Predicting Stock Market Trends through Monte Carlo Simulation

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***Abstract*—The stock market, often seen as a realm of boundless opportunities for those with average incomes to build their wealth, is notorious for causing financial losses for many investors. The present research uses the Python programming language to collect and evaluate data from financial websites in order to analyze the market's volatility. The strategy used is simulating stock prices in the company Samsung using the Geometric Brownian Motion (GBM) mathematical model. These areas' stocks are used as the dataset for simulations that are carried out over a thousand cycles. The average return of a stock and the standard deviation of past returns are the two most important factors in these simulations. This study provides insightful information for retail traders through the implementation of Monte Carlo Analysis in finance.**

***Index Terms*—Stock Market, Volatility, Python Programming Language, Geometric Brownian Motion (GBM), Dataset, Simulations, Cycles, Average Return, Standard Deviation, Retail Traders, Monte Carlo Analysis**

I. Introduction

Has anyone ever thought about how researchers predict where stock values will go in the future? Monte Carlo Simulation is one method they use to do this. It's similar to a super-smart computer game that predicts what might occur based on many scenarios. Monte Carlo Simulation is a fancy name for a process that simulates many scenarios using numbers that are randomly generated. Assume you want to determine your odds of winning a game that requires some luck. Rather than simply guessing, Monte Carlo Simulation allows a computer to play the game several times with varying luck results. By repeating this process, we may have a decent understanding of the probable outcomes. Basically, Monte Carlo Simulation is a powerful tool in finance that helps predict stock prices by considering various factors like company performance, market trends, and economic changes. It generates thousands or millions of predictions, each based on slightly different circumstances. This approach helps experts understand potential risks and rewards, enabling investors to make more informed decisions.

A great representation of a challenging dynamic system is the financial market. A tremendously helpful approach in many fields, such as the study of operations, theoretical gaming, physics, business, and finance, is the Monte Carlo simulation. It is a method for comprehending how risk and uncertainty affect a decision while making such. Due to fluctuations on a daily basis in both the supply and the demand of stock prices brought on by the avarice and fear of traders and investors from all over the world, the market is very volatile and random. The efficient market hypothesis (EMH) states that in situations when share prices represent a corresponding value, the market discounts every detail that is accessible [1]. As an outcome, conquering the market over time is unfeasible. Hedge funds, despite this, may often outperform the market. In this context, Berkshire Hathaway, a holding firm led by the legendary investor Warren Buffett, returned an average of 20.5% a year, while the S&P 500 index returned an aggregate of just 8% on an annual basis.

Some financiers relentlessly generate a profit in the market year after year. Mathematicians consequently created a number of scientific models in the hope to predict future stock values. Neural networks, fuzzy inference systems, machine learning methods, different ARIMA models, Monte Carlo simulation, and GARCH models constitute some of the models [2], [3]. Robert Brown designed the Geometric Brownian Motion (GBM) model in 1827. It is a concrete instance of this kind of a model. In order to determine the anticipated return and volatility, this study uses the GBM to investigate and assess data from the previous ten years' historical closing prices of the S&P 500 (SPX) and Kuala Lumpur Composite Index (KLCI) [4]. Samsung was the primary focus of this study. GBM was implemented for this study because it makes use of the Monte Carlo Simulation to forecast future stock price movement based on the indices' historical performance.

Studying the performance of stock markets is of the utmost significance because, as Albert Einstein once said, "Small sums snowball into huge amounts." This phenomenon is known as the power of compounding. The abstract, introduction, literature review, problem statement, aims and objectives, research questions, importance of the study, research methodology, system overview, and conclusion make up the framework of this article.

II. Problem Statement

The predictive models employed by hedge funds to anticipate stock prices require in-depth analysis. Monte Carlo Simulation is a robust probability-based mathematical approach which serves as the foundation in analyzing stock market data as well as assisting in understanding risks and potential returns. Andrea and Juan (2019) leveraged this technology to compute probabilities within their Simulating Profit Loss model, significantly enhancing the accuracy of their simulations [5].

Beyond the limits of finance, Monte Carlo Simulation is also used in diverse fields such as computational biology and physical sciences. A demonstration of this versatility lies in the work of Zawin, Siti, and Mohd (2020), who utilized the Monte Carlo Simulation to model the prices of Malaysian gold [6]. This study aims to push the boundaries further by merging the Geometric Brownian Motion (GBM) model and data analysis into Monte Carlo Simulation. The goal is to forecast future stock prices amidst the unpredictable stock market landscape. Studies report that around 67% of traders experience losses in the stock market which further motivates this research [7]. We hope to use Monte Carlo analysis to help everyday traders perform better and generate profit.

