

Computer Simulations and Risk Assessment in Financial Markets:

Apple Stock Price Prediction

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Abstract

This paper presents a detailed analysis of financial risk assessment using computer simulations, focusing on Apple Inc. as a case study. It employs methods like Monte Carlo simulations and bootstrapping to estimate Value at Risk (VaR) and Expected Shortfall (ES) in different market conditions.

1. Introduction

In the ever-evolving landscape of financial markets, risk assessment remains a cornerstone for investors and portfolio managers. The ability to predict and prepare for potential losses is crucial in making informed investment decisions. This paper delves into the realm of computer simulations as a tool for financial risk assessment, offering a fresh perspective on traditional methods. Our focus lies on Apple Inc., a leading player in the technology sector, whose stock performance offers a rich dataset for analysis. Apple's prominence in the market and its influence on global economic trends make it an ideal subject for this study.

The primary aim of this research is to employ advanced computer simulations, specifically Monte Carlo simulations and bootstrapping techniques, to estimate Value at Risk (VaR) and Expected Shortfall (ES) for Apple Inc.'s stock. These methods provide a more dynamic and nuanced understanding of risk compared to traditional models. By analyzing historical stock price data, this study seeks to illustrate the potential of simulation-based approaches in capturing the complexity and volatility of financial markets. The outcome aims to benefit investors and portfolio managers by offering deeper insights into risk management strategies.

2. Data Analysis

The analysis of Apple Inc.'s stock price data is central to this research, focusing on the application of Value at Risk (VaR) and Expected Shortfall (ES) calculations. Our dataset consists of the historical stock prices of Apple, which provides a substantial basis for a thorough risk assessment. The initial steps involve importing necessary Python libraries and loading the dataset for preprocessing and analysis.

Data Preprocessing

To enhance the robustness of our analysis, a series of data preprocessing steps are meticulously undertaken. The dataset is enriched by manually incorporating additional time-related features, which include the day of the week, month, quarter, year, week of the year, and day of the year. This augmentation of the dataset ensures a more granular and insightful analysis, as it expands the dimensionality with more variables while maintaining the original observation count. A critical step in our preprocessing involves calculating the daily returns, a fundamental metric in financial analysis. An initial observation of these returns over the last five years did not reveal any distinct patterns or trends, particularly when assessing monthly returns. To delve deeper, we transitioned to a more macroscopic view, analyzing the monthly charts encompassing the entire dataset. This broader perspective unveiled a more pronounced correlation of returns with years, rather than with months. Consequently, this insight led us to the strategic decision to cluster the data by years instead of months. This approach is anticipated to yield more coherent and meaningful insights into the temporal trends and patterns in Apple Inc.'s stock performance.

K-means Clustering

The analysis employs K-means clustering, a method to categorize annual returns of Apple Inc.'s stock into distinct groups based on their characteristics. Initially, the dataset is transformed to facilitate clustering: the data is converted to a datetime format, and annual returns are computed. To determine the optimal number of clusters, the Elbow Method is applied, visualizing the sum of squared errors (SSE) against a range of cluster counts. This method identifies a point where increasing the number of clusters does not significantly improve the fit, suggesting an optimal cluster count. For our analysis, three clusters represent different return profiles: 'Negative/Low Positive Returns', 'Moderate Positive Returns', and 'Highest Positive Returns'.

Cluster Analysis and Data Segmentation

The dataset is then clustered using the K-means algorithm. Each year is assigned to one of the three clusters based on its annual return. This classification allows for a nuanced analysis of stock performance across different market conditions. Further, the dataset is segmented based on these clusters, preparing for subsequent analysis that takes into account the unique characteristics of each cluster.

Test Set Creation for Model Evaluation

A critical step in our analysis is the creation of a holdout test set. To ensure robust and reliable model evaluation, each cluster's data is divided into two parts: 80% for training and validation, and 20% for a 'clean' holdout test set. This division is crucial to prevent contamination of the test set with training data, ensuring that the model's performance is evaluated on unseen data.

Moving Average Calculation

Moving forward, the focus shifts to calculating the moving average for each cluster. This step is instrumental in smoothing out short-term fluctuations and highlighting longer-term trends in the stock price. The moving averages provide valuable insights into the general direction and momentum of the stock within each cluster, offering a clearer understanding of the stock's behavior under different market conditions.

3. Methodology

Analyzing the Latest 360 Data Points

A key part of our methodology involves a detailed analysis of the most recent data. For each of the three clusters identified earlier - 'Negative/Low Positive Returns', 'Moderate Positive Returns', and 'Highest Positive Returns' - the latest 360 data points are extracted and scrutinized. This is accomplished by creating a new data frame for each cluster and selecting the last 360 records. These data points are then visualized using line plots, providing a clear picture of the recent trends and behaviors within each cluster.

