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Monte Carlo Simulation Forecasting the Prices of Selected Stocks in the Automotive Sector

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ABSTRACT

Investors are exposed to risk and uncertainty because of changes in financial markets' prices. Investors perceive the risks associated with changes in the market prices as higher due to inaccuracy in predicting future returns because of fluctuations in prices. For this reason, they adopt different risk management methods that reduce or eliminate these risks. This research relies on Monte Carlo Simulation technique in predicting forthcoming yield rates from three companies operating under Turkish automotive segment namely, Dogus Automotive (DOAS), Tofas (TOASO) and Ford Otosan (FROTO). The simulation, which runs from January 1, 2023, to December 31, 2023, gives investors research-based insights that help them make strategic investment choices in times of high volatility in the market. According to the results, by modeling prospective future scenarios, MCS can be employed as a viable means of predicting stock prices in financial markets which subsequently helps people make rational investments thereby securing profitable ventures. Furthermore, this study offers practical suggestions in the form of MCS-generated volatility ranges. Investors can determine when it is advisable to buy or sell stocks in order to reduce potential losses and increase profits by setting realistic price objectives and allocating the portfolio differently in accordance with these calls.

Keywords: Risk Management, Financial Markets, Automotive Industry, Stock Forecasting, Monte Carlo Simulation.

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Introduction

Monte Carlo Simulation (MCS) is an eminently practical computational technique that embraces probabilistic modelling as part of quantifying the risks or uncertainties regarding wide-field analysis, including engineering, physics, and finance. It generates several random scenarios to forecast outcomes and quantify risk, hence becoming a key technique in risk assessment and decision-making. The automotive industry is one of the most volatile, meaning that its stock prices fluctuate dynamically. Therefore, it is also a very good area where MCS can be applied to perform investment planning and risk management.

MCS has been deployed in analyzes regarding stock price trends, sales forecasting, and optimization of investment strategies in the automotive field. This paper uses the Monte Carlo method to simulate the stock price movements regarding the selection of three key automotive companies listed in Borsa Istanbul: Dogus Automotive, Tofas, and Ford Otosan. For this, the work will give a model-based approach using historical stock price data from January 1, 2023, to December 31, 2023, so that the investor could hedge the volatility of the Turkish automotive sector. First, the following sections briefly outline the applications of MCS in risk management and automotive analysis. Following this will be the described methodology in detail, including the algorithm that has been undertaken for the Monte Carlo Simulations. Then it will present findings from the data simulations. This structure is necessary to ensure that investors and researchers alike recognize the practical and theoretical contributions of this study.

Literature Review

The Monte Carlo Simulation is a strong computer technique that has seen its application in engineering, physics, and finance, among other areas. It constitutes one of the major tools for risk assessment and decision-making by the generation of diverse events, together with their probabilities. This section reviews pertinent literature concerning the application of MCS in financial risk management and the automotive sector, highlighting its versatility and relevance.

Monte Carlo Simulation in Risk Management

Monte Carlo Simulation has also shown versatility in the different industries in which risk management is necessary. MCS allows analysts to gauge possible outcomes of alternative scenarios, thus reducing uncertainty of outcome that one is trying to reach. In service quality management, [1] use MCS to delve deep into how risk influences service quality gaps. The findings place greater emphasis on the role of MCS in service management with respect to effecting plans and managing uncertainties, among other roles. A nested MCS approach with regression in respect to financial risk estimation is proposed in [2]. Such a model was applied in catering to financial risks and further expanded the scope of contribution by MCS in the management of critical financial circumstances [3]. It has also presented such research that explains how MCS can enhance financial forecasting in modelling various risk factors, thereby enhancing overall accuracy and reliability in the prediction.

Application of Monte Carlo Simulation in the Automotive Sector

The automotive industry is fast-moving, sensitive to changes in the economy and market, and is increasingly integrating MCS to perform forecasting and optimization of operations. MCS has been estimated in the analysis of stock, filtering later accounting records, sales forecasting, and investment planning in the automotive industry. For instance, [4] combined MCS with DEA in support of a decision-making process about the selection of a green car. Their work involved how MCS could be extended to include multiple variables so that comprehensive risk and scenario analysis would be carried out, catering to particular needs of the automotive industry. The application of MCS in the automotive sector for sales forecasting was also presented by [5] . Their research showed that MCS has the capability of modeling periodic sales patterns, which would eventually help investors and automotive companies have a timely insight into making necessary decisions. These studies together give an example of the flexibility of MCS in solving multi-dimensional complex problems in the automotive industry. In computational finance, MCS has also been utilized for various applications, such as stock price analysis and risk evaluation within the automotive sector [6]. MCS's role in this domain emphasizes its capacity to provide financial insights by modelling stock market behaviour under different economic conditions. This capability is particularly relevant to the automotive sector, which must navigate fluctuating market dynamics and investor expectations. As such, most literature supports the application of MCS to stock market forecasting using its apparent capability for modeling complex financial phenomena. For instance, [7] , while using an MCS approach, simulated the movement of stock prices; thus, this technique was applied to the uncertain nature of daily fluctuations in stock prices. Running several simulations based on historical data, the study by [7] provided valuable insights into possible future price ranges, which are crucial for both short-term and long-term investors. This study underscored the flexibility of MCS in generating realistic price predictions, especially for volatile markets where conventional models fall short.

