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Stochastic Price Corrections in Leading Blue-Chip Stocks Using Ornstein-Uhlenbeck Analysis

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Abstract This paper applies the Ornstein-Uhlenbeck technique to investigate price corrections within the area of top blue-chip equities. This article also examines the characteristics and performance of prominent blue-chip companies, which are usually considered the cornerstone of reliable, long-term investment portfolios. Blue-chip stocks represent large, financially stable corporations with a history of steady performance, substantial market capitalization, and a reputation for dependability. These stocks are shares of major, well-established, and financially reliable firms with a solid reputation for stability and performance. Most often, they are leaders in their field, making them appealing to both individual and institutional investors seeking lower-risk, predictable returns over time. Investors consider blue-chip firms for their steady balance sheets, continuous revenue, profitability, and low debt levels. Many blue-chip corporations pay dividends, delivering regular and usually growing payments to shareholders. Therefore, understanding these stochastic price corrections is vital for investors and market analysts attempting to manage volatility and enhance trading strategies. In this research paper, the Ornstein-Uhlenbeck model, a stochastic differential equation, is employed due to its proficiency in describing mean-reverting behavior found in financial markets. By estimating parameters such as the mean reversion rate, long-term mean, and volatility using historical price data, the model provides insights into the dynamics of price corrections over time. Through simulations and empirical analysis, this study illustrates how the Ornstein-Uhlenbeck process can offer valuable predictions and assessments of price corrections for five major blue-chip stocks, including Apple, Microsoft, Amazon, Google, and Tesla, using Python version 3.10.14. This approach aids investors in making informed decisions within the dynamic landscape of blue-chip stock investments. The analysis results indicate that although differences exist between the actual price movements of all observed blue-chip stocks, Brownian movements for these stocks are close to zero. Although different points of oscillation were observed for each blue-chip stock, a similar mean-reverting behavior was identified across all measured stocks. Thus, it can be concluded that the Ornstein-Uhlenbeck model, combined with Brownian motion, is a crucial method for mean reversion that effectively manages stochastic price corrections for leading blue-chip stocks.

Keywords Blue Chip, Brownian Movement, Mean, Ornstein-Uhlenbeck, Volatility

1. Introduction

Aalen [1] defined stochastic differential equations of the Ornstein-Uhlenbeck (OU) process as being commonly used to mimic mean-reverting behavior in a number of disciplines, including finance. This process, named after Leonard Ornstein and George Eugene Uhlenbeck, is particularly useful for understanding the dynamics of systems that tend to fluctuate around an equilibrium level or long-term mean. The Ornstein-Uhlenbeck process, a biological convergence process, has been researched for its influence on first-passage time distribution and hazard rate profiles, offering insights into quasi-stationarity and financial modeling. Research frequently applies probability theory for statistical investigations, with OU processes extensively employed in the domains of finance and econometrics.

Barndorff-Nielsen et al. [2] described stochastic volatility models for financial products using volatility mechanisms based on positive OU processes, studied alongside financial information. Recent studies have focused on optimization in proportional reinsurance and investment. Promislow and Young [3] derived an analytical equation for the least ruin probability in a Brownian motion with drift risk model. Bai and Guo [4] addressed optimization issues involving several hazardous assets under a no-shorting condition. Zhang et al. [5] optimized the expected exponential utility of terminal wealth in the presence of hazardous assets and transaction fees. Schmidli [6] established an ideal technique for reducing disaster probability, while Liang and Guo [7] introduced the adjustment coefficient.

In one such study, various aspects of asset price representation were analyzed using the Ornstein-Uhlenbeck process driven by a Lévy process. The stochastic volatility model devised by Barndorff-Nielsen and Shephard [8] allowed the volatility parameter to follow a self-decomposable distribution. Onalan [9] discussed the calibration of moments associated with both the Lévy process and the OU process, applied to actual data series for validation purposes. Barndorff-Nielsen and O.E. [10] devised continuous-time stochastic volatility models, which have gained prominence for representing high-frequency and moderate-frequency financial data. These models perform remarkably well in managing stock price data that fluctuates rapidly.

