our project for optimising investment portfolios has been implemented. Python is used to analyse large amounts of data such as NumPy or Pandas, due to its strong financial tools and libraries. In order to ensure that the built-in portfolios are applied and efficient, real market data from reliable sources should also be incorporated into the project.

First, we thoroughly examined the performance of numerous companies over the span of ten years. The material was then painstakingly sorted and organised by firm names and dates, enabling efficient data processing. The rate of return for each business was then calculated, taking into account the percentage change in value over time. We determined the yearly average return as well as the 10-year average return for each company to get a complete picture. These measures offered important insights into the financial health and expansion of the companies and functioned as indications of annual and overall performance. The 10-year average returns of several corporations were effectively visualised and contrasted in our final presentation of our findings using a clean and concise bar chart.

After computing the ten year mean returns in respect of each company, as a gauge of individual firms' volatility and risks, we calculate the Standard Deviations for such Average Returns. In order to assess the extent of variance in companies' performance throughout the decade, this deviation has given us useful information about the distribution of data points according to the mean. We've created these standard deviation values in order to help us make our conclusions. In order to further improve the clarity of our findings, we presented a clear and instructive bar chart which showed that for each company there was an approximate deviation from the mean 10 year return.

Following that, we concentrated on determining the covariance between various securities contained inside the dataset. We were able to gather important information about the relationships and dependencies of these assets through the creation of a covariance matrix, providing us with an early clue as to which investment would be most appropriate.

To simulate an investment scenario, we randomly allocated an $8000 budget across a variable number of companies in the dataset. After selecting six to seven different company names, we randomly assigned weights ranging from 0 to 1. These weights were adjusted to 1, which represents the proportion of the budget allocated to each company as a result of normalisation. By applying the assigned amounts in line with normalised weights, we have been able to distribute them fairly between selected companies and generate a summary of their contribution to the investment portfolio. To make it easy to understand the results of this study, we have printed select companies with their relevant weightings and corresponding allocated amounts which are an overview of investment distribution processes as well as helping in determining future investment decisions.

After allocating capital to the chosen businesses, we continued by determining the performance measures for the portfolio. In particular, the return of individual companies based upon their allocated resources has been merged to establish a portfolio's yearly returns. The next step was to calculate the annual variance and standard deviation, which gave us information about the portfolio's risk and volatility over time.

Then to illustrate our findings in a visual manner, we have used the following line charts for each calendar year's return, annual variance and portfolio standard deviation. This graphical representation enabled us to monitor portfolio performance and risk levels over the period under review, which made it possible to gain a better understanding of overall financial dynamics.
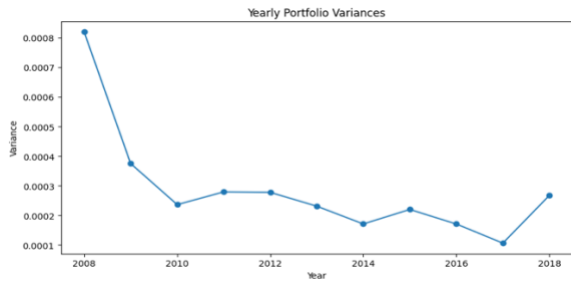

Fig 4. Yearly Portfolio Returns
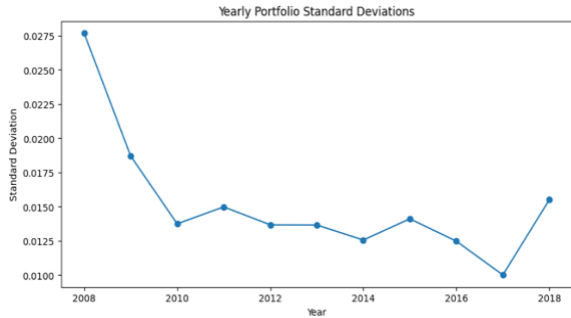
Fig 5. Yearly Portfolio Variances

Fig 6. Yearly Portfolio Standard Deviations

Now In this work, we used Python to implement the Efficient Frontier idea from Modern Portfolio Theory (MPT) to help with risk management and portfolio optimisation. The efficient frontier refers to a set of ideal portfolios which offer the highest expected return for an identified amount of risk. In this context, we have established the risk free rate to be 5% for our analysis. Then, in order to ensure that the weights of each asset were combined into 1 we set up 500 randomly selected portfolios with different proportions of assets. These portfolios have been created on the basis of an historical 10 year mean return, which has been derived from a database.