Broader Applications of Monte Carlo Simulation

The effectiveness of Monte Carlo Simulation is not confined to either financial or automotive sectors. As an instance, research works have adopted MCS in the biomedical engineering field, such as the modelling of photon migration in tissues see in [8]. This, therefore, points out how flexible and precise MCS can become when applied within various contexts that demand probabilistic modelling-from design safety in vehicles to manufacturing optimization. Applications of MCS are so varied that it confirms MCS's status as a basic instrument to solve problems that are complex and present elements of uncertainty and variability.

Novelty and Contributions

Although Monte Carlo Simulation is already well-established in many areas, such as finance and the automotive sector, for stock price forecasting in the automotive sector within Turkey, it has not been well explored. While past research, [9], has applied MCS in broader financial risk assessments and portfolio management contexts. The current paper tries to fill up this research gap by focusing on the application of MCS on stock prices of the companies Dogus Automotive: DOAS, Tofas: TOASO, and Ford Otosan: FROTO. It goes on to provide a customized model, taking into consideration unique market and economic conditions which impact the Turkish automotive industry, an extremely important emerging market that holds serious influence these days. Although new in regional focus, this study underlines the practical implications of MCS for investors in the Turkish automotive sector. Using a broad dataset and controlling the localized economic variables, it provides a framework that could be replicated for other emerging markets across similar dynamics. The methodology followed in this paper bridges the gap between theoretical modeling and real practice needs of investors; hence, it is a valuable tool deeply needed for risk assessment and investment planning. Though the Monte Carlo Simulation has proven helpful in financial forecasting and automotive analysis around the world, the application of this study to Turkish automotive stocks ushers in an entirely new dimension and enhances the understanding of localized market dynamics with much insight and practical applications that go long in contributing towards the greater literature with regard to stock market forecasting in emerging markets.

Assessing Simulation Accuracy and Reliability

In any case, ensuring the reliability of the Monte Carlo Simulation model for this study involves assessing the validity of simulated stock price distributions against historical data metrics like mean, variance, and volatility. While traditional MCS provides only a probabilistic range of future outcomes, the model's predictive reliability can be further advanced by estimating input parameters through advanced statistical techniques. Then, there is ABC that contains Approximate Bayesian Computation with Sequential Monte Carlo Sampling and Adaptive Importance Sampling as strong methods to update the input parameters without explicit usage of likelihood functions see in [10]. These likelihood-free Bayesian methods enable parameter estimation when direct computation is not feasible, thus enhancing model accuracy. Integrating these would allow better validation of simulation results through iterative tuning of input parameters, thereby improving the model's capability to accurately project underlying market dynamics. Although this approach was not used in the current study, its adoption offers a viable avenue for future research, particularly when it comes to the situation of stock price simulation in emerging markets with limited historical data. Using this method will result in improved model accuracy that is consistent with current financial market stochastic modelling techniques rather than being ambiguous.

Methodology

This study tries to predict the future values of some selected stocks in the Turkish automotive industry, namely the equities of Dogus Automotive (DOAS), Tofas (TOASO), and Ford Otosan (FROTO) listed in BIST, by using the approach of Monte Carlo Simulation. The aim is to provide a probabilistic outlook for the future prices of stocks, hence enabling investors to have the insight they may need to make better decisions in these volatile markets. This analysis uses data from investing.com for end-of-day closing prices of the subject stocks from January 1, 2021, through December 31, 2023. There are 749 records of each stock in the dataset, representing three complete years of up and down changes. These historical prices form the basis for the estimation of future stock movements by simulation.

Python was required to be used for generating the Monte Carlo Simulation, as it can model the randomness and uncertainty at which the prices change. Through the simulation, the code will use the provided historical return values to calculate the value of daily and annual volatility for every security. For volatility here, or the standard deviation of daily returns, quantified, is very critical in characterizing the size and frequency of variations in price over time. Calculation of volatility includes computation of the standard deviation in daily changes and scaling up the same into an annual level, considering 365 or 252 days. MCS was run with 10.000 random values, running the stock prices ten times for generating a range of possible future scenarios. The algorithm follows a basic stochastic process:

Monte Carlo Simulation Algorithm

The process of Monte Carlo simulation used in this study is structured as follows:

Input Parameters

P_0 : Initial stock price (determined from historical data).

μ: Anticipated daily return (presumed to be 0 for simplicity).