Griffin [11] investigated the combination of non-Gaussian Ornstein-Uhlenbeck processes and jump processes in a proposed model for the dynamics of electricity spot prices, which considers seasonal variations and sudden price increases. This model not only ensures positive spot prices but also simplifies the analysis of electricity forward and future contracts. Benth [12] examined a two-dimensional random diffusion model to address the pricing problem for European call options. Perelló [13] studied the Ornstein-Uhlenbeck subordination process and log-Brownian motion, used to characterize price dynamics. In cases of significant volatility fluctuations, it computes an approximate option price.

Significant advances over conventional approaches were demonstrated by da Fonseca [14], who utilized the Ornstein-Uhlenbeck model to analyze non-Gaussian stock market data using transition probability and characteristic function formalism. This work emphasizes decay trends and convergence in logarithmic returns. In modern applications, mean-reverting mechanisms and geometric Brownian motion are often used to establish pricing dynamics. Bormetti [15] concluded by presenting analytical formulations of the characteristic function and probability distribution for two scenarios: one where Y exceeds volatility levels and another with limited stationary variance.

There seems to be a necessity for further experimental investigation of stocks in diverse sectors to grasp the breadth of value provided by Ornstein-Uhlenbeck analysis. One such sector is the blue-chip stock segment, which has traditionally demonstrated significant scale effects in the stock market. This study aims to examine the consequences of Ornstein-Uhlenbeck analysis for the blue-chip stock sector.

The purpose of the study may be described as follows:

- To identify the true pricing for each of the five blue-chip stocks.
- To determine the Brownian motion for each of the five blue-chip stocks.
- To develop an Ornstein-Uhlenbeck process line for each of the five blue-chip stocks.
- To determine the influence of the comparison between real prices, Brownian motion, and the Ornstein-Uhlenbeck process line for each of the five blue-chip stocks.

The paper is arranged as follows: Section 2 addresses the background and relevant work; Section 3 describes the hypothesis; Section 4 discusses the experimental design employing frequency tables and charts. The results of the study are reported in Section 5, along with a correlation and sentiment summary. Conclusions of the research are presented in Section 6. Finally, future directions for the research are outlined in Section 7.

2. Background and Related Work

2.1. Actual Prices

Elton [16] found in a study that security prices are commonly influenced by anticipations regarding corporate and economic factors. Nonetheless, minimal attention has been given to investigating such anticipatory information. The present study delves into the impact of earnings-per-share expectations on share prices. The consensus estimate of earnings per share is deemed to have already been factored into the share price. Individuals or corporate executives who invest in high-growth equities based on consensus projections may not yield additional returns.

To determine the precise value of equities, one typically requires information regarding the prevailing market price of the shares as well as any supplementary charges or expenses linked to their acquisition. Determining the specific price per share necessitates the following steps:

- Market Price at Present: This denotes the existing trading value of a share on the stock exchange.

- Brokerage Charges: These charges are related to the expenses enforced by the broker for carrying out the transaction.
- Taxation: Depending on the designated jurisdiction, it may be vital to take into consideration taxes such as stamp duty or transaction tax.

Formula to Calculate Actual Share Price:

Actual Share Price=Market Price+ Brokerage Fee +Taxes/Other Fees (1)

Definitions:

1. Benjamin Graham [17] defined it as "The market price is the price at which a share is currently trading on the stock exchange. It is the price agreed upon by a willing buyer and a willing seller." - "The Intelligent Investor."
2. Warren Buffett [18] in "Berkshire Hathaway Letters" mentioned "Intrinsic value is an all-important concept that offers the only logical approach to evaluating the relative attractiveness of investments and businesses. Intrinsic value is the discounted value of the cash that can be taken out of a business during its remaining life."
3. John C. Bogle [19] on Mutual Funds stated that "Net Asset Value is the per-share value of the fund's assets, less any liabilities, divided by the number of shares outstanding. It represents the underlying value of a share in the fund."
4. Burton G. Malkiel [20] mentioned in "A Random Walk Down Wall Street" that "The adjusted closing price reflects the stock's value after accounting for all corporate actions, including dividends, stock splits, and new stock offerings. It provides a more accurate representation of a stock's true value over time."
5. Aswath Damodaran [21] mentioned in Damodaran on Valuation: Security Analysis for Investment and Corporate Finance, "Fair market value is the price at which an asset would change hands between a willing buyer and a willing seller when both parties have reasonable knowledge of the relevant facts and are under no compulsion to buy or sell."
6. Peter Lynch [22] in "One Up on Wall Street" described that "The purchase price of a stock is not just the market price per share but also includes any brokerage fees and taxes. This total cost should be considered when evaluating the profitability of an investment."