Then using the Covariance Matrix of Asset Returns, we have calculated to expect a return and standard deviations for the portfolio. In order to evaluate risk adjusted returns, we calculate an excess portfolio return by taking out a risk-free rate from the portfolio's asset value. Finally, we were able to see an following efficient frontier using a scatter plot with portfolio excess returns on the y - axis and portfolio standard deviations on the x - axis. Each point's colour on the following figure denoted the excess return to standard deviation ratio, which reflected the risk-adjusted return. Using an efficient frontier we have been able to identify the best portfolios based on our tolerance for risk and return expectations, which has provided us with valuable information in order to make informed investment decisions.
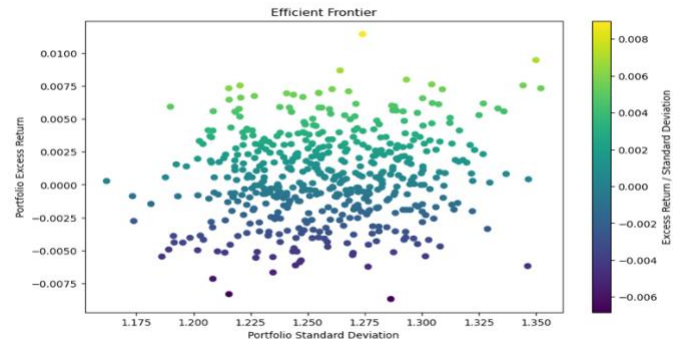

Fig 7. Efficient Frontier

Then, in our implementation, we evaluated risk-adjusted performance using the Sharpe ratios and Sortino index. A 5% risk-free rate has been established. By deducting the risk-free rate from the average returns during that period, the excess return of 10 years has been computed. The Sharpe ratio measured the return for each risk unit.

We have broadened our research, which concentrates on negative risks, to incorporate the Sortino ratio. Metrics have been placed in DataFrame pandas to provide a quick summary to help investors make investment decisions by finding equities that offer better risk-adjusted returns.

At this stage of implementation, the Sharpe ratio and Sortino index have been used to optimise our portfolio. These risk-adjusted performance criteria have been used in randomly created portfolios. The Sortino index focused on downside risk, whereas the Sharpe ratio evaluated return per unit of risk. Using a scatter plot visualisation of an efficient frontier, the portfolio with the highest risk-return profiles has been identified. This portfolio is built on a strong Sharpe ratio and Sortino index.

Then, to complete the findings, we calculate statistical measures for each firm and each year, such as the mean, standard deviation, 10th percentile, and 90th percentile of gross profit. The next step is to determine the daily gross profit for various companies. A thorough evaluation of a company's financial performance is possible because of the condensed data supporting risk analysis and investment selection.

We then carried out an thorough analysis of gross sales for individual companies, taking into account historically high closing prices and volumes. Using a Daily Gross Profit calculation and the production of significant statistics such as mean, standard deviations, 10th quintuplicate or ninety percent we were able to

obtain valuable information on each company's financial performance. We have made good investment choices and optimised portfolio allocation as a result of these discoveries.

By using bar graphs, we have shown historical patterns in the mean gross income, standard deviations, 10th percentiles, and 90th percentile for each organisation. Our grasp of profitability and risk, which serves as the guiding concept for successful portfolio strategies, has been strengthened by these graphic representations. Due to our thorough analysis, we were able to link investments with finance goals, which gave us the confidence to make wise investment decisions.

Then for our implementation, we forecasted 'AAPL' (Apple Inc.)'s future price changes using a Monte Carlo simulation. We computed the log returns by examining previous closing prices and ran more than 1000 simulations. With this simulation, we got a crucial insight into the potential price trajectory over the next few years, providing us with a 95% confidence interval that is useful for making wise investment decisions.