σ: Daily volatility (determined by utilising historical data):

$$\sigma = \frac{\text{Annual Volatility}}{\sqrt{\text{Number of Trading Days}}}$$

T: The simulation's duration (244 days in this study).

N: The quantity of simulations (10 on each stock).

Δt: Time step (1 day).

Output

${P_t}^i$: Stock prices simulated over T days for N simulations.

Algorithm

Initialize Parameters:

Extract P_0 based on the stock's initial price.

Compute σ (daily volatility) from historical data.

Run Simulations

For $i = 1$ to N:

$$Set\ P_t^i[0] = P_0.$$

For $t = 1$ to T:

Generate a random variable Z_t from $N(0,1)$.

Compute $P_t^i[t]$ using the formula:

$$P_t^i[t] = P_t^i[t-1] \times \exp\left((\mu - 0.5\sigma^2)\Delta t + \sigma\sqrt{\Delta t}Z_t\right)$$

Aggregate Simulation Results

Determine the mean, median, and standard deviation of descriptive statistics for each simulation.

Output Results:

Return the P_t range of potential stock prices together with related statistics.

These parameters form the basis of our Python simulation, which aims to mimic stock price evolution over a prescribed period. Each time this simulation is run, a new time series of stock prices is obtained, which can model the random behaviour of the market as well as historical volatility patterns. When iterated several times, the simulation captures the range of possible outcomes; thus, providing a probabilistic distribution of future stock prices. This method not only estimates the central tendency, i.e. the mean, but also outlines the extremes and variability of stock prices.

After the execution of MCS, the outputs were processed to derive a mean, median, standard deviation, and range of forecasted prices for all stocks. Descriptive statistical values, which are the mean price-DOAS at 101.96 TL, TOASO at 116.55 TL, and FROTO at 396.21 TL—are matched against their respective observed historical values to assure the correctness and relevance of the simulation. The critical evaluation of the volatility values for each stock is 0.0333 for DOAS, 0.0296 for TOASO, and 0.0298 for FROTO. The values give insight into each company's exposure to the swinging of prices and risk, which is significant for investors with a view to calculating market stability.

Furthermore, a sensitivity analysis has been done in this respect by changing the number of iterations and volatility levels to see its reflection in forecast accuracy. This will help in making the model robust under different scenarios and lend more credibility to the results. The following results identify some aspects of how external market forces—economic conditions or political events—might influence stock behaviour and point to the importance of a simulation-based approach in investment planning. The Python code used in this analysis section is hosted on the GitHub page of the project for reproducibility and transparency. Based on this, other researchers and practitioners can review the methodology and replicate it, hence allowing the model to be adapted for further studies or different market conditions. This gives a systematic approach, showing in practice how the Monte Carlo Simulation applies to financial forecasting, tailor-made for specific automotive cases in Turkey. At the same time, this is an instrument for investors to devise strategic moves that reduce their risk and further optimize their investment portfolio. The Python codes and simulation results used in this study are made openly available on GitHub for transparency and reproducibility. Scripts for Monte Carlo simulations, stock price forecasting models, and data pretreatment are all included in the repository. Access to the codes is available on the Monte Carlo Simulation in Stock Price Forecasting.

A technique that generates random numbers is used in Monte Carlo Simulation to examine the impact of random variables on a system. By employing the inverse of the distribution function, the input variables are produced in accordance with a particular probability distribution. The inverse probability distribution function can be used by computers to convert uniformly quickly and easily generated random integers in the range [0-1] into any distribution. Assume, for instance, that the function f represents the relationship between the dependent variable Y and two random variables (X_1, X_2). The relationship in this instance can be stated as follows:

$$Y = f(X_1, X_2)$$

If the X_1, distributions and X_2, are known (such as the Normal Distribution), the distribution parameters (μ_x : Mean and σ_x: Standard Deviation) are also provided, random numbers for X values can be generated multiple times, and the associated Y values can be computed by using the function f. As a result, statistics regarding Y can be derived. A bigger sample size improves the accuracy of the results. To achieve optimal results when applying Monte Carlo Simulation to deterministic systems, a sufficient number of random numbers must be generated. These figures could be in the thousands or tens of thousands in some applications, underscoring the necessity for computing power. Monte Carlo simulation has shown to be a dependable method in stochastic simulation processes when properly planned and applied with a big enough sample size [11]. Monte Carlo Simulation can be used to produce desired distributions by producing an adequate number of random numbers with uniform distributions. Following a few guidelines and making the most of Monte Carlo Simulation at each stage of the process will guarantee high-quality simulation.