2.2. Brownian Motion

Klafter [23] reported that Brownian motion gives a robust framework for studying and replicating the stochastic changes of stock values. This notion serves as a fundamental basis for several financial concepts and frameworks, allowing stakeholders and specialists to evaluate risk, value financial instruments, and increase the quality of investment decisions.

1. Geometric Brownian Motion (GBM):

In the realm of finance, one frequently encounters the utilization of Geometric Brownian Motion (GBM) as a model for stock prices. Reddy [24] in his study on GBM, depicts a mathematical model where the natural logarithm of the stock price conforms to a Brownian motion with a specified drift parameter. The expression defining GBM is:

$$\mathrm{d}s_t = \mu s_t + \sigma s_t \, \mathrm{d}\omega_t \quad (2)$$

where:

s_t is the stock price at time

μ is the drift term, representing the expected return.

σ is the volatility term, representing the standard deviation of returns.

ω_t is a standard Brownian motion or Wiener process.

2. Black-Scholes Model:

Reddy [24] also discussed the Black-Scholes model in option pricing based on the assumption that the stock price moves in tandem with GBM. The partial differential equation used by the model is as follows:

$$\frac{\partial V}{\partial t} + \frac{1}{2}\sigma^2 s^2 \frac{\partial^2 V}{\partial s^2} + rS\frac{\partial V}{\partial s} - rV = 0 \quad (3)$$

where:

V is the price of the option

S is the current stock price

t is time

r is the risk-free interest rate

σ sigma is the volatility of the stock

3. Monte Carlo Simulations:

Brownian motion is a tool used in Monte Carlo simulations to model stock price patterns in the future. Reddy [24] concluded that analysts can evaluate the risk and return of financial assets and predict the probability distribution of future prices by simulating multiple probable price pathways.

Discrete form representation of the GBM is as follows:

$$s_{t+\Delta t} = s_t exp((\mu - \frac{1}{2}\sigma^2)\Delta t + \sigma \in \sqrt{\Delta t}) \quad (4)$$

where,

ϵ is a random variable drawn from a standard normal distribution.

By simulating the stock price over time, we may observe how it changes in accordance with Brownian motion principles using GBM.

Regarding a typical Brownian motion B(t): At each given time t, the process's anticipated value, or mean, is zero:

E[B(t)] has a value of 0.

Var(B(t)) =t is the process variation at any given time t.

Therefore, the ideal Brownian motion

B(t) is defined by:

B(t)~N(0,t)

where,

N (0, t) represents a normal distribution with mean 0 and variance t.

Definitions:

1. Norbert Wiener [25] defined Brownian motion as "A Wiener process, also known as Brownian motion, is a continuous-time stochastic process with stationary, independent increments that are normally distributed."
2. Benoît B. Mandelbrot [26] mentioned Brownian motion as "Brownian motion is a fundamental model for random movement continuously, exhibiting self-similarity and stationarity."
3. In Paul Samuelson ([27] words, Brownian motion is a continuous stochastic process used to model random movements in financial markets, forming the basis for modern financial theory."

It shows that short-term stock price fluctuations are random and unexpected, which is consistent with the Efficient Market Hypothesis.

2.3. Ornstein-Uhlenbeck Process

Stochastic differential equations (SDEs) of the Ornstein-Uhlenbeck (OU) process type are frequently employed to simulate mean-reverting behavior in financial markets.

The OU process can be expressed as

$$\mathrm{d}x_t = \theta(\mu - x_t)d_t + \sigma\,\mathrm{d}\omega_t \tag{5}$$

where:

X_t is the price of the asset at time t.

θ is the rate of mean reversion.

μ is the long-term mean level to which the process reverts.

σ is the volatility of the process.

W_t is a Wiener process or Brownian motion.

