RES MILITARIS

Social Science Journal

DECIPHERING MARKET DYNAMICS USING MARKOV CHAIN MODELS

Veena Budhraja

*Professor,*Department of Statistics,Sri Venkateswara College,University of Delhi,Delhi, India

Puja Thapliyal

*Formerly Assistant. Professor,*Department of Statistics,University of Delhi

Abhimanyu Budhraja

*Assistant. Professor,*Department of Economics

Sri Guru Gobind Singh College of Commerce,University of Delhi,Delhi, India

Arushi Mathur

*Student,*Department of Statistics,Sri Venkateswara College

University of Delhi,Delhi, India

Kanishk Bansal

*Student,*Department of Statistics,Sri Venkateswara College

University of Delhi,Delhi, India

Abstract

This study applies Markov chain models to analyze stock market dynamics, focusing on the Sensex index and a representative portfolio. The research reveals significant similarities in the stationary distributions of the Sensex and its portfolio TPMs, suggesting parallel behaviors. Additionally, it evaluates the efficiency of stocks within the portfolio by examining their stationary probabilities and Mean Recurrence Times. The findings, validated through chi-square tests for goodness of fit, provide novel insights into stock market behavior and offer valuable guidance for investors and traders in their decision-making processes.

KEY WORDS: Markov Chain, Stationary Distribution, Transition Matrix, Chi Square test

1. INTRODUCTION

In the constantly evolving and unpredictable realm of stock markets, understanding the nuances of market behavior is paramount for investors and traders. Stock markets are known for being unpredictable, changing rapidly in ways that aren't always easy to understand. But this doesn't stop investors and researchers from trying to find patterns and methods to make sense of these ups and downs. This article delves into such a method – the application of Markov chain models – to analyze stock market dynamics, particularly focusing on the Sensex index and a selected portfolio of stocks.

Kaya and Karsligil (2010) emphasize that predicting stock prices involves more than just financial numbers; the overall economy and information flow are also critical factors. This complex interplay makes stock market forecasting a daunting yet crucial task.

Building on the foundation laid by Doubleday and Esunge (2010) in modeling the Dow Jones Industrial Average, this research employs Markov chain models to offer a new perspective on stock market behavior. The study by Agwuegbo et al. (2010) similarly analyzes market trends by determining probabilities of transitions between various states. Jones and Smith (2009) delve into Markov theory and its properties, applying it to two models of the Dow Jones Industrial Average and a specific stock portfolio within it. This approach is complemented by Choji et al.'s (2013) application of the Markov chain model to forecast the performance of two leading Nigerian banks, using a six-year dataset to predict share price movements. D. Zhang and X. Zhang's (2009) study on China's stock market underlines the suitability of Markov chains for analyzing and predicting stock market indexes and closing prices, emphasizing the model's lack of after-effects. Otieno et al.'s (2015) research on the Nairobi Securities Exchange uses Markov chains to forecast trends in Safaricom's share prices, employing a four-year dataset for their predictions. Also, incorporating insights from Kallah-Dagadu et al.'s study on using Markov chain techniques for portfolio construction on the GSE, we calculated mean recurrence time taken by a stock to reach a state of gain.

In this study, Transition Probability Matrices (TPMs) have been constructed for the Sensex and a carefully selected portfolio from its stocks, including major companies like Reliance Industries Limited, Tata Consultancy Services, HDFC Bank, ICICI Bank, and Hindustan Unilever Limited. By defining states based on the closing values of the market and the stocks, and categorizing them into two- and six-state models, an in-depth analysis of market dynamics has been conducted. The striking similarity in the stationary distributions of the Sensex and its portfolio's TPMs reveals an intriguing alignment in their behaviors. Moreover, the research extends to identifying the most efficient stock within the portfolio. By analyzing the stationary probabilities and Mean Recurrence Time of each stock, and employing chi-square tests for goodness of fit, this study aims to determine which stock consistently reaches a state of gain in the shortest time.

In our analysis, a sample of 50 days was randomly selected from the population data, which encompassed a total of 244 trading days. Remarkably, the TPMs derived from this sample exhibited a striking resemblance to the TPMs computed from the entire population dataset. This similarity underscores the representativeness of our sampling methodology and the robustness of the study in capturing the underlying market dynamics over the specified period.

By understanding the likelihood of various market states and the efficiency of individual stocks, investors can make more informed decisions, potentially leading to higher returns. This approach not only enhances the investor's knowledge but also contributes to the broader field of financial analysis, offering a fresh perspective on the application of stochastic models in stock market prediction. In essence, this article not only contributes to the academic discourse on stock market forecasting but also serves as a practical guide for investors seeking to navigate the complexities of the stock market with a more analytical and informed approach.