The Monte Carlo Method's Mathematical Analysis

Numbers uniformly distributed between 0 and 1 are a basic tool for numerically modelling an experiment or event in the Monte Carlo method. Usually represented by the letter *q,* these numbers are produced by computer programmes. These arbitrary numbers are gathered from measurement or experiment set values. The probability of each number, however, varies, with some numbers having larger or lower probabilities than others. As opposed to sets with equal probabilities, this results in a set with varied probabilities. A set of random numbers is said to be uniformly distributed when all the probabilities are equal, meaning that any value has the same probability of happening. This technique is very helpful for projecting or modelling the results of a given experiment or occurrence. A significant number of random numbers, frequently produced by computers, are needed for the Monte Carlo approach. These numbers have the statistical characteristics of random numbers even though they are generated sequentially in accordance with a predetermined method, hence they are not completely random. Numerous numerical analysis and simulations employ this technique. The *'Mixed Congruential Method*,' denoted by the following formula, can be used to create random numbers:

$$P_i = int\left(\frac{a.x_i}{b.r_i}\right) \tag{1}$$

$$X_{i+1} = a.x_i - b.r_i \tag{2}$$

$$q_i = \frac{x_{i+1}}{b} \tag{3}$$

The following relation can be used to display the algorithm for this method:

$$x_i = (a.x_{i-1} + c)(\text{mod m}) \tag{4}$$

where the initial value of the positive integer sequence x_i is x_0. m is a greater positive integer than a and b, which are also positive integers. After multiplying x_{i-1} by a, the sequence x_i is determined. The modulus regarding m is then calculated. The starting value, x_0, in the "Mixed Congruential Method," is a positive integer. The created number sequence's elements are divided by m to create a new series with values between 0 and 1. The properties of the random number sequence are determined by the values a, c, and m. The sequence has a finite end and will eventually recur; the period of the repetition will depend on the values of m, a, and c. It can be extended the duration by choosing suitable values for m, a, and c.

Let us consider an event for which we want to model the probability distribution over an interval (a, b), where the frequency function $f(x)$ gives each value x a specific likelihood of occurring. The following calculates the likelihood that a value will fall between x and $x + dx$:

$$P(x).dx = \frac{f(x).dx}{\int_a^b f(x).dx} \tag{5}$$

The Probability Density Function, or $P(x)$, is defined as follows for the Total Probability Density Function:

$$Q(x) = \int_a^x P(x').dx' \tag{6}$$

Over the interval (a, b), the value of $Q(x)$ assumes random values in the 0– 1 range. We can relate $P(x)$ to T since the frequency function, which shows how often each value x occurs, has a uniform distribution:

$$T = Q(x) \tag{7}$$

The following is the derivation of the Fundamental Monte Carlo Principle using Equations (5), (6) and (7):

$$T = \frac{\int_a^x f(x').dx'}{\int_a^b f(x).dx} \tag{8}$$

The Fundamental Monte Carlo Principle is the name given to this equation. Depending on T, the following inversion transformation is obtained by inverting in Equation (8), [12]:

$$x = P^{-1}(T) \tag{9}$$

In this part of the study, a Monte Carlo simulation will be used to project the future value of specific automotive industry stocks for those who are interested in investing in the sector. This section will give an overview of the Turkish automotive industry and its volatility before doing a data analysis. The end-of-day closing prices of equities traded between January 1, 2021, and December 31, 2023, were the source of the data used in this study, which was obtained from investing.com. Monte Carlo simulation was used with Python programming language to generate 1,000 random values and simulate the equities ten times to forecast their prices. Educating prospective investors is the goal.

Findings and Discussion

The Automotive Sector in Turkey

Turkey's automobile industry is an essential part of the nation's industrial and economic framework. Turkey's industrialization progress has been greatly aided by the production of automobiles, a sector whose diversity and capacity are growing, and which makes the nation more competitive internationally. Turkey is one of the biggest automakers in Europe. The industry produces a wide range of goods, including as trucks, buses, commercial vehicles, and agricultural machines, in addition to passenger cars. Turkey's strength and adaptability in the automotive sector are strengthened by this diversity.

A significant number of the cars made are exported. Turkey's trade balance and economic growth are significantly influenced by its automobile exports. Turkish automakers provide premium cars at affordable prices to be competitive in global markets. Turkey's automobile industry has prospered mostly because of a strong supply chain and logistics system. Manufacturers maintain a streamlined production process by effectively utilising parts acquired from both domestic and international vendors. Furthermore, significant resources are allocated towards research and development (R&D) to consistently enhance production procedures and generate inventive resolutions. In conclusion, Turkey's automobile industry is essential to the nation's economic growth. With a robust supply chain, wide export network, high production capacity, and an emphasis on research and development, Turkey is likely to maintain its prominent position in the global automotive industry and flourish going forward.

Volatility

The term "volatility" refers to the variation in asset prices in financial markets during a specific time period. It gauges how frequently and how strongly prices shift in unexpected ways. Put differently, volatility represents the speed and range of price changes for an asset. Usually, statistical computations like standard deviation or percentage change rates are used to quantify volatility. These measurements are employed to examine how the price of an asset changes over a given period. Low volatility denotes more steady and predictable market movements, whereas high volatility indicates the possibility of abrupt and significant price swings.