The Monte Carlo simulation has been a useful tool in financial forecasting, enabling us to assess risks and optimize investment strategies. Then the Visualization of the mean simulated prices and confidence interval further facilitated comprehension and empowered better decision-making.
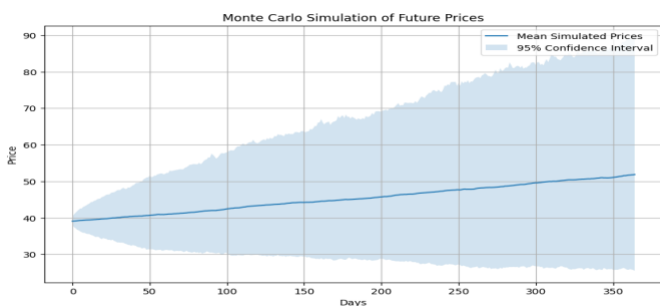

Fig 8. Monte Carlo Simulation of Future Prices for 'Apple Inc.'

For calculating call option price estimates, our method used a Monte Carlo simulation. Using a geometric Brownian motion technique and 1000 simulations with 252 steps, we have constructed stock price pathways. Option payoffs were calculated and discounted to present value using a 5% risk-free rate and 20% volatility with a strike price of 100 and a 1-year expiry. This simulation facilitates the investor's ability to

make well-informed choices on option investment and risk management.

The call option pricing and possible outcomes were clarified by the Monte Carlo simulation. A simulation of stock price pathways and an estimate of the pay-out for options will help investors judge option pricing more accurately and make wise investment decisions. Effective risk management and financial goal alignment will be made possible by this analysis.

Finally, a histogram has been utilised to show the distribution of the final stock prices from the Monte Carlo simulation. This will help investors assess the level of uncertainty associated with option pricing and will give us a better idea of the kind of outcome we may anticipate. This plot gave investors a graphical depiction of how the option would progress towards its next price level by giving them simulated values and a 95% confidence interval. This helped investors analyse risk and make strategic decisions.
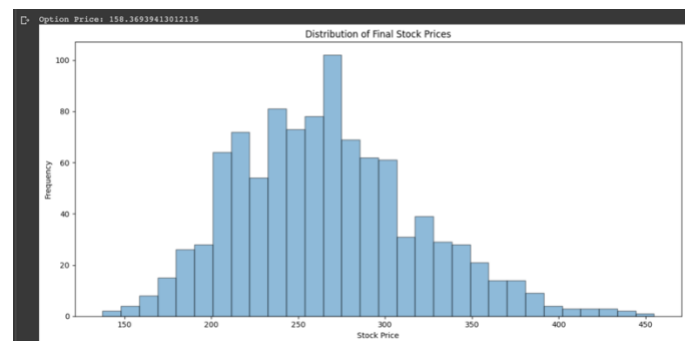

Fig 9 Distribution of the Final Stock Prices

In this section, we successfully carried out the steps essential for risk and return management and visualised the outcomes. The results of our implementation will be examined in the next section.

VIII. **Evaluation**

We analyse the outcomes of our implementation for risk analysis in the evaluation section. This evaluation strives to understand the implementations we've completed thoroughly. Let us now conduct a thorough examination of our findings.

The evaluation begins by visualising comparing 10-year average returns for various companies in a bar chart. This graph shows how each company performed throughout the given time frame. Investors can discover businesses that have historically produced better returns

by looking at the height of the bar and then using that information to decide on possible investment possibilities. Bar charts are a valuable tool for evaluating investment strategies and portfolio diversification and comparing various companies' long-term performance. Let's now think about additional analysis to understand better the data and how it affects investing choices.
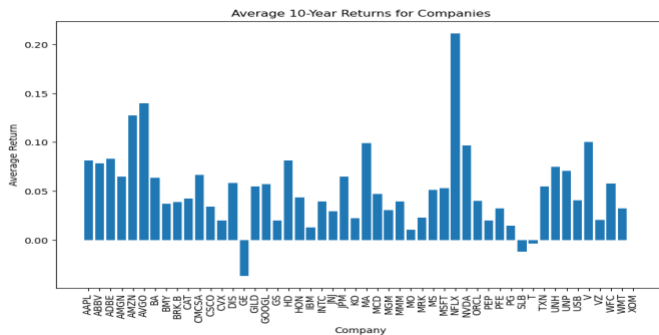