2. PRELIMINARIES

2.1 The Markov Chain model. A random walk is said to exhibit the Markov property if the position of the walk at time n depends only upon the position of the walk at time $n-1$. If we call our random variable X_n, then:

$$P(X_n = j | X_{n-1} = i) = p_{ij} \tag{1}$$

is independent of $X_{n-2}, X_{n-3}, \ldots, X_1$ so that the state of X at time n depends only upon the state of X at step $n-1$. Here each p_{ij} for $j = 1,2, \ldots$ is a probability row vector describing every possible transition from state i to any other available state in the system.

$$\sum_{j=1}^{m} p_{ij} = 1 \quad \forall\, i \tag{2}$$

Thus,

$$P(X_{n+1} = i_{n+1} | X_n = i_n, X_{n-1} = i_{n-1} \ldots) = P(X_{n+1} = i_{n+1} | X_n = i_n) \tag{3}$$

And $p_{ij}^{(m)} = P(X_n = j | X_{n-m} = i)$ (4)

indicates m-step transition.

The process of moving from one state of the system to another with the associated probabilities of each transition is known as the chain. It is said that every step taken in a chain possessing the Markov property depends only upon the immediately preceding step. It can easily be seen how calculating probabilities of a series, or chain, of events in a Markov system is greatly simplified due to this Markov property. Instead of concerning ourselves with the entire path a random variable might have taken to arrive at its current state, we need only consider its state directly before a given point of interest.

2.2 Transition Matrix. The transition probabilities form an $m \times m$ transitional probability matrix T, where:

$$T = [p_{ij}] = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \vdots & \vdots & \cdots & \vdots \\ p_{m1} & p_{m2} & \cdots & p_{mm} \end{bmatrix}$$

Each row of T is the probability distribution relating to a transition from state i to state j.

States i and j are said to communicate if there exists a path between them. It must be true that i is reachable from j in a finite number of transitions and also that j is reachable from i in a finite number of transitions for any two states i and j to communicate. A state i is said to be periodic if all paths leading from state i back to i have a length that is a multiple of some integer k, such that $k > 0$ for the smallest possible k. If all states of a chain communicate and are not periodic, then the chain is said to be ergodic.

2.3 Stationary Distribution. The probability distribution $\{v_j\}$ is called stationary distribution of a Markov Chain with transition probabilities p_{jk} if

$$v_k = \sum_j v_j p_{jk} \text{ such that } v_j \geq 0 \text{ and } \sum v_j = 1$$

i.e., whether a Markov System regardless of the initial state j, reaches a stable state after a large number of transitions.

A chain is said to have a steady state distribution if there exists a vector v such that given a transition matrix T,

$$vT = v \tag{5}$$

If a chain is ergodic then we are guaranteed the existence of this steady state vector v. This steady state vector can be viewed as the distribution of a random variable in the long run. This steady state probability vector v of an m state random walk can also be obtained as:

$$\lim_{n\to\infty} T^n = \begin{bmatrix} v_1 & v_2 & \cdots & v_m \\ v_1 & v_2 & \cdots & v_m \\ \vdots & \vdots & \cdots & \vdots \\ v_1 & v_2 & \cdots & v_m \end{bmatrix} \tag{6}$$

2.4 Recurrent property. Consider a state that is arbitrary but fixed, i, and define an integer $n \geq 1$; then,

$$f_{ii}^{(n)} = \{X_n = i, X_j \neq i, j = 1,2,..,n-1 | X_0 = i\} \tag{7}$$

It implies that $f_{ii}^{(n)}$ is the likelihood that the first return to state i, from state i, happens at the n^{th} transition. However, given that

$$p_{ii}^{(n)} = \sum_{k=0}^{n} f_{ii}^{(k)}\, p_{ii}^{(n-k)}, \qquad n \geq 1 \tag{8}$$

If state i is aperiodic, then

$$p_{ii}^{(n)} \to 1/\mu_{ii} \quad , as\ n \to \infty. \tag{9}$$

2.5 The Chi-square Test. The test for goodness of fit was used to test the null hypothesis that the steady-state probabilities are stable and consistent.

3. METHODOLOGY

3.1 The Portfolio. A stock portfolio was created, consisting of Reliance Industries Limited, Tata Consultancy Services, HDFC Bank, ICICI Bank, and Hindustan Unilever Limited. A notional investment of ₹10,00,000 was allocated across these stocks, in proportion with their respective market capitalizations. The daily value of this portfolio was determined using the daily prices of these stocks. From these values, percentage changes were computed, which were then utilized to construct Transition Probability Matrices 3 and 4.