Volatility is a key concept for investors since low volatility offers more stable and low-risk investment options, while high volatility frequently raises investment risk. Investors can manage risk, create investment strategies, and optimise their portfolios to meet return goals by analysing volatility. As a result, investors keep a careful eye on volatility since it is seen as a key indication in financial markets. By calculating the standard deviation of daily fluctuations using historical data, annual stock volatility is computed. By dividing the yearly volatility by the square root of the number of trading days in a year, one may get the daily volatility.

Table 1. Descriptive Statistical Values of Three-Year Share Prices (TL) of DOAS, TOASO and FROTO

Statistic	DOAS(TL)	TOASO(TL)	FROTO(TL)
Mean	101,96	116,55	396,21
Standard Error	2,99	3,12	9,19
Median	71,27	79,06	294,58
Mode	23,00	26,99	154,46
Standard Deviation	82,07	85,33	251,45
Variance	6735,95	7280,773	63226,09
Kurtosis	0,93	0,76	0,85
Skewness	-0,37	-0,81	-0,65
Range	297,48	279,06	854,31
Minimum Value	19,16	24,64	110,69
Maximum Value	316,64	303,70	965,00
Volatility	0,033	0,03	0,03
Number of Points	749	749	749

The study's descriptive statistics for the equities under examination are shown in

Table 1. There are 749 data points for the stocks that are included in this simulation. Dogus Automotive has an average price of 101.96TL, Tofas has an average price of 116.55 TL, and Ford Otosan has an average price of 396.21TL when examining the three-year averages of the stock prices. The range of prices for DOAS was 19.16 TL at the lowest and 316.64 TL at the most. The lowest TOASO price was 24.64 TL, while the highest price was 303.70 TL. The lowest and maximum prices for FROTO were 110.69 and 965 TL, respectively. These stock markets' three-year volatility values are as follows: The volatility of Dogus Automotive (DOAS), Tofas (TOASO), and Ford Otosan (FROTO) is 0.0333, 0.0296, and 0.0298, respectively. The difference in volatility between FROTO and DOAS is 0.0035, and the difference between TOASO and DOAS is 0.0037. The volatility of FROTO and TOASO differs by 0.0002. Therefore, in comparison to the other companies,

Dogus Automotive has displayed more notable price swings over time in terms of volatility.

Figure 1. Line chart of DOAS share prices between 01.01.2021-31.12.2023.

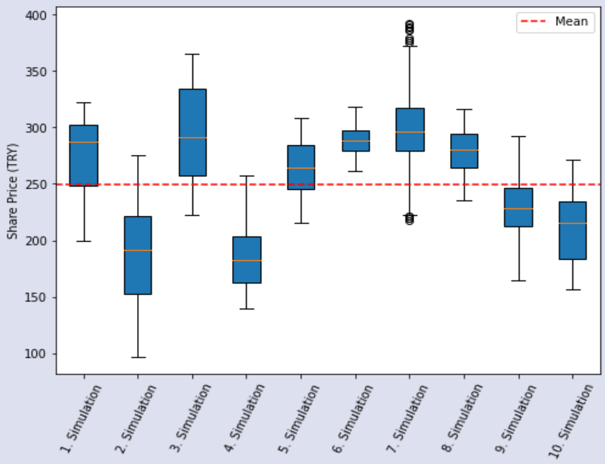


Figure 2. A box plot of ten chosen stock price simulations from 10,000 Monte Carlo simulation of data for DOAS stock runs is shown, with the average simulated price denoted by the red dotted line.

A line graph showing Dogus Automotive's share values over a three-year period is shown in Figure 1. Over a period of more than a year, from January 4, 2021, to March 4, 2022, the prices remained below 50 TL. The price increased to over 185 TL after exceeding 50 TL, then decreased to approximately 135 TL. Prices demonstrated a rising trend from May 4, 2023, to September 4, 2023. During this time, they reached at 316.64 TL, following which they began to decrease

The results of ten simulations of the DOAS stock price over a three-year period are shown in the box plot in **Hata! Başvuru kaynağı bulunamadı.**. From 200 to 300 TL forward, most of the simulations converge, with very little deviation until day 82 or so. This convergence suggests consistent early-stage patterns because it shows a shared beginning trajectory across the simulations. The simulations begin to deviate around day 82, suggesting more volatility in the behaviour of stock prices. The impact of economic variables, market dynamics, or other unforeseen occurrences influencing stock prices could be reflected in this disparity. As the simulated time ends, the results point to an increased number of possible outcomes; most simulations estimate stock prices in the range of 100 to 300 TL. The seventh, eighth, and tenth simulations exhibit more extreme behaviour, underscoring the need to consider the entire range of possible results and the risk of outliers. This box plot highlights the need of conducting several runs to accurately represent the range of possible market behaviours by illuminating the various degrees of uncertainty in long-term stock price simulations.