Research shows the effectiveness of Monte Carlo Simulation as a phenomenal tool for predicting business risks and predicting stock market events. Due to the unpredictable nature of the stock market, many investors, especially the novice, lose money. This study shows that even newcomers could benefit from using Monte Carlo methods. The integration of Monte Carlo along with the GBM model and data analysis is a promising venture for advancement in the financial sector. The model ensures a raise in shareholder outcomes and encourages better decision-making for the investors.

Monte Carlo Simulation is a powerful tool for probabilistic analysis that aids in understanding potential risks and gains in finance. Its expansion into other domains is also notable in reshaping trading strategies which further emphasizes the possibilities. This study aims to merge it with other such domains to predict stock prices better and help regular traders do well in the stock market.

III. Research Aims, Objective & Research Questions

A widely used approach for implementing unpredictability to financial simulations is the Monte Carlo technique, which is based on principles of probability. That's why in order to predict stock values, this paper is going to use comprehensive Monte Carlo Analysis with Python. By executing several simulations, emphasizing on Samsung's stock over the next year. Drift and shock values were the two key parameters for the Geometric Brownian Motion (GBM) model. The whole data was obtained using market data from stooq.com throughout the last several years. In order to simulate future market stock movements based on historical volatility, the outputs of the GBM model were merged into the Monte Carlo Analysis. The research study nevertheless chose to emphasize the need for caution when interpreting the data, highlighting the fallacious assumption of predictability and established probability distributions in price developments.

The implementation kicked off with an assessment and transfer of data, and then the GBM model emerged with significant features including projected annual return and predicted annual volatility. The research aimed to forecast Samsung's stock price through 1000 simulations. It highlighted how crucial it was to choose a timeframe that closely matched the projection period or manually set figures for the expected annual volatility and predicted annual return.

The main emphasis was the Monte Carlo Simulation approach, which generated a list of results by recording each iteration over the specified function a certain number of times. Equations from a 2016 study article were included into the GBM approach to generate a more comprehensive data model. Detailed calculations involving the expected annual rate of return, annualized expected annual volatility, and random volatility were used to make the appearance at the final stock price.

With the goal to gain perspective into a stock's potential future performance, the research examined probability distributions, mean distributions, and standard deviation distributions. Because an investor might consider both before and after buying a stock. The model's robustness, sensitivity to changes in input parameters, and discrepancies between simulated and real market behavior were all extensively evaluated throughout the discussion phase. The successful implementation of the Monte Carlo simulation strategy in stock price prediction scenarios was validated via comparisons with other prediction methods, giving investors a comprehensive grasp of likely future events in the dynamic and unpredictable financial market environment.

The Geometric Brownian Motion (GBM) model was chosen for its simplicity, familiarity, and ease of application in financial modeling, notably in stock market predictions. It is a practical alternative due to its simple mathematical formulation, efficacy, and historical use in trading options. But there are other alternative models available, including ARIMA, GARCH, different machine learning models such as Gradient Boosting, LSTM and stochastic volatility models, each with its own set of strengths. The choice of a model is influenced by factors such as data properties, analytic aims, and base assumptions. Researchers frequently experiment with several models to discover the one that best fits the characteristics of the financial time series under examination, while factors like data availability and computational effectiveness also play a part in the process of making decisions.

IV. Significance Of The Research

In accordance with a JP Morgan survey, 53% of traders consider projected and real-time market conditions as the most important data tool, highlighting the importance of precise analysis of market trends [8]. This agreement emphasizes how important it is for traders to have access to legitimate predicted insights. A notable problem for individual traders is the absence of sophisticated instruments generally accessible to institutional hedge funds, which contributes to their vulnerability to stock market losses. To fill this void, the current study provides an important addition by providing exact information on Samsung using a scientific and quantitative methodology.