Definitions:

1. Lars Onsager [28] mentioned it as "The Ornstein-Uhlenbeck process describes the velocity of a particle undergoing Brownian motion with friction, characterized by a mean-reverting behavior."
2. C. W. Gardiner [29] defined it as "The Ornstein-Uhlenbeck process is a Gaussian process with a mean-reverting drift term and constant volatility, often used to model systems with a tendency to return to a long-term mean."
3. Ioannis Karatzas and Steven Shreve [30] explained that "The Ornstein-Uhlenbeck process is a stochastic differential equation given by $dX_t=\theta(\mu-X_t)\,dt+\sigma\,dW_t$, where θ is the rate of mean reversion, μ is the long-term mean, and σ is the volatility."

The Gaussian distribution, stationarity, and mean-reverting behavior of the Ornstein-Uhlenbeck process make it a flexible stochastic process.

The Ornstein-Uhlenbeck (OU) process is a popular model for analyzing mean reversion in financial time series, including blue-chip stocks. The OU process helps in predicting future stock prices by assuming that prices will revert to a long-term mean. This process can be particularly useful for blue-chip stocks, which tend to have more stable and predictable price movements compared to more volatile stocks.

The above facts suggest that a study needs to be conducted on blue chip stocks to understand the efficiency of Ornstein-Uhlenbeck (OU) process. Also, Brownian movement comparison was undertaken to understand the stochastic price movement phenomenon.

3. Hypothesis

For Null hypothesis (h_0),

1. No difference exists between actual prices of the five blue chip stocks. (**H_{0a}**)
2. No differences exist between Brownian motion of the five blue chip stocks. (**H_{0b}**)
3. No differences exist between Ornstein-Uhlenbeck process line for each of the five blue chip stocks. (**H_{0c}**)

4. Experimental Design

In the initial stage, stock tickers were used for extraction of daily stock data for blue chip stocks using stockhistory function in Microsoft office 365. Descriptive analysis revealed the pricing behavior of such stocks between 01-01-2014 to 10-12-2024. The Brownian movement and Ornstein-Uhlenbeck (OU) process enabled true comparison between the lines for actual prices, meaning reverting behavior of Brownian motion and Ornstein-Uhlenbeck (OU) line movement.

4.1. Web Sources

The data for the five blue chips stocks were extracted using python version 3.10.14 coding with their identifiable stock tickers (See Table 1).

Table 1. Stock name with tickers (Source: Author analysis)

Si. No.	STOCK NAME	TICKER
1	Apple	AAPL
2	Microsoft	MSFT
3	Amazon	AMZN
4	Google	GOOGL
5	Tesla	TSLA

4.2. Price Mean and Variance

The mean and variance for each of the blue chip's stocks have been calculated. The means and variance of AAPL (Apple stocks) are $140.8 and $108.71, which seems close as compared to other blue chips stocks. This suggests that data from AAPL relatively consistent, symmetrically distributed, follows a normal distribution and the chances of outliers in the distribution are very less. On the other hand, high gaps between mean and variance of Tesla and Microsoft indicate high chances of outlier as the data may be skewed (see Table 2).

Table 2. Blue chip shares descriptives (Source: Author analysis)

STOCK TICKER	MEAN	VARIANCE	MIN	MAX
AAPL	88.8	4193.99	17.84	246.75
MSFT	173.03	15166.49	34.98	467.56
AMZN	92.80	3180.61	14.34	227.03
GOOGL	77.14	1921.26	24.85	191.18
TSLA	104.74	12172.59	9.28	409.96
1. TIME -PERIOD: 01-01-2014 to 10-12-2024.				
2. ALL PRICES IN USD				

4.3. Price Simulation

Price simulation for all the five stocks was done using Python version 3.10.14.

4.3.1. Apple (Ticker: AAPL)

The actual prices for AAPL vary between 17.84 USD to 246.75 USD between the period of 01-01-2014 to 10-12-2024 (2753 trading days). The Brownian motion moves close to zero and mean (μ=88.80) and standard deviation (σ =64.76). The Ornstein-Uhlenbeck process fluctuates between -200 USD to 400 USD throughout the entire period (Figure 1).

4.3.2. Microsoft (Ticker: MSFT)

The actual price for MSFT varies between 34.98 USD to 467.56USD between the period of 01-01-2014 to 10-12-2024 (2753 stock trading days). The Brownian motion moves close to zero and mean (μ=173.03) and standard deviation ($\sigma = 123.15$). The Ornstein-Uhlenbeck process fluctuates between -250 USD to 750 USD throughout the entire period (Figure 2).