Figure 3. Line chart of FROTO share prices between 01.01.2021-31.12.2023.

A line graph illustrating the share prices of Ford Otosan during a three-year period appears in Figure 3. The share price remained below the 200 TL amount from January 4, 2021, until November 4, 2021. Prices changed between 200 and 400 TL on November 4, 2022, and November 4, 2021. On March 4, early in 2023, the share price launched an unsuccessful attempt to exceed 600 TL.

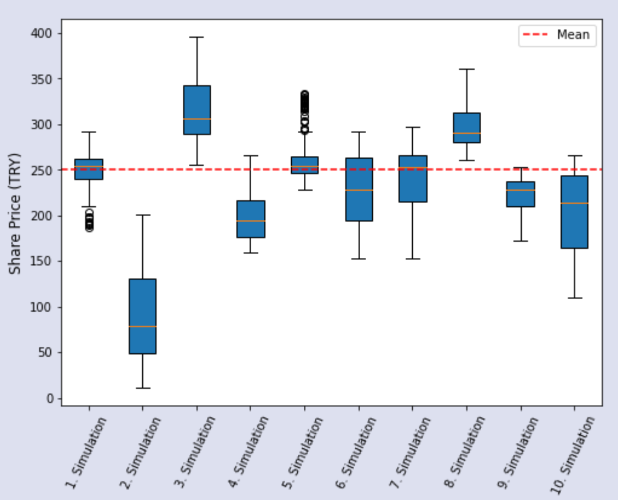


Figure 4. A box plot of ten chosen stock price simulations from 10,000 Monte Carlo simulation of data for FROTO stock runs is shown, with the average simulated price denoted by the red dotted line.

However, the share price increased above 600 TL between May 4, 2023, and July 4, 2023, eventually peaking at 965 TL. The share price demonstrated a declining tendency after this level. **Hata! Başvuru kaynağı bulunamadı.** illustrate the outcomes of ten simulations for a three-year forecast of FROTO stock prices. As a steady baseline throughout simulations, share prices normally oscillate at the beginning between 600 and 850 TRY. This relative stability lasts until about day 127, at which point the simulations start to show more divergence, suggesting that as the timeframe goes on, stock price volatility would rise. Two unique patterns appear as the simulations approach closer to their endings. The eighth simulation in the first pattern presents a variety of share values that increase to 900 TRY. The remaining simulations illustrate the second pattern, demonstrating share price variations within a narrower range, usually between 600 and 800 TRY, indicating a more cautious growth trajectory. In the previous simulation, there is an outlier that reaches over 900 TRY, indicating an uncommon occurrence or extreme circumstance. With an expanded distribution and the highest median of any simulation, the eighth one suggests more variability or uncertainty. The diversity of these simulations highlights varying market circumstances and possible stock price movements, highlighting the intrinsic uncertainty of long-term forecasts. A range of results from this divergence can be utilised to evaluate risk and guide investment plans.

Figure 5.Line chart of TOASO share prices between 01.01.2021-31.12.2023.

A line graph representing the share prices of Tofas during a three-year period can be seen in Figure 5. At less than 50 TL, the share price remained until November 4, 2021. There was a 50–100 TL variation in the share price from November 4, 2021, and November 4, 2022. Between July 4, 2023, and September 4, 2023, Tofas reached its peak value of 303.70 TL. After that, it continued to decline and eventually reached approximately 200 TL.

After ten simulation tests utilising a three-year period of TOASO stock data, the box plot in Figure 6 displays a starting range for share values between 150 and 250 TL. This first convergence suggests a consistent starting point for the simulations, implying that they started with remarkably similar values.

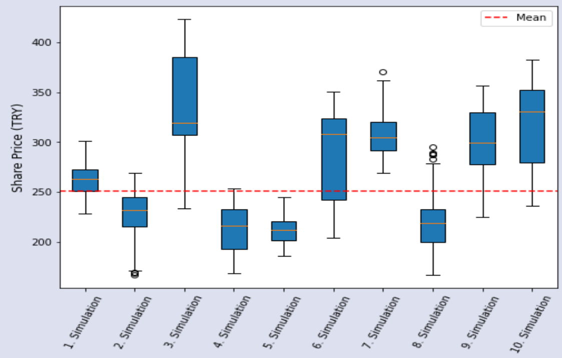


Figure 6. A box plot of ten chosen stock price simulations from 10,000 Monte Carlo simulation of data for TOASO stock runs is shown, with the average simulated price denoted by the red dotted line.