To give insights to retail traders, the study specifically takes advantage of Monte Carlo Simulation, an innovative modeling approach. This strategy goes beyond typical assessments, providing a more detailed insight of future market patterns. The study uses Monte Carlo Simulation to provide more accurate forecasts to retail traders, allowing them to make better-informed judgments. This emphasis on scientific and quantitative techniques not only fills a vital vacuum in the availability of sophisticated tools for retail traders, but it also corresponds with a rising realization of the essential role correct prediction plays in risk mitigation and overall trading results.

V. Literature Review

The Monte Carlo method is actively used for assessing price options, particularly considering the inherent uncertainty involved with financial assets like options [9]. While the Monte Carlo technique is well-known in option pricing, its application in forecasting stock returns is less common. Although some informal study has been undertaken in this area, most of it by amateur shareholders, the shortage of substantially published scholarly studies on the issue exposes a void in this particular aspect. Additionally, the current research tries to overcome the knowledge gap by incorporating ideas from domains other than just stock market simulation modeling. This paper attempts to contribute to a largely unexplored research subject by integrating information and approaches from relevant disciplines, bringing a new viewpoint on predicting stock returns through the use of the Monte Carlo methodology.

A. Current Stock Market Situation

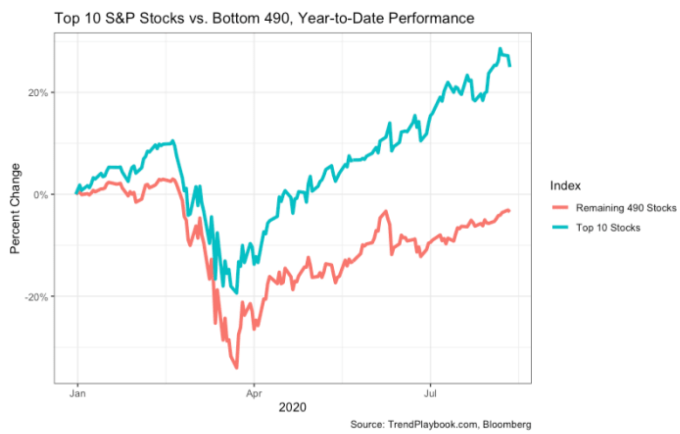


Fig. 1. Top 10 S&P stocks vs. bottom 490, year to date performance

The graphic above compares the cap-weighted results of the 10 largest stocks at the beginning of the year 2020 to the other 490. The red line represents the S&P(Stocks and prices) 500 without those 10 stocks. At last count, the 10 largest S&P 500 equities had gained 25% on average this year. If they are excluded, the S&P 500 is down 3.4%. But what's most interesting is what's been occurring recently: while the largest stocks have been dragging the S&P to record highs since February 2020, the S&P minus those 10 names is still lower than it was only two months ago. Basically, the COVID-19 epidemic caused severe instability and disruption in the global stock market in 2020. The pandemic-driven sell-off in March 2020 prompted government intervention and incentive programs, which helped to stabilize markets. The technology and healthcare industries remained resilient, owing to rising demand for freelance solutions and healthcare advancements. Markets began to rebound in the second half of 2020, buoyed by encouraging news regarding vaccine research. Recovery times varied by region and country, with some Asian markets rebounding swiftly and others taking longer. A healthy IPO market was aided by tech stock booms and IPOs. However, continued uncertainties and geopolitical tensions exacerbated financial market concern [10].

Company	Ticker	S&P Weight at 1/1/20
Apple	AAPL	4.6%
Microsoft	MSFT	4.2%
Alphabet	GOOG, GOOGL	3.2%
Amazon.com	AMZN	3.2%
Facebook	FB	2.1%
Berkshire Hathaway	BRK.B	1.9%
JPMorgan	JPM	1.5%
Johnson & Johnson	JNJ	1.3%
Visa	V	1.3%
Walmart	WMT	1.2%

Fig. 2. Ten stocks that made up the "buy list" at the start of 2020

The 2020 COVID chaos was the quickest and biggest crash in stock market history. Based to the LPL Analysis illustration, the stock market has had 11 bear markets since 1956, including the iconic Dot Com Crash and Subprime Mortgage Crisis, but has recovered [11].

