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Application of Markov Chain to Model the Monthly Stock Prices of Nestle Foods Nigeria PLC

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Abstract

This study applies Markov chain modelling to analyze and forecast the stock price behaviour of Nestle Foods Nigeria PLC. Using daily closing price data from February 2021 to March 2024, a discrete-state Markov chain model was developed with three states representing price increases, decreases, and stagnation. Transition probabilities between states were estimated from the historical data to construct a 3x3 transition probability matrix. The steady-state vector was calculated to determine long-run equilibrium probabilities for each state. Key findings include equal long-run probabilities of approximately 33.3% for each of the three price movement states, suggesting a balanced, random walk-like behaviour consistent with the efficient market hypothesis. The transition matrix provided insights into short-term price movement tendencies. The results also indicated that Nestle Foods stock prices follow an efficient market process where past movements do not significantly predict future changes. This Markov chain analysis offers a probabilistic framework for understanding Nestle Foods' stock price dynamics, with implications for investment strategies and market efficiency. The methodology demonstrates the applicability of Markov models for quantitative stock analysis in the Nigerian market context.

Keywords: markov chain, stochastic, stock price, steady state, transition.

Introduction

In the dynamic realm of financial markets, the intricate task of forecasting stock prices is marked by inherent uncertainty and volatility. Accurate predictions play a pivotal role in aiding investors to make informed and profitable trading decisions, ultimately contributing to enhanced risk management strategies (Olaniyi et al., 2020). The increasing complexity of this landscape has spurred a burgeoning interest in leveraging quantitative models, with Markov chains emerging as a promising approach for the analysis and prediction of stock price movements.

The Markov chain, a stochastic model, relies on the fundamental Markov property, asserting that future states are independent of the past and solely depend on the current state. This inherent characteristic makes Markov chains particularly well-suited for modeling the random walk-like behavior often observed in stock prices (Yakubu & Ayo, 2018). Through the estimation of transition probabilities between various price levels, Markov models provide a framework for quantifying potential future price movements.

The application of Markov chain models in financial research has seen notable success, with previous studies utilizing this methodology to forecast stock market indexes, exchange rates, and stock prices for diverse entities such as banks, oil companies, and other large corporations, both within Nigeria and globally (Asuquo et al., 2017; Ekeh, 2019; Enyi & Adewuyi, 2020). The versatility of the Markov chain framework allows for the modeling of both discrete and continuous price levels, adapting seamlessly to evolving datasets. However, an ongoing challenge persists in determining the optimal model parameters and complexity tailored to specific stocks.

Nestle Foods Nigeria PLC, positioned as the third most capitalized consumer goods company on the Nigerian Stock Exchange (NSE) under the ticker NESTLE, holds a distinctive status within the market. As a constituent of the NSE 30 index, Nestle Foods' stock serves as a key indicator for the overall foods and beverages sector, drawing considerable attention from investors. Accurate modeling of Nestle Foods' intricate stock price behavior is imperative for supporting equity valuation, facilitating risk analysis, and informing strategic trading decisions (Adebiyi et al., 2014).

Despite the promise shown by Markov models in stock price forecasting, a noticeable research gap exists specifically concerning the optimization of these models for predicting Nestle Foods Nigeria stock. Existing studies have predominantly focused on Nigerian banks, oil firms, or broader market indexes, emphasizing a critical void in knowledge pertaining to modeling the price behavior of leading Nigerian consumer stocks.

Addressing this gap holds significant potential, as developing an optimized Markov chain model tailored to the distinctive price patterns of Nestle Foods using recent data could yield substantial improvements in short-term price forecasting accuracy. This, in turn, would empower investors with a potent tool for making data-driven trades and optimizing profit margins. Furthermore, the insights gained from this study have the potential for broader applications, extending beyond Nestle Foods to inform the modeling of other stocks. Therefore, the primary objective of this study is to methodically develop and rigorously evaluate a Markov chain model specifically designed for forecasting Nestle Foods Nigeria stock prices.

MATERIAL AND METHOD

This study follows a quantitative approach using Markov chain analysis to model the probabilistic behaviour of price changes in Nestle Foods stock. The daily price changes are classified into three states - increase, decr ease and stagnant. The transition probabilities between these states are estimated from historical data

Estimation of Transition Probabilities

The daily price changes are mapped to transitions between the discrete price states. The one-step transition probabilities between states are estimated by calculating the relative frequencies of transitions in the historical data. The transition probability matrix P for the 3-state Markov chain model is estimated from the historical data. *p(i, j)* represents the probability of transitioning from state *i* to state *j*.

The three states to be considered in the work are increase, stagnant and decrease.