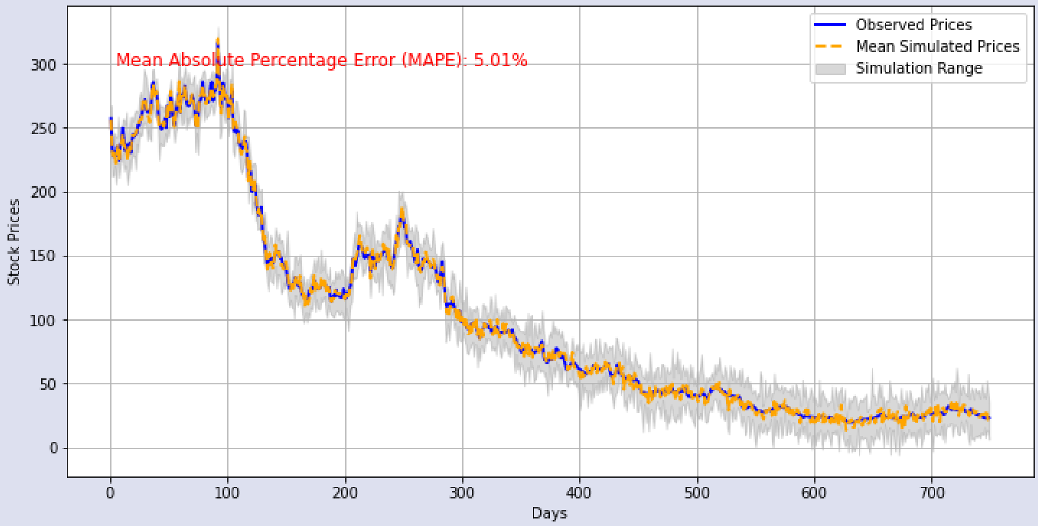
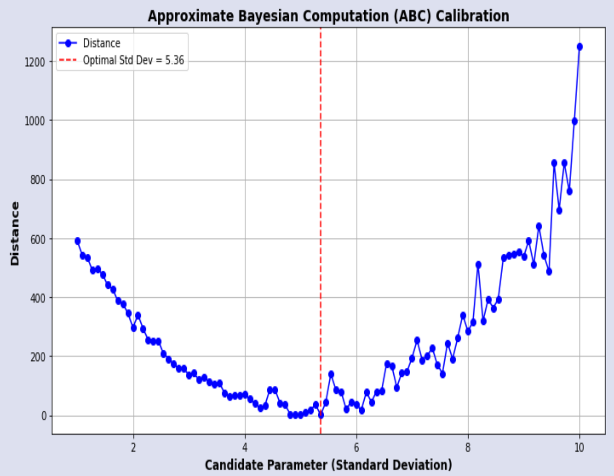


Figure 7. A comparison of the mean absolute percentage error (MAPE) of 5.01% between the observed and simulated stock prices.

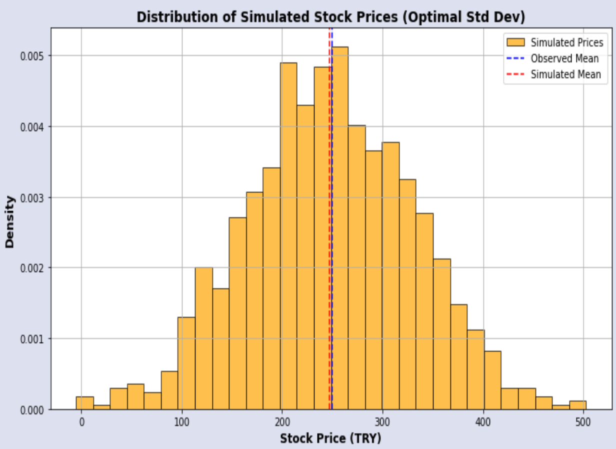
The Figure 7 highlights the model's performance by comparing observed stock prices over a certain period with their simulated counterparts. The orange dashed line (mean simulated prices), and the grey shaded region (simulation range) represent the simulated data, and the blue line represents the observed prices, which are used as a reference to assess the correctness of the simulated data. The simulation approach effectively represents the underlying patterns and variability of the observed stock prices, as evidenced by the comparatively low Mean Absolute Percentage Error (MAPE) of 5.01%. Although the fluctuation within the simulation range highlights the need for additional refinement to reduce uncertainty in forecasts, this alignment points to the model's potential for real-world applications in forecasting or risk assessment.

We calibrated the simulation parameter (standard deviation) using Approximate Bayesian Computation (ABC) to guarantee simulation correctness. This strategy minimized the distance between the simulated and observed stock price statistics (mean and standard deviation). The calibration procedure appears in Figure 8 a), where candidate standard deviation values were assessed according to simply how far they deviated from historical measures.

The ideal standard deviation, which minimises the discrepancy between simulated and observed statistics, is shown by the red dotted line. By bringing the model into line with actual stock price movements, this calibration improves simulation accuracy. b) uses the ideal parameter to compare the distributions of stock prices in the simulation with the real world. The blue and red dashed lines display the observed and simulated means, respectively, and the histogram depicts the simulated prices. The simulation's authenticity is confirmed by the tight alignment of both means and the comparable distribution spread.