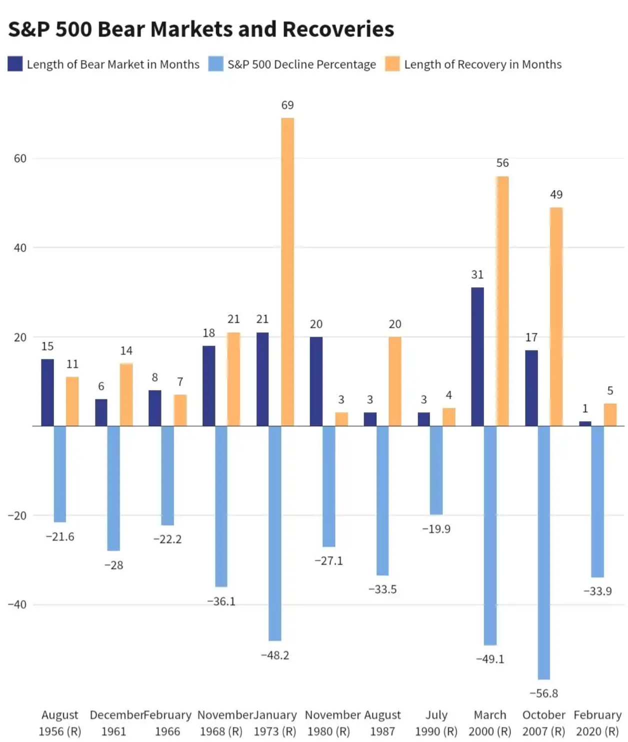


Fig. 3. SPX Bear Market and Recoveries [12]

If we look at the figure above, one factor is certain, as that following a bear market, there will be another bull market. The sole distinction is that bad and weak firms may fail, but strong and resilient companies will become ever more powerful. However, the period required to restore to pre-crash levels might be lengthy. The bear market in the 2008 crisis lasted 17 months, but it took 49 months to recover to pre-crash levels. The recuperation time was about three times that of the bear. As a result, a fundamental concern when discussing managing the bear market is, "Can you hold that long?" Can you hold for at least 5.5 years? [12]

B. Geometric Brownian Motion(GBM)

A geometric Brownian motion (GBM) is a continuous-time stochastic process in which the logarithm of an arbitrarily variable quantity follows a Brownian motion (also known as a Wiener process) involving drift. Johannes Voit's GBM model for foreseeing market prices, originally released in 2005, is a continuous-time stochastic method in which the logarithm of the randomly fluctuating variable follows a Brownian motion with drift [13]. GBM is a continuous-time chaotic procedure that obeys the Stochastic Differential Equation (SDE):

$$\mathrm{dSt} = \mu \mathrm{Stdt} + \mu \mathrm{StdBt} \qquad \text{(i)}$$

Here, St represents a stochastic process and Bt represents a Brownian motion is distinguished by the following characteristics:

- The increments in B are both stationary and independent.
- B0 = 0
- The increments in B are Gaussian.

The SDE (Stochastic Differential Equation) in the current research is that each increment over time causes the stock price to move with a drift (µStdt) along with a shock (µStdBt). The drift represents the overall trend of the stock's price, whereas the shock represents an arbitrary amount of volatility acting upon the stock's price. The shock is what causes the noise in the form of a curve.

C. Drift

Drift, which represents a stock's expected daily return, is estimated in the Geometric Brownian Motion (GBM) model using statistical metrics obtained from its previous performance [14]. Joel Liden's Drift formula requires determining the mean (μ) and standard deviation (σ) of prior returns:

$$\text{Drift} = \mu - \frac{1}{2}\sigma^2 \qquad \text{(ii)}$$

This method incorporates information on the central tendency and volatility of past stock values. The Drift component of the GBM model improves prediction accuracy by taking into account both the predicted average return and the influence of previous volatility on future stock price movements. Here, μ is the stock's mean logarithmic return and σ^2 is the variance. Because Drift gives insights into the overall direction of the stock, provided it adopts a standard distribution, the stock's past anticipated return is extended into the future to estimate prices.

D. Shock

A recent research used the GBM model to assess and forecast Malaysian gold prices [6]. "Shock" was defined in the study as asset price volatility as assessed by the standard deviation of historical returns using a formula. This comprehensive method sought to capture the subtle dynamics of Malaysia's gold market, taking into account macroeconomic variables, global market trends, and geopolitical events. The study's emphasis on quantitative measurements, such as the standard deviation formula, contributed to a more accurate portrayal of gold price variations over time, providing useful information for financial stakeholders.

$$\text{Shock} = \sigma \cdot Z(\text{Rand}(0;1)) \tag{iii}$$

The standard deviation of the stock's price (σ) and a random number (Z) following a normal distribution define future stock volatility in the Geometric Brownian Motion (GBM) model. The σ parameter assesses the stock's intrinsic risk and uncertainty, representing its deviation from the mean. The random element, represented by Z, introduces stochasticity to the model, simulating the volatility of financial markets. The interaction between intrinsic volatility and random market fluctuations is captured by the combined effect of the standard deviation and the random weight from the normal distribution, giving a sophisticated framework for forecasting future stock movements.