4.3.3. Amazon (Ticker: AMZN)

The actual prices for AMZN vary between 14.34 USD to 227.03 USD during the period of 01-01-2014 to 10-12-2024 (2753 stock trading days). The Brownian motion moves close to zero and mean (μ=92.08) and standard deviation ($\sigma = 56.39$). The Ornstein-Uhlenbeck process fluctuates between -250 USD to 400 USD throughout the entire period (Figure 3).

4.3.4. Google (Ticker: GOOGL)

The actual prices for GOOGL vary between 24.85 USD to 191.18 USD during the period of 01-01-2014 to 10-12-2024 (2753 stock trading days). The Brownian motion moves close to zero and mean (μ=77.14) and standard deviation ($\sigma = 43.83$). The Ornstein-Uhlenbeck process fluctuates between -100 USD to 250 USD throughout the entire period (Figure 4).

4.3.5. Tesla (Ticker: TSLA)

The actual prices for TESLA vary between 9.28 USD to 409.96 USD during the period of 01-01-2020 to 01-01-2024 (1200 trading days). The Brownian motion moves close to zero and mean (μ=104.71) and standard deviation ($\sigma = 110.32$). The Ornstein-Uhlenbeck process fluctuates between -250 USD to 400 USD throughout the entire period (Figure 5).

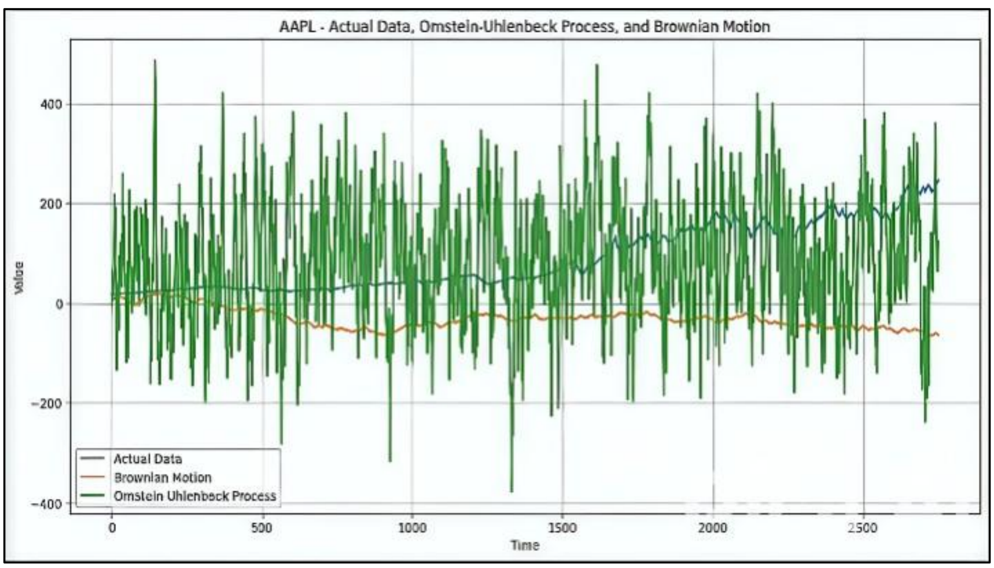

Figure 1. Price simulation for APPLE share stocks. (Source: Author analysis)