Fig 10. Average 10 – Year Returns for Companies

To continue the evaluation, we further investigate the risks connected to each company's investment by visualising the standard deviation of returns over ten years using bar charts. The historical earnings fluctuation for several corporations is seen in this graph. More excellent bars represent businesses with more erratic results, implying greater investment risk. A smaller bar, on the other hand, denotes firms with a more stable history of earnings and might be less risky.

Investors must comprehend a company's risk profile to manage their investment portfolios responsibly. Investors can better comprehend the risk-reward trade-off and match their investing plan with their risk tolerance by examining the standard deviation of returns over a ten-year period. A more educated approach to portfolio construction and risk management is made possible thanks to the insights gathered from this analysis. Investigate more facets of the data to acquire thorough understanding for wise investing choices.
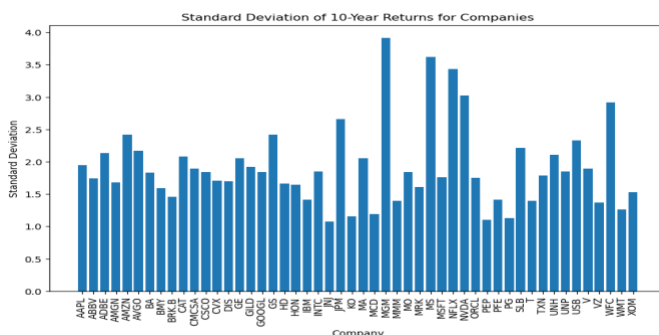

Fig 11. Standard Deviation of 10 – Year Returns for Companies

The performance of various portfolios is then evaluated using the Sortino Index and the Sharpe Ratio. The Sortino Index concentrates on downside risk, whereas the Sharpe Ratio assesses risk-adjusted returns. We determine the portfolios with the highest Sharpe Ratio and Sortino Index by computing these metrics for each portfolio. The best portfolio has an excess return of 0.0114 and a standard deviation of 1.2741, where the Sortino Index for the identical portfolio is 2.1010, while the Sharpe Ratio is 0.0090. These findings provide a valuable understanding of portfolio performance, which enables investment managers to select best portfolios on the basis of their preferences for risk return.

To further illustrate the trade-off between portfolio return and risk, plot the efficiency frontier. Investors can make educated judgements to optimise their investment strategies by referring to the portfolios with the greatest Sharpe Ratio and Sortino Index represented by the highlighted points in the following graph. Effective frontier visualisation enhances knowledge of risk management and portfolio diversification, assisting investors in creating well-balanced portfolios.
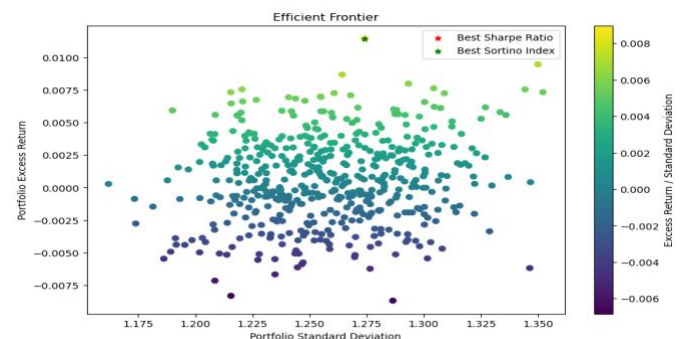

Fig 12. Portfolio with highest risk – return profile highlighted in efficient frontier

Our implementation included conducting a Monte Carlo simulation to forecast future pricing changes for Apple Inc. We calculated its 95% confidence intervals using more than 1,000 simulations. This offers insightful information for sound investing choices. The ability to visualise average simulated prices and confidence intervals improved comprehension and decision-making. Key statistical indicators such as mean price, standard deviation, 10th percentile, 90th percentile, chance of reaching target price, and 5th percentile (VaR) were calculated in later reviews. The median price for Apple Inc. is $45.49, with a standard deviation of 3.86, a 10th percentile price of $40.24, and a 90th percentile price of $51.04. The 5th percentile (VaR) is 39.53, and the likelihood of attaining the target price is 68.77%.