E. Monte Carlo Simulations

Monte Carlo Simulation is an excellent tool for forecasting stock market movements, especially when prior share prices have exhibited random behavior with little changes [15]. This method includes a variety of computing techniques that use randomness to estimate likely outcomes. Monte Carlo simulations are performed after identifying the variables of the Geometric Brownian Motion (GBM) model, including *Drift* and *Shock*, using the formula:

$$\text{Price}_i = \text{Price}_{i-1} \cdot e^{(\mu - \frac{1}{2}\sigma^2 + \sigma \cdot Z(\text{Rand}(0;1))} \tag{iv}$$

The chosen period for calculating *Drift* and *Shock* is followed by repeated Monte Carlo simulations, and the results are visually examined. Because it is unlikely that a stock will perfectly follow a single simulation, repeats are required to discover the best fit line among simulations. The most likely outcome of future stock prices is then calculated using mathematical models such as Linear Regression based on a large sample of Monte Carlo Simulations, increasing the predictability of forecasts in the volatile financial market.

VI. Research Methodology

A detailed assessment of important measures, such as the Open, High, Low, and Close of daily stock prices, was done to completely analyze the performance of the stock prices of a tech giant named SAMSUNG. This entailed gathering data from trustworthy sources, with an emphasis on accuracy and accessibility. A website named Stooq was chosen for this study because they provide related dataset and Application Programming Interface (API) for easy accessibility to their treasury of stock market information.

Following that, Monte Carlo Simulation was used to provide a forward-looking projection of market patterns based on past stock prices. The first stage was to acquire essential market pricing data from the chosen platforms(Stooq), which was then rigorously structured and saved into an Excel file to allow for further data modification.

The use of data cleaning procedures to the Excel file was a vital stage in the process. This process intended to remove any unnecessary data, such as missing or incorrectly stated prices, to ensure the dataset's authenticity and legitimacy. The Python programming language, known for its vast libraries such as NumPy and Pandas, was used to conduct a thorough study of stock market movements.

For displaying the results of Monte Carlo simulations, the GOOGLE COLABORATORY was used as the tool of choice. The platform provides a complete perspective of future stock price estimates through a large number of simulations, assisting in the understanding of possible market moves.

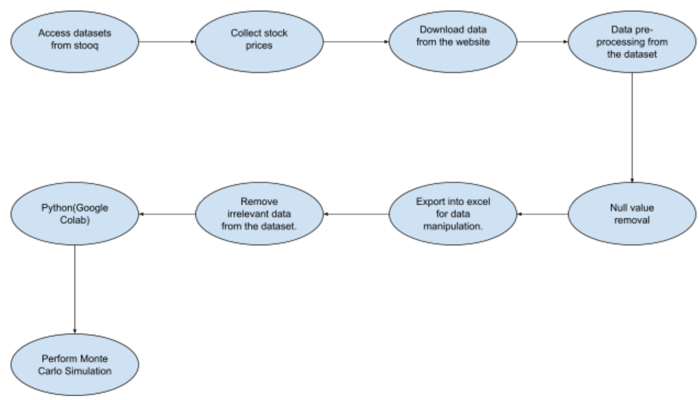


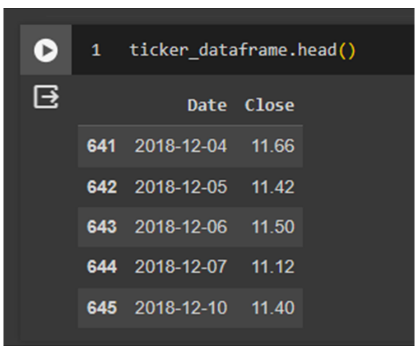
Fig. 4. Flowchart

VII. Implementation, Results and Discussion

To avoid biased findings, the Monte Carlo Analysis was executed several times using Python and a large number of simulations. The GBM model's parameters, such as Drift and Shock values, were based on market statistics from stooq.com for the last few years. The data outputs from the GBM model were then combined with Monte Carlo Analysis to simulate the future movement of market indexes based on past volatility.