3.2 Model specification. Specifically, four models have been developed:

- Probabilities of the entire Sensex moving up or down
- Probabilities of Sensex moving between partitions of the possible gains and losses
- Probabilities of a specific portfolio of stocks moving up or down
- Probabilities of a specific portfolio of stocks moving between partitions of possible gains and losses

The transition matrices were estimated based on 247 transitions obtained from closing values of the BSE Sensex [9] from October 11, 2022 to October 10, 2023. The closing values were categorized using Microsoft Excel.

Model (1) focuses on the Bombay Stock Exchange (BSE) Sensex movements and is defined by two scenarios:

State 1: Market's closing value is the same or higher than that of the previous day

State 2: Market's closing value drops below the previous day's closing figure

Model (2) is a bit more detailed and categorizes the movements of the SENSEX based on the percentage change in its value:

State 1: Large jump up (gain greater than 1.30%)

State 2: Moderate jump up (gain between 0.69% and 1.30%)

State 3: Small jump up (gain between 0.061% and 0.69%)

State 4: Small jump down (loss between -0.57% and 0.061%)

State 5: Moderate jump down (loss between -1.18% and -0.57%)

State 6: Large jump down (loss greater than -1.18%)

The boundaries specified within the parentheses earlier were derived by creating a histogram that mapped out the frequency of daily percentage variations in the value of the Sensex. Interestingly, the percentage changes in Sensex (FIGURE 3.2.1), portfolio (FIGURE 3.2.2) and share prices followed normal distribution as because index value and share prices usually change by small amounts and do so often, while large changes are less common.

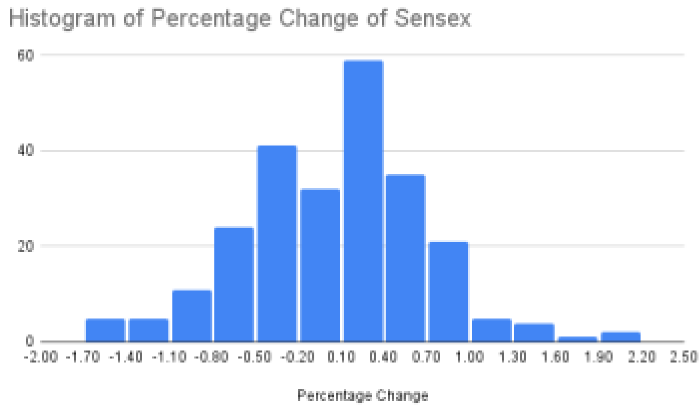


FIGURE 3.2.1

The concept of 95% confidence interval was thereby applied to calculate the limits for six-state TPMs.

State Limits Determination

- *Large Jump Up/Down:*

Up: Greater than $\mu + 1.96\sigma$. This captures changes that are significantly higher than the average, falling in the top 2.5% of all changes (assuming normal distribution).

Down: Less than $\mu - 1.96\sigma$. This represents changes significantly lower than the average, also in the bottom 2.5%.

- *Moderate Jump Up/Down:*

Up: Between $\mu + 1\sigma$ and $\mu + 1.96\sigma$. These changes are above average but not as extreme as the large jumps.

Down: Between $\mu - 1\sigma$ and $\mu - 1.96\sigma$. These are below average but not to the extent of large jumps.

- *Small Jump Up/Down:*

Up: Between μ and $\mu + 1\sigma$. These are slight increases, within the range of what's typically expected.

Down: Between μ and $\mu - 1\sigma$. These are slight decreases, again within the range of normal fluctuations.

Further, the core aim of the article is to compare the price movements between the Sensex and a specifically curated portfolio of stocks from it. To initiate this, a portfolio was crafted comprising selected stocks from the Sensex: Reliance Industries Limited, Tata Consultancy Services, HDFC Bank, ICICI Bank Ltd., and Hindustan Unilever. This portfolio was infused with an investment capital of ₹10,00,000, with the distribution of funds across each stock being proportional to the company's market capitalization.

For Model (3), TPM was developed, which was based on the percentage changes in the portfolio's value, structured into two simple states:

State 1: Portfolio's value is the same or higher than that of the previous day
State 2: Portfolio’s value drops below the previous day's closing figure

For Model (4), a more nuanced state space was incorporated to capture various levels of gains and losses in the portfolio's value:
State 1: Large jump up (gain greater than 1.43%)
State 2: Moderate jump up (gain between 0.75% and 1.43%)
State 3: Small jump up (gain between 0.038% and 0.75%)
State 4: Small jump down (loss between -0.67% and 0.038%)
State 5: Moderate jump down (loss between -1.36% and -0.67%)
State 6: Large jump down (loss greater than -1.36%)

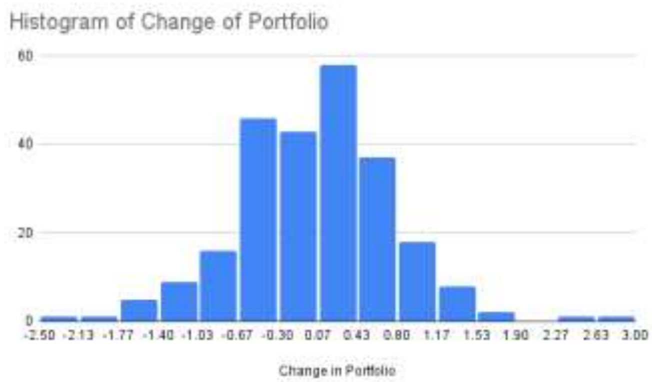


FIGURE 3.2.2

These models are tailored to analyze and interpret the fluctuation patterns of the portfolio's value.