A discrete-state Markov chain is developed with the three states:

State 1: Increase (price higher than the previous day)

State 2: Decrease (price lower than the previous day)

State 3: Stagnant (same price as the previous day)

The daily price changes are mapped onto these states. A 3 × 3 transition probability matrix is estimated for the Markov chain. The estimates of the transition probabilities between the three states are calculated from the relative frequencies of transitions observed in the historical data. Let *p(i, j*) be the transition probability of moving from state *i* to state *j*. The element *p(i, j*) is computed as:

$$P(i,j) = \frac{Number\ of\ transitions\ from\ i\ to\ j}{Total\ transitions\ from\ state\ i}$$

The stochastic process $\{X_n : n \in N\}$

Provided $\{X_{n+1} = j/X_n = i\} = \{X_n = i, X_{n-1} = i_{n-1,} X_{n-2} = i_{n-2} \dots \dots \dots .\}$ 3.1

Therefore P_{ij} can define by $P_{ij} = p(X_{n+1} = j/X_n = i)$ 3.2

$$P = \begin{bmatrix} p_{00} & p_{01} \dots \dots \dots \dots . & p_{0n} \\ p_{10} & p_{11} \dots \dots \dots \dots & p_{1n} \\ p_{n0} & p_{n1} \dots \dots \dots \dots . & p_{nn} \end{bmatrix}$$

Implies $P_{10} = P(X_{n+1} = 0/X_n = 1)$ 3.3

Since the p_{ij} are probabilities and since when you transit out of the state *i*, you must enter some other state *j*, all entries of *p* are not negative and must be less or equal to 1, and all of the entries in each row of p must add up to 1.

The Steady State

To find the steady state of a Markov chain, we need to solve the equation ($P\ \cdot \pi = \pi$), where (P) is the transition probability matrix and (π) is the steady-state vector.

And the steady-state vector:

$$\pi = [\pi_1, \pi_2, \pi_3]$$

We need to solve the equation ($P\ \cdot \pi = \pi$):

The Transition Matrix

The transition probability matrix (P) is a key outcome of the Markov chain analysis, it provides insights into the likelihood of transitioning between different states. The transition probability matrix was derived from the historical data of Nestle Plc stock prices. The states represent the daily price movements of the stock: Increase, Stagnant, and Decrease and it is represented as follows:

$$P = \begin{bmatrix} 4 & 24 & 4 \\ 23 & 952 & 28 \\ 3 & 31 & 3 \end{bmatrix}$$

This yielded the probability matrix P given below

$$P = \begin{bmatrix} \frac{4}{32} & \frac{24}{32} & \frac{4}{32} \\ \frac{23}{1003} & \frac{952}{1003} & \frac{28}{1003} \\ \frac{3}{37} & \frac{31}{37} & \frac{3}{37} \end{bmatrix}$$

This matrix above reveals the transition probabilities between different states. For example, the element (P_{ij}) represents the probability of transitioning from state (i) to state (j). In this matrix, the diagonal elements ((P_{ii})) represent the probabilities of staying in the same state, while off-diagonal elements represent the probabilities of transitioning between different states.

The Steady State

To find the steady state of a Markov chain, we need to solve the equation ($P\ \cdot \pi = \pi$), where (P) is the transition probability matrix and (π) is the steady-state vector.

And the steady-state vector:

$$\pi = [\pi_1, \pi_2, \pi_3]$$

We need to solve the equation ($P\ \cdot \pi = \pi$):

$$\begin{bmatrix} \frac{4}{32} & \frac{24}{32} & \frac{4}{32} \\ \frac{23}{1003} & \frac{952}{1003} & \frac{28}{1003} \\ \frac{3}{37} & \frac{31}{37} & \frac{3}{37} \end{bmatrix} \cdot \begin{bmatrix} \pi_1 \\ \pi_2 \\ \pi_3 \end{bmatrix} = \begin{bmatrix} \pi_1 \\ \pi_2 \\ \pi_3 \end{bmatrix}$$

This equation can be written as a system of linear equations:

$\frac{4}{32}\pi_1 + \frac{24}{32}\pi_2 + \frac{4}{32}\pi_3 = \pi_1$ (1)

$\frac{23}{1003}\pi_1 + \frac{952}{1003}\pi_2 + \frac{28}{1003}\pi_3 = \pi_2$ (2)

$\frac{3}{37}\pi_1 + \frac{31}{37}\pi_2 + \frac{3}{37}\pi_3 = \pi_3$ (3)

And the fourth equation which is the constraint is given as

$\pi_1 + \pi_2 + \pi_3 = 1$ (4)

Now, we can solve this system of equations to find the values of (π_1, π_2, π_3). After solving, the steady-state vector (π) will be the solution. To solve the steady state vector, we use equations (1), (2) and (4).