The Monte Carlo approach, which relies on the concept of probability, is extensively used, and suggested for including uncertainties, and normally 1000 or 10000 runs are performed. One of the difficulties that investors face is evaluating the likelihood of stock price movement, or the possibility that the price will reach a specific level. One solution to this problem is to replicate price fluctuation using the Monte Carlo approach. In the simplest terms, the Monte Carlo approach presupposes that a certain phenomenon (price movement) is predictable, that we know its probability distribution, and that we can therefore mimic it. These assumptions are erroneous. As a result, an analyst must use caution when interpreting the results. Let us begin our investigation. First, we'll determine what data to work with and download it. Second, we will create our model using GBM (Geometric Brownian Motion) and define essential model parameters. Finally, we'll run a simulation and visualize the results. Using 1000 simulations, we will model Samsung's stock price over the coming year. We will utilize data from the previous 5 years to determine model parameters (anticipated annual return and expected yearly volatility). The period in which we build our assumptions is the most important aspect of the model. An analyst should select a timeframe that is more like the circumstances in the forecast period or manually give the value of projected annual return along with anticipated yearly volatility. Following that, we obtain the most recent historical data on the stock's prices, clean the data, and choose the time period that interests us.

Let's look at our data:



```
1  ticker_dataframe.head()
```

	Date	Close
641	2018-12-04	11.66
642	2018-12-05	11.42
643	2018-12-06	11.50
644	2018-12-07	11.12
645	2018-12-10	11.40