Additionally, we forecasted the security's price at day 100 to be $42.54.

In this evaluation section, we computed and displayed the evolution of Apple Inc.'s stock price. We used drift and volatility values to replicate random profits and get insight into prospective market swings. Line charts aid investors in making educated investment decisions based on reasonable expectations by visually representing predicted price fluctuations over time. We examine statistical indicators produced from stock performance in the next part to evaluate their influence on investment strategy further.
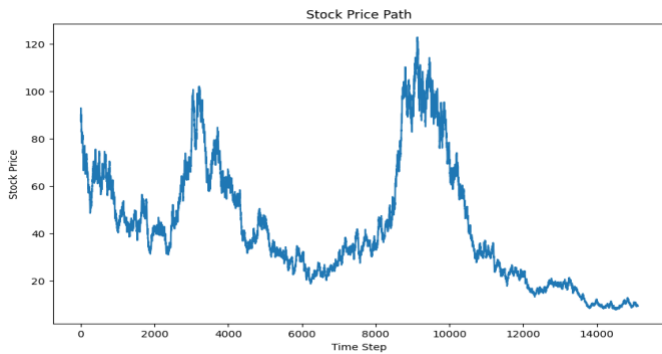

Fig 13. Stock Price Path for Apple Inc.

For the evaluation part, we forecasted Apple Inc.'s future price fluctuations using Monte Carlo simulation and provided a 95% confidence interval to help investors make smarter investment choices. A glimpse of the mean simulated pricing and statistical measurements helped with decision-making. A stock price path evaluation improved insight into the creation of investing strategies. Investors will benefit from these studies by having access to crucial tools for making informed decisions that take into consideration plausible situations.

IX. Limitations

The limitations of the research analysis are based upon a dependence on historical stock prices and technical indicators, as well as its need to know basic components such as fundamentals, economic effects or industry developments that have an impact on stock prices. During times of high volatility or regime transitions, simplified statistical models that are used to assess risk and return might not accurately reflect the complexity of the market. Price prediction relies on random sampling and Monte Carlo simulations, which may not always be true in real-world situations. Transaction costs, taxes, and market liquidity are not

taken into account, which affects the accuracy of profitability estimates. Key risk-adjusted indicators like the Sharpe ratio are disregarded when measurements on mean return and standard deviation are the primary focus. In addition, due to the fact that this algorithm uses several instances of the same historic data, it is missing a problem with data sniffing. These weaknesses combined will indicate that the use of more robust models to make future investment decisions is necessary in order to take appropriate account of fundamental causes.

X. Conclusion

In conclusion, our study analysed stock performance using historical stock market data and found investing opportunities. In order to understand trends, average returns, and price simulations in the future, the study used Monte Carlo simulations. Investors should exercise caution, though, as relying exclusively on historical data has its limitations. Despite its flaws, the study offers insightful information on stock market analysis and investment tactics. Overall, while acknowledging the dynamic nature of financial markets, this research offers the framework for making investing decisions that are better informed.

XI. Future Work

This study could be improved in the future by using sentiment analysis to assess market sentiment and its effect on stock prices. To increase the precision of stock price predictions, more sophisticated machine learning methods like neural networks can be applied. In addition, research on the integration of macroeconomic indicators and alternative data sources, as well as the development of real-time analytical capabilities, may help us gain a deeper knowledge of market behaviour. Additionally, taking into account risk management techniques and expanding the analysis to developing markets like cryptocurrencies can offer investors helpful information. Future research could enhance stock market analysis by employing these techniques and offering investors useful resources and insights for making better decisions.