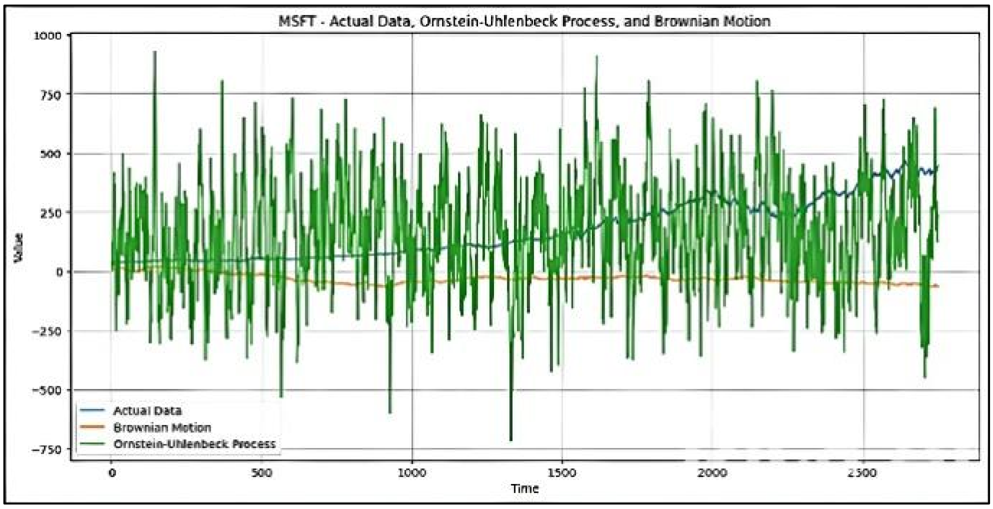

Figure 2. Price simulation for MICROSOFT share stocks. (Source: Author analysis)

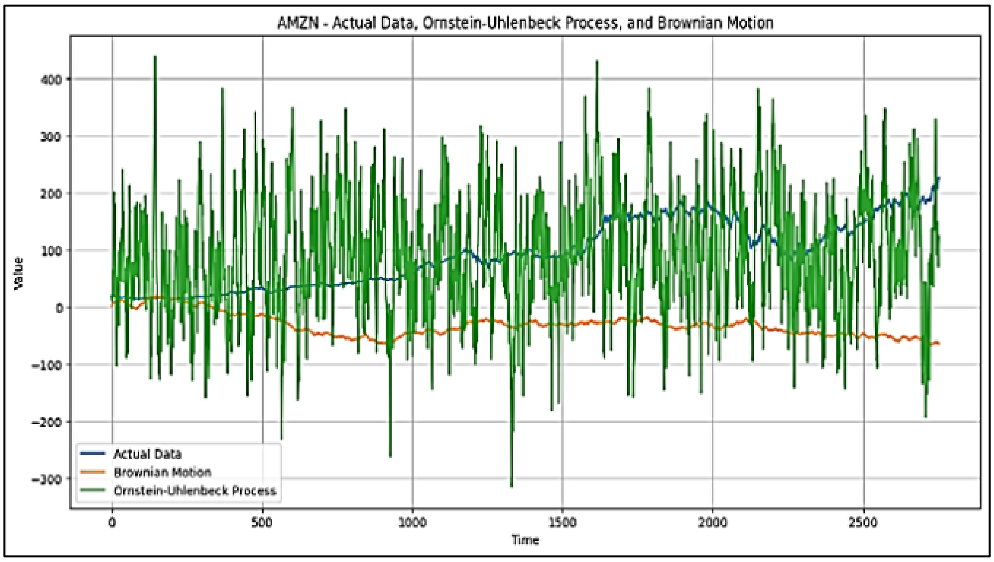

Figure 3. Price simulation for AMAZON share stocks. (Source: Author analysis)

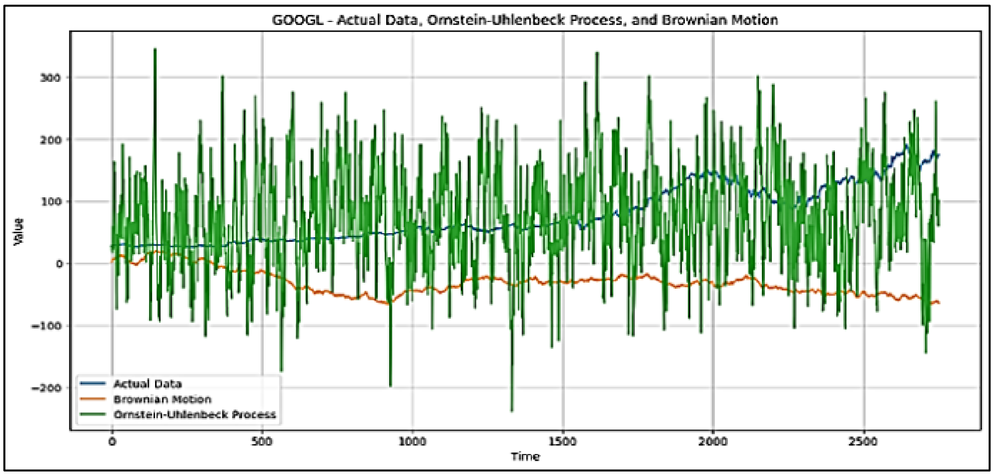

Figure 4. Price simulation for GOOGLE share stocks. (Source: Author analysis)