Fig. 5. Data

Fig. 6. Time Series 01

Fig. 7. Time Series 02

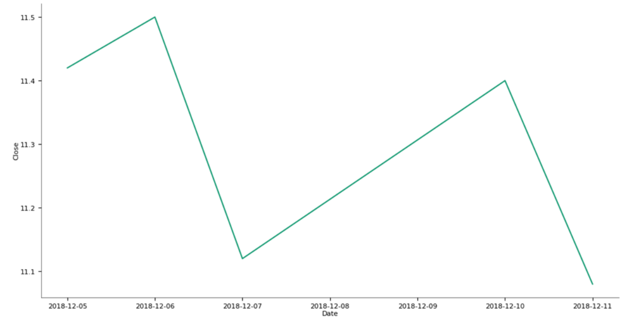


Fig. 8. Time Series 03

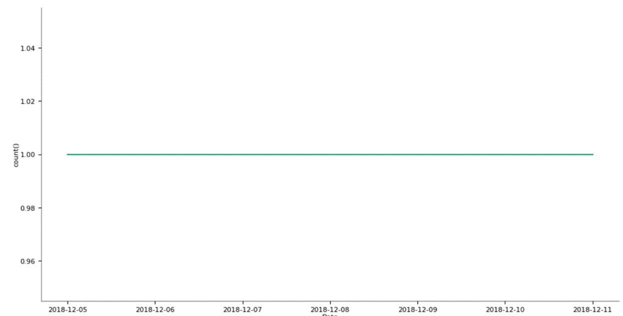


Fig. 9. Time Series 04

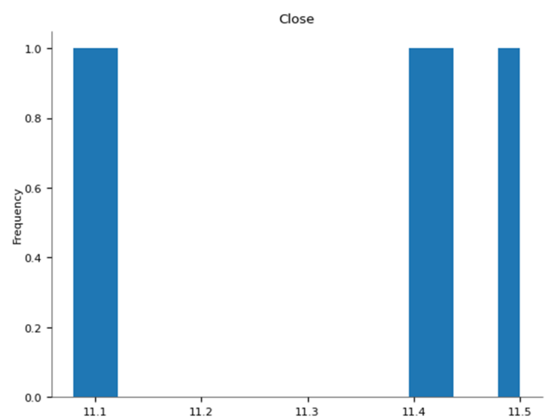


Fig. 10. Data Distribution

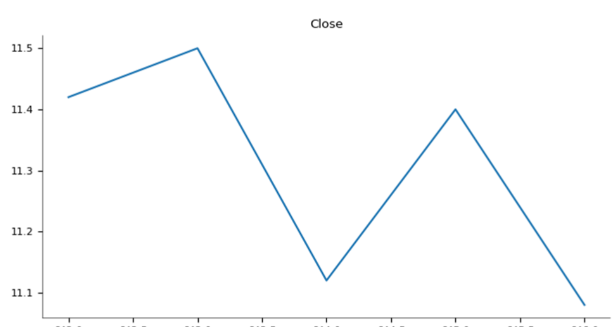
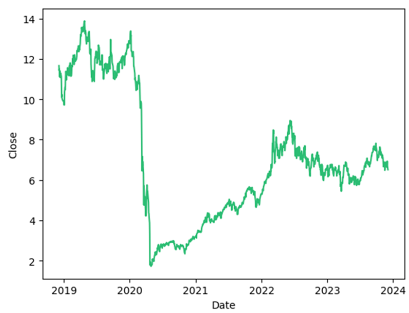


Fig. 11. Data Values

Now, the data's are being processed and plotted in the following graph:



Now we will focus on making the model for simulation. As mentioned earlier, we will focus on the Monte Carlo Method and GBM method. Our Monte Carlo function is extremely simple: it iterates over the specified function a certain number of times, records each iteration, and produces a list of outcomes. The Geometric Brownian Motion function on the other hand, is a little more complicated. The equations we're employing are from a 2016 research article by Reddy and colleagues [17].

The final stock price is obtained from the following equation:

$$S_{t+\Delta t} = S_t \exp\left[(\mu - \frac{\hat{\sigma}^2}{2})\Delta t + \hat{\sigma}\epsilon\sqrt{\Delta t}\right] \tag{1}$$

Where,

t - starting point in time

$\triangle$t - forecast period

S_t - price in t moment in time

$S_{t+\triangle t}$ - price at the end of the forecast period

μ - expected annual rate of return; in this example we use CAGR

$\hat{\sigma}$ - annualized expected annual volatility

ϵ - random volatility obtained as a random number drawn from N(0, 1)

To get the annualized expected volatility we use the following equation

$$\hat{\sigma} = \frac{s}{\sqrt{\tau}}$$

$$\tau = \frac{\triangle t}{N}$$

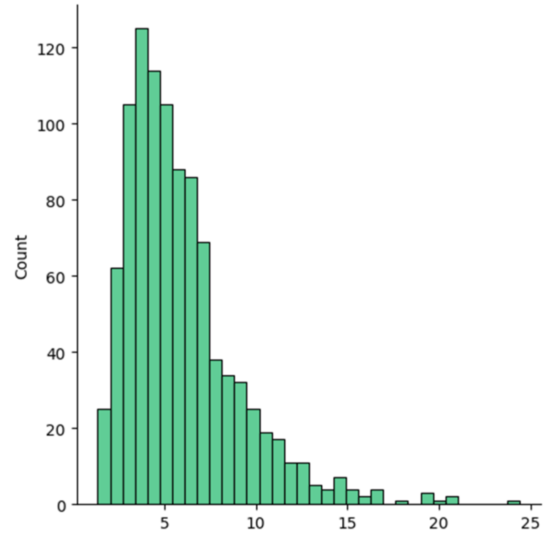
Where,

s - standard deviation of daily rate of return

τ - interval measured in years

N - number of trading days in internal

After we implemented the following equations into the python code, there is one thing left to do, and that is to run the simulation and observe the results. After running 1000 simulations, we get the results. The results are being shown in the graph:



We obtained the data, built the model, and conducted the simulation. From here, we may start looking for percentiles values that interest us. From our simulation, we get the following results:

5 percentile: 2.455772358969184
25 percentile: 3.7466479790837193
50 percentile: 5.181789348442312
75 percentile: 7.219908558053326
95 percentile: 11.709486269363019

The results may vary for every time we run the simulation, but the core logic is the same as before. Basically Monte Carlo Simulation for stock price prediction is the use of statistical modeling tools to simulate the multiple possible future trajectories of a stock's value. The simulation provides a range of different possibilities by adding random factors and entering historical data, allowing analysts to analyze the likelihood of distinct price moves. After running the simulation, the results show a full collection of probable stock price possibilities, emphasizing the inherent unpredictability in financial markets. The Monte Carlo Simulation findings in forecasting stock prices may then be evaluated and understood. This research examines important variables such as mean, standard deviation, and probability distributions to get insight into a stock's possible future performance. Furthermore, the data may identify significant risk factors and unusual scenarios for investors to consider.