Sensitivity Analysis: VaR and Expected Shortfall

In this research, sensitivity analysis plays a crucial role in assessing financial risk, particularly through the calculation of Value at Risk (VaR) and Expected Shortfall (ES) at a 5% threshold. To achieve this, two distinct but complementary computational methods are employed: Monte Carlo simulations and the Bootstrap method.

Monte Carlo Simulations for VaR and ES

The Monte Carlo method in our study involves simulating a range of possible future returns for Apple Inc.'s stock based on a normal distribution fitted to the historical data. The `monte_carlo_var_es` function accomplishes this by generating 10,000 hypothetical return scenarios, reflecting the potential variability in stock performance. The Value at Risk (VaR) is then calculated as the 5th percentile of these simulated returns, representing a threshold below which we expect losses only 5% of the time. The Expected Shortfall (ES), on the other hand, is determined as the average of the simulated returns that are worse than the VaR, providing an estimate of the average loss in the worst 5% of cases.

Bootstrap Method for Empirical Analysis

Complementing the theoretical approach of Monte Carlo simulations, the `bootstrap_var_es` function employs the Bootstrap method for an empirical analysis of risk. This technique resamples the historical data 10,000 times, allowing for the construction of a distribution of returns that is grounded in actual historical performance. The Value at Risk (VaR) is then derived as the average of the 5th percentile of these samples, while the Expected Shortfall (ES) is calculated from the average of the worst-case losses in the bootstrap samples. This method provides a data-centric view of risk, emphasizing the empirical realities of the stock's historical behavior.

4. Results

Analysis of Monte Carlo Simulation Results

The Monte Carlo simulation results yield key insights into the risk profiles associated with three distinct clusters of Apple Inc.'s stock performance, now interpreted with positive VaR and ES values. In the 'Negative/Low Positive Returns' cluster, the Value at Risk (VaR) is calculated at 0.7913%, and the Expected Shortfall (ES) at 0.9600%. This indicates that in the worst 5% of cases, losses are not expected to exceed 0.7913% of the portfolio value, with an average loss in these scenarios being around 0.9600%. This cluster thus shows the highest potential for losses among the three. In contrast, the 'Moderate Positive Returns' cluster demonstrates a lower risk level, with a VaR of 0.3307% and an ES of 0.4447%, reflecting more stable and predictable stock performance. Finally, the 'Highest Positive Returns' cluster exhibits the lowest risk profile, with a VaR of just 0.1277% and an ES of 0.2626%. This suggests that scenarios with higher returns are typically associated with lower potential losses, underscoring a lower risk of significant financial setbacks in these conditions.

Bootstrap Method Results and Comparative Analysis

In contrast, the Bootstrap method yields slightly different risk estimates. For the 'Negative/Low Positive Returns' cluster, the VaR and ES are 0.8382% and 1.1207%, respectively, indicating a slightly higher risk profile compared to the Monte Carlo results. The 'Moderate Positive Returns' and 'Highest Positive Returns' clusters also exhibit higher risk measures with the Bootstrap method, with VaR values of 0.3649% and 0.1700%, and ES values of 0.4993% and 0.3062%, respectively. These results suggest that when empirical data is more heavily weighted, as in the Bootstrap method, the risk estimates are slightly higher, emphasizing the importance of considering historical data trends in risk assessment.

5. Conclusion

The comparative analysis of the Monte Carlo and Bootstrap methods in this study reveals significant insights into the financial risk assessment of Apple Inc.'s stock. The Monte Carlo simulations, rooted in theoretical modeling, presented a varying degree of risk across different performance clusters. Notably, the 'Highest Positive Returns' cluster exhibited the lowest risk, with VaR and ES values suggesting less exposure to extreme losses. This aligns with the expectation that higher returns typically correlate with lower risk in favorable market conditions. In contrast, the Bootstrap method, which emphasizes empirical data, yielded slightly higher risk estimates for each cluster. This discrepancy underscores the impact of historical market trends on risk assessment, suggesting that real-world data can often reveal a higher risk profile than theoretical models alone.

These findings highlight the critical importance of employing a diverse set of analytical tools in financial risk assessment. While Monte Carlo simulations offer a perspective based on probabilistic models, the Bootstrap method provides a reality check grounded in historical performance. This dual approach not only enriches the understanding of Apple Inc.'s stock behavior in different market scenarios but also demonstrates the necessity of balancing theoretical modeling with empirical analysis in financial decision-making. The insights gained from this study are particularly valuable for investors and portfolio managers, providing a more nuanced view of risk that can inform better investment strategies. Future research can expand on this approach by applying these methods to other financial instruments and market conditions, further enhancing the tools available for sophisticated risk management in the complex and ever-changing landscape of financial markets.