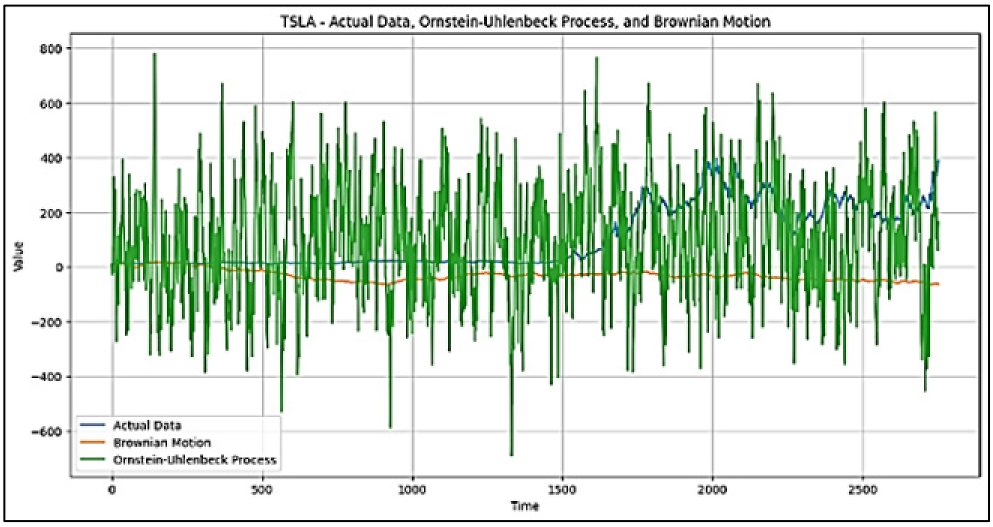

Figure 5. Price simulation for TESLA share stocks. (Source: Author analysis)

4.4. Cross Validation Results

AAPL and GOOGL have relatively lower RMSE values, suggesting that the OU model performs better in predicting their stock prices compared to the other stocks listed (See Table 3).

Table 3. Blue chip shares cross validation for Ornstein-Uhlenbeck (OU) process (Source: Author analysis)

STOCK TICKERS	MEAN RMSE
AAPL	54.80
MSFT	146.47
AMZN	104.83
GOOGL	52.63
TSLA	105.66

MSFT, AMZN, and TSLA have higher RMSE values, indicating that the OU model's predictions for these stocks are less accurate (See Table 3).

The results obtained strengthen the probabilistic usage of Ornstein-Uhlenbeck model for blue chip stocks.

5. Results

The results obtained through Brownian and Orstein Uhlenback analysis can be put together as:

1. The dataset of AAPL relatively consistent, symmetrically distributed, follows a normal distribution because of less gap between its meaning (140.81) and variance (108.71) respectively (See Table 2).
2. The chances of outliers exist in cases of Tesla and Microsoft as skewed distribution was observed during analysis (See Table 2).
3. The actual prices of all the Blue-Chip Stocks i.e. Apple, Microsoft, Google, Amazon, Tesla (APPL, MSFT, GOOGL, AMZ, TSLA) are market dependent and fluctuations were observed in all the cases (during the time of 01-01-2020 to 01-01-2024) (See Table 2).
4. The Brownian motion lines for (APPL, MSFT, GOOGL, AMZ, TSLA) are close to zero and indicate stationarities for all stocks (See Figure 1, Figure 2, Figure 3, Figure 4 and Figure 5).
5. The Ornstein-Uhlenbeck process line oscillates around 50 USD for APPL, at 132 USD for MSFT, at 52 USD for GOOGL, and 24 USD for TSLA. A similar mean reverting behavior has been observed in all the stock prices as observed (See Figure 1, Figure 2, Figure 3, Figure 4 and Figure 5).

6. Conclusions

Based on the results as seen above, we can conclude that partial similarity is evident in all cases.