(a)



(b)

Figure 8. a) The difference in stock price statistics between simulations and observations as a function of the chosen standard deviation parameter. b) A comparison between the observed historical mean (blue dashed line) and the simulated stock price distribution (orange histogram).

The prices largely followed a similar trajectory over the course of the simulations, suggesting little variation or variance in the results. This initial phase stability raises the possibility that common underlying forces are driving the stock price, resulting in a consistent pattern across simulations. But as the simulations continued, especially in the last part of the year, the box plot clearly demonstrates a divergence, with share prices changing dramatically from simulation to simulation. This greater range suggests that as time passed on, outside influences or arbitrary movements had a bigger impact on the stock price, which increased its volatility and unpredictability. The inherent unpredictability of long-term stock price simulations is demonstrated by this box plot pattern, underscoring the significance of performing repeated simulations to capture a wider range of outcomes. The final divergence highlights the possibility of large fluctuations in stock price, which is important for risk assessment and financial planning.

Table 2. Monte Carlo Simulation Values of Shares (TL)

	DOAS	TOASO	FROTO
Starting Price	257	210	739,5
Daily Volatility	3,33%	2,96%	2,99 %
Annual Volatility	52,78%	47,02%	47,4%
Mean	254,9790	203,2083	742,6018
Median	221,3507	181,4836	681,8091
Standard Deviation	137,1685	96,3172	344,0281
Quartiles			
25 %	157,8000	136,2762	504,5080
50 %	221,3507	181,4836	681,8091
75 %	318,7190	248,3489	923,4383

Investigating at the annual volatility rates presented in Table 2, we can see that Dogus Automotive has an annual volatility of 52.78%, Tofas has an annual volatility of 47.02%, and Ford Otosan has an annual volatility of 47.4%. This suggests that Tofas and Ford Otosan have comparable annual volatility, although Dogus Automotive has marginally greater volatility. When comparing the averages, the share prices of Dogus Automotive, Tofas, and Ford Otosan are 254.98 TL, 203.21 TL, and 742.60 TL, respectively.

Conclusion

Transformations and volatility in financial markets cause risk to become more pronounced for both small and large investors. In this process, managing and minimizing risk effectively is becoming increasingly important. For this reason, there is an increasing interest in risk-related studies in various disciplines. Predicting risk and identifying all possible scenarios in advance and taking precautions is becoming increasingly critical for investors. The complexity and uncertainties in the global financial structure encourage the continuous development of new approaches and strategies in risk management. Investors are increasingly relying on analytical tools and risk management techniques based on mathematical models to reduce the risks in their portfolios and minimize potential losses. This contributes to the adoption of a more informed and well-founded approach to financial decision-making. The Monte Carlo Simulation method allows us to obtain different measurement results with random numbers. Therefore, it is necessary to look at the environment in which the companies are located when analysing the values that emerge in this simulation research. This study has been conducted to give an insight to people who desire to purchase shares in the automotive sector. The annual prices of Dogus Automotive, Tofas and Ford Otosan stocks for three years are estimated by Monte Carlo Simulation. The results of Monte Carlo Simulation were analysed in the study. According to the simulation study, the annual forecast values of the three stocks examined were reached with ten different simulations. When we look at the volatilities of the stocks, it is observed that the annual volatility of Dogus Automotive is 52.78%, the annual volatility of Tofas is 47.02% and the annual volatility of Ford Otosan is 47.40%. In this case, the annual volatilities of Tofas and Ford Otosan are close and Dogus Automotive is slightly higher than the others. When daily volatilities are analysed, it is observed that Dogus Automotive, Tofas and Ford Otosan have 3.33%, 2.96% and 2.99%, respectively. The daily volatilities of all three stocks are close to the annual volatilities of Tofas and Ford Otosan, while Dogus Automotive is slightly higher. It is observed that all three stocks experience similar fluctuations in the financial markets. In this simulation, when the initial and average prices of the shares are analysed, it is observed that the initial price of Dogus Automotive in this simulation is TL 257 and the average price is TL 254.9790. In the simulation for Tofas, the initial price was TL 210, and the average price was TL 203.2083 and in the simulation for Ford Otosan, the initial price was 739.5 and the average price was TL 742.6018. In the comparison of the standard deviations of the three stocks in the simulation, it was observed that the standard deviation of Dogus Automotive data was 137.1685. The standard deviation of Tofas's data is 96.3172. Finally, the standard deviation of the data belonging to Ford Otosan was observed as 344.0281. When only the standard deviations of the three shares are considered, it is observed that there is a difference between them. As a result of the simulations, it was observed that all three stocks were similar, their volatilities were very close, and Tofas was slightly ahead of the others when looking at their standard deviations. However, it should be kept in mind that various factors such as market conditions, economic conditions, political events, trade volume, natural disasters, company activities, speculation will affect the prices of the shares. In this simulation, share prices are estimated only to give an idea to the investor.

Conflicts of interest

There are no conflicts of interest in this work.

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