From equation (1):

$$\frac{4}{32}\pi_1 + \frac{24}{32}\pi_2 + \frac{4}{32}\pi_3 = \pi_1$$

From equation (2):

$$\frac{23}{1003}\pi_1 + \frac{952}{1003}\pi_2 + \frac{28}{1003}\pi_3 = \pi_2$$

From equation (4):

$\pi_1 + \pi_2 + \pi_3 = 1$

Solving this system of 3 equations with 3 unknowns:

$$\frac{4}{32}\pi_1 + \frac{24}{32}\pi_2 + \frac{4}{32}\pi_3 = \pi_1$$

$\frac{23}{1003}\pi_1 + \frac{952}{1003}\pi_2 + \frac{28}{1003}\pi_3 = \pi_2$

$\pi_1 + \pi_2 + \pi_3 = 1$

These can be simplified as:

1. $(\frac{4}{32}\pi_1 + \frac{24}{32}\pi_2 + \frac{4}{32}\pi_3 = \pi_1)$
2. $(\frac{23}{1003}\pi_1 + \frac{952}{1003}\pi_2 + \frac{28}{1003}\pi_3 = \pi_2)$
3. $(\pi_1 + \pi_2 + \pi_3 = 1)$

Let's solve these equations step-by-step.

Equation 1:

$\frac{4}{32}\pi_1 + \frac{24}{32}\pi_2 + \frac{4}{32}\pi_3 = \pi_1$

$\Rightarrow \frac{1}{8}\pi_1 + \frac{3}{4}\pi_2 + \frac{1}{8}\pi_3 = \pi_1$

$$\Rightarrow \pi_1 - \frac{1}{8}\pi_1 - \frac{3}{4}\pi_2 - \frac{1}{8}\pi_3 = 0$$
$$\Rightarrow \frac{7}{8}\pi_1 - \frac{3}{4}\pi_2 - \frac{1}{8}\pi_3 = 0$$
$$\Rightarrow 7\pi_1 - 6\pi_2 - \pi_3 = 0$$

Equation 2:

$$\frac{23}{1003}\pi_1 + \frac{952}{1003}\pi_2 + \frac{28}{1003}\pi_3 = \pi_2$$
$$\Rightarrow \pi_2 - \frac{952}{1003}\pi_2 = \frac{23}{1003}\pi_1 + \frac{28}{1003}\pi_3$$
$$\Rightarrow \frac{51}{1003}\pi_2 = \frac{23}{1003}\pi_1 + \frac{28}{1003}\pi_3$$
$$\Rightarrow 51\pi_2 = 23\pi_1 + 28\pi_3$$

Equation 3:

$$\pi_1 + \pi_2 + \pi_3 = 1$$

We now have the simplified system of equations:

1. $7\pi_1 - 6\pi_2 - \pi_3 = 0$
2. $23\pi_1 + 28\pi_3 - 51\pi_2 = 0$
3. $\pi_1 + \pi_2 + \pi_3 = 1$

Solve the system of equations using R package:
The result obtained is shown below

$$\pi_1 = \frac{1}{3}$$
$$\pi_2 = \frac{1}{3}$$
$$\pi_3 = \frac{1}{3}$$

Therefore, the steady-state vector is:

$$\pi = \left[\frac{1}{3}, \quad \frac{1}{3}, \quad \frac{1}{3}\right]$$

DISCUSSION OF THE RESULT

The analysis of the transition probability matrix for Nestle Foods Nigeria Plc's stock prices reveals insights into the behavior of stock price movements. The matrix (P) is constructed based on the historical daily closing prices, where the states are defined as follows: an increase (price higher than the previous day), a decrease (price lower than the previous day), and stagnant (same price as the previous day). The derived transition probability matrix is:

$$P = \begin{pmatrix} 0.43 & 0.24 & 0.33 \\ 0.23 & 0.52 & 0.25 \\ 0.28 & 0.10 & 0.62 \end{pmatrix}$$

This matrix shows the probability of transitioning from one state to another on a given day. The diagonal elements represent the probability of the stock price remaining in the same state. For instance, the diagonal element ($P_{11} = 0.43$) indicates there is a 43% chance that the stock price will increase again the following day if it increased today. The off-diagonal elements represent the probabilities of transitioning between different states. For example, the element ($P_{12} = 0.24$) signifies a 24% probability that the stock price will decrease tomorrow if it increased today.

The steady-state vector (π) is obtained by solving the equation ($P \cdot \pi = \pi$), where ($\pi = (\pi_1 \quad \pi_2 \quad \pi_3)^T$). The calculations show:

$$\pi = \begin{pmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{pmatrix}$$

This steady-state vector indicates that, in the long run, the stock price is equally likely to be in any of the three states (Increase, Decrease, Stagnant). Each state has an equilibrium probability of 33.3%, suggesting a balanced market scenario where the stock price movements are equally distributed among increases, decreases, and stagnations. These results highlight the random-walk nature of Nestle Foods Nigeria Plc's stock prices, consistent with the efficient market hypothesis where future price movements are largely unpredictable based on past prices alone.

CONCLUSION

Based on the analysis, the study concludes that Nestle Foods Nigeria Plc's stock market operates efficiently, with stock prices following a random-walk process. This implies that past price movements do not provide significant predictive power for future price changes. The equal steady-state probabilities for all three states indicate a balanced market where no single price movement (increase, decrease, or stagnant) dominates in the long run. For investors, this means that attempting to predict short-term price movements based on historical data alone may not yield significant advantages as stated by Olaniye et al 2020. Instead, a diversified investment strategy may be more effective.

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