XII. References

[1] Ta, V.-D., Liu, C.-M. and Addis, D. (2018). Prediction and Portfolio Optimization in Quantitative Trading Using Machine Learning Techniques. *Proceedings of the Ninth International Symposium on Information and*

Communication Technology - SoICT 2018. doi:https://doi.org/10.1145/3287921.3287963.

[2] Sen, J., Dutta, A. and Mehtab, S. (2021). Stock Portfolio Optimization Using a Deep Learning LSTM Model. *2021 IEEE Mysore Sub Section International Conference (MysuruCon)*, [online] pp.263–271. doi:https://doi.org/10.1109/MysuruCon52639.2021.9641662.

[3] Y. -H. Chou, Y. -C. Jiang and S. -Y. Kuo, "Portfolio Optimization in Both Long and Short Selling Trading Using Trend Ratios and Quantum-Inspired Evolutionary Algorithms," in IEEE Access, vol. 9, pp. 152115-152130, 2021, doi: 10.1109/ACCESS.2021.3126652.

[4] M. Safiudeen and M. H. Miraz, "Portfolio Optimization by Asset Allocation," 2022 International Conference on Computing, Networking, Telecommunications & Engineering Sciences Applications (CoNTESA), Skopje, North Macedonia, 2022, pp. 62-65, doi: 10.1109/CoNTESA57046.2022.10011354.

[5] Fernández-Rendón, J. and Rodríguez-Vázquez, K. (2014). Portfolio optimization using an integer genetic algorithm. *Proceedings of the Companion Publication of the 2014 Annual Conference on Genetic and Evolutionary Computation.*
doi:https://doi.org/10.1145/2598394.2602278.

[6] Castro, J.G., Tito, E.A. and Brandão, L.E. (2021). Optimization of a Portfolio of Investment Projects: A Real Options Approach Using the Omega Measure. *Journal of Risk and Financial Management*, 14(11), p.530. doi:https://doi.org/10.3390/jrfm14110530.

[7] Leung, Pui-Lam , et al. *An Improved Estimation to Make Markowitz's Portfolio Optimization Theory Users Friendly and Estimation Accurate with Application on the US Stock Market Investment*. European Journal of Operational Research, 25 May 2011.

[8] Zaimovic, Arnaut-Berilo, A., & Mustafic, A. (2017). Portfolio Diversification in the South-East European Equity Markets. South East European Journal of Economics and Business, 12(1), 126–135. https://doi.org/10.1515/jeb-2017-0010

[9] Low, & Chin, Y.-B. (2013). Refinements to the Sharpe Ratio - Evidence from Malaysian Equity Funds. Global Economic Review, 42(1), 72–97. https://doi.org/10.1080/1226508X.2013.769818

[10] Aldieri, Amendola, A., & Candila, V. (2023). The Impact of ESG Scores on Risk Market Performance. Sustainability (Basel, Switzerland), 15(9), 7183–. https://doi.org/10.3390/su15097183

[11] HeWu and LiuPing, "Empirical Study of the applicability of Capital Asset Pricing Model in Shanghai A-share market," 2011 2nd International Conference on Artificial Intelligence, Management Science and Electronic Commerce (AIMSEC), Deng Feng, China, 2011, pp. 1101-1104, doi: 10.1109/AIMSEC.2011.6010805.

[12] S. Raychaudhuri, "Introduction to Monte Carlo simulation," 2008 Winter Simulation Conference, Miami, FL, USA, 2008, pp. 91-100, doi: 10.1109/WSC.2008.4736059.

[13] G. E. Evans and B. Jones, "The Application of Monte Carlo Simulation in Finance, Economics and Operations Management," 2009 WRI World Congress on Computer Science and Information Engineering, Los Angeles, CA, USA, 2009, pp. 379-383, doi: 10.1109/CSIE.2009.703.

[14] Huei-Wen Teng. 2017. A spherical Monte Carlo approach for calculating value-at-risk and expected shortfall in financial risk management. In Proceedings of the 2017 Winter Simulation Conference (WSC '17). IEEE Press, Article 31, 1–12.