Therefore, the following hypotheses are true:

1. Differences exist between the actual price movements for all observed Blue-Chip stocks. So, the hypothesis, no differences exist between actual prices of the five blue chip stocks (**H_{0a}**) stands as incorrect.
2. Brownian movements for all observed Blue-Chip stocks are close to zero. So, the hypothesis, no differences exist between Brownian motion of the five blue chip stocks (**H_{0b}**) stands as correct.
3. Although different points of oscillation were observed for prices of each Blue-Chip stocks, a similar mean reverting behavior has been identified for all observed Blue-Chip stocks. So, the hypothesis no differences exist between Ornstein-Uhlenbeck process line for each of the five blue chip stocks. (**H_{0c}**) stands as correct.

The stock behavior (low, medium and high fluctuating stocks) can be tested for Brownian movements followed by Ornstein Uhlenback process. This can assist in mean reversion or setting equilibrium position for stocks under observation (See Figure 6).

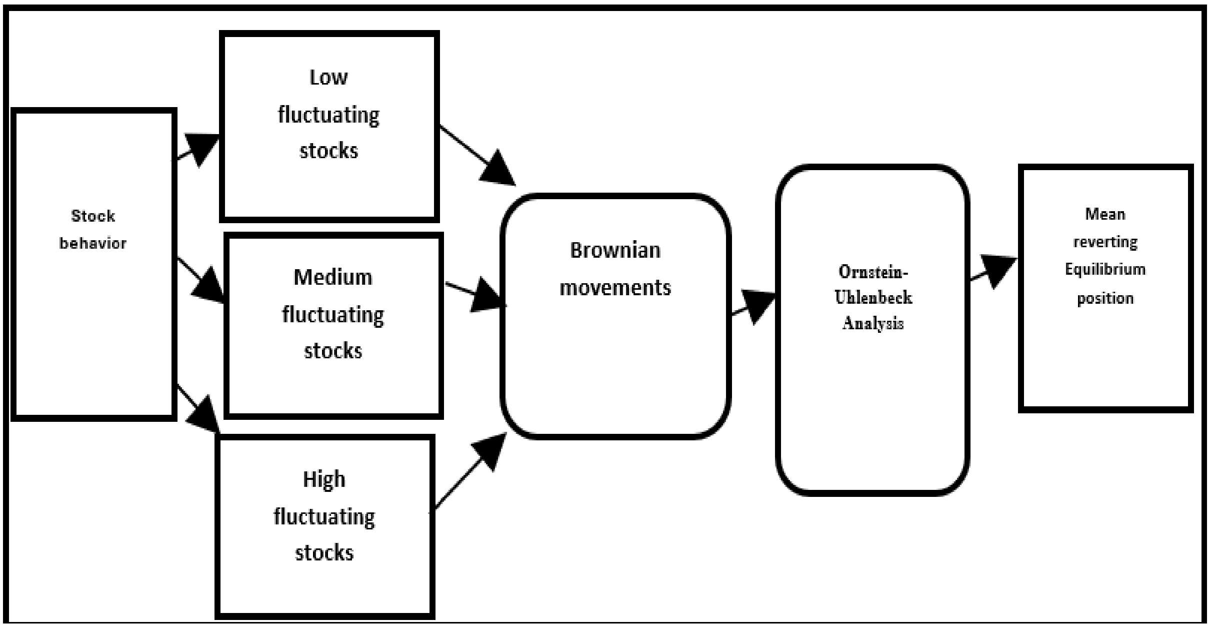

Figure 6. Understanding mean reversion using Ornstein-Uhlenbeck process (Source: Author analysis)

Therefore, the above results imply that both Brownian movements and Ornstein-Uhlenbeck process line are necessary to bring stability in all the major blue chip stock shares.

The future work related to further deployment of the above-mentioned model may include:

1. Differentiation in results can be achieved by expanding the dataset or time period of analysis.
2. If the above dataset is randomized with respect to source, then some results may change over a period of time.
3. There are more possibilities of generating different results if more complex data fluctuations are observed and included for analysis.

The author declares no conflict of interest related to this research. The study was conducted independently, and there were no financial or personal relationships that could have influenced the outcomes reported in this manuscript.

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