The discussion phase of the Monte Carlo Simulation on stock prices entails an extensive review of the results. Analysts assess the model's robustness by taking into account the sensitivity of outcomes to changes in input parameters as well as the dependability of assumptions made throughout the simulation. Disparities between simulated and actual market behavior are investigated, and the model's shortcomings are acknowledged. This phase is critical for improving the simulation's predicted accuracy and making improvements to increase its dependability. Furthermore, comparisons with different prediction approaches may be included in the discussion in order to confirm the usefulness of the Monte Carlo simulation approach in the particular scenario about stock price prediction. Finally, the implementation, results, and discussion of Monte Carlo Simulation in projecting stock prices provide a thorough picture of probable future scenarios, assisting investors in making educated decisions on the constantly changing and uncertain financial market landscape.

VIII. Limitations & Forthcoming Research

Our study's approach has associated limitations that needs to be acknowledged, and there are conceivable further study routes to overcome these limitations:

A. Limitations

- **Data Quality and Sources:** The accuracy of the forecasts is strongly dependent on the data quality. The reliability of the Monte Carlo Simulation findings may be impacted if the historical stock price data received from internet sources includes oversights or is not entirely representative.
- **GBM Model Assumptions:** The Geometric Brownian Motion (GBM) model considers constant parameters like Shock and drift, which may not be the case in all market situations. Alterations from these presumptions might cause errors in forecasts.
- **Market Dynamics:** Economic events, geopolitical happenings, and regulatory changes all have an impact on financial markets. The GBM model may not fully reflect the intricacies of these dynamic factors, perhaps leading to disparities between expected and actual shifts in markets.
- **Overfitting danger:** There is a danger of overfitting the model to historical data when tweaking parameters or running plenty of Monte Carlo Simulations. As a result, the model can operate well on historical data but terribly on fresh, unknown data.

B. Forthcoming Research

- **Model Comparison:** Future research could inquire into the efficiency of other prediction models besides the GBM model. Comparing findings using other models, such as machine learning algorithms or hybrid models, may give insights into whether approaches are more effective in projecting stock values.
- **Involving more Parameters:** Improve the model's prediction powers by including extra relevant variables such as macroeconomic indicators, sector-confined data from financial publications and social media platforms. This might lead to a better understanding of stock market dynamics.
- **Dynamic Model Parameters:** Design models that can respond to shifting market situations through allowance for dynamic parameters. This might entail applying machine learning techniques to continually update model parameters depending on changing market patterns.
- **Risk Management measures:** Investigate and incorporate risk management measures into the forecasting framework. Assessing the uncertainty associated with forecasts and adding risk mitigation techniques can improve the research's practical application for investors.
- **Real-time Data Analysis:** Create methodologies for real-time data analysis and prediction. This would include developing models that can continually assess incoming data to produce up-to-the-minute forecasts, enabling for more rapid and informed decision-making.
- **Back-testing and Verification:** Perform thorough back-testing and verification procedures utilizing out-of-sample data to examine the model's resilience and generalizability. This would offer a more thorough assessment of the model's predicted ability.

The work can contribute to the continuous development of dependable and precise prediction models for stock market forecasting by addressing these limitations and investigating these options for future research.

IX. Conclusion

To achieve impartial results in stock market forecasts, we used Monte Carlo Analysis, which was run using Python with multiple simulations. The parameters of the Geometric Brownian Motion (GBM) model were carefully calculated using market statistics, allowing for a robust Monte Carlo simulation. While we acknowledged the generally accepted usefulness of the Monte Carlo technique in dealing with uncertainty, we emphasized caution due to underlying assumptions.

The study illustrated the Monte Carlo Simulation GBM model's actual applicability, demonstrating its great accuracy in fulfilling objectives. This method has the potential to help traders make informed judgments based on detailed insights into previous and predicted market movements. We ran a simulation and plotted the results. We modeled Samsung's stock price during the last year using 1000 simulations. We used data from the preceding five years to calculate model parameters such as predicted annual return and expected yearly volatility. The most crucial part of the model was the time span in which we established our assumptions. This highlights the Monte Carlo method's potential as a helpful decision-making tool, leading to a need for more research to show its application in larger corporate situations. Overall, our findings contribute to the advancement of advanced analytical tools and the refinement of financial modeling approaches in the dynamic finance industry.

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