3.3 Sampling technique. A sample comprising 50 trading days was selected from a larger dataset that spanned 244 trading days. This selection was carried out using a simple random sampling technique, focusing exclusively on the BSE Sensex data.
The study involved the creation of two distinct TPMs based on the sampled data - Model (a) and Model (b) - each characterized by different state definitions.

For ***Model (a):***
State 1: Market's closing value is the same or higher than that of the previous day
State 2: Market's closing value drops below the previous day's closing figure

For ***Model (b):***
State 1: Large jump up (gain greater than 1.41%)
State 2: Moderate jump up (gain between 0.76% and 1.41%)
State 3: Small jump up (gain between 0.07% and 0.76%)

State 4: Small jump down (loss between -0.61% and 0.07%)
State 5: Moderate jump down (loss between -1.26% and -0.61%)
State 6: Large jump down (loss greater than -1.26%)

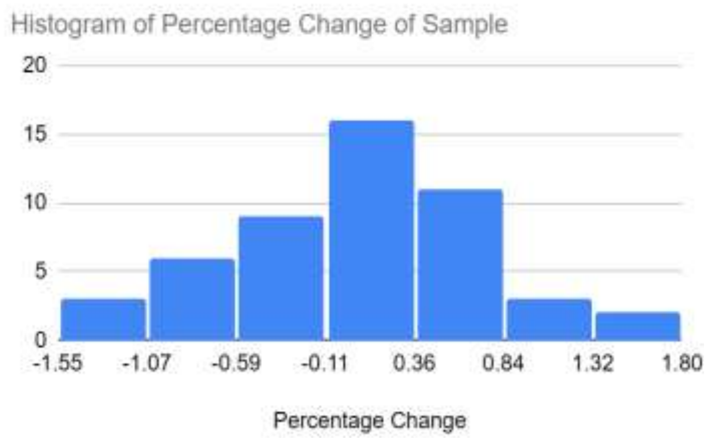


FIGURE 3.3.1

The percentage changes in Sensex for sample data *(FIGURE 3.3.1)* also followed normal distribution.
These state definitions were designed to capture varying magnitudes of market movements, both upward and downward, providing a nuanced understanding of the market dynamics as observed in the Sensex.

4. RESULTS

The transition matrix T_1 for ***model (1)*** was found to be:

$$T_1 = \begin{matrix} S_1 \\ S_2 \end{matrix} \begin{pmatrix} S_1 & S_2 \\ 0.6286 & 0.3714 \\ 0.5 & 0.5 \end{pmatrix}$$

$$T_1^6 = \begin{pmatrix} 0.5738 & 0.4262 \\ 0.5738 & 0.4262 \end{pmatrix}$$

indicating that $v_1 = (0.5738, 0.4262)$.

The transition matrix T_2 for ***model (2)*** was found to be:

$$T_2 = \begin{matrix} S_1 \\ S_2 \\ S_3 \\ S_4 \\ S_5 \\ S_6 \end{matrix} \begin{pmatrix} S_1 & S_2 & S_3 & S_4 & S_5 & S_6 \\ 0 & 0.3333 & 0.1667 & 0.3333 & 0.1667 & 0 \\ 0.037 & 0.1111 & 0.5926 & 0.1111 & 0.1111 & 0.037 \\ 0.0187 & 0.0748 & 0.514 & 0.2617 & 0.1121 & 0.0187 \\ 0 & 0.1045 & 0.4328 & 0.3284 & 0.1045 & 0.0299 \\ 0.1034 & 0.1724 & 0.1724 & 0.3448 & 0.1724 & 0.0345 \\ 0 & 0.1429 & 0.1429 & 0.2857 & 0.2857 & 0.1429 \end{pmatrix}$$

$$T_2^8 = \begin{pmatrix} 0.0249 & 0.1073 & 0.4383 & 0.2767 & 0.1237 & 0.0288 \\ 0.0249 & 0.1073 & 0.4383 & 0.2767 & 0.1237 & 0.0288 \\ 0.0249 & 0.1073 & 0.4383 & 0.2767 & 0.1237 & 0.0288 \\ 0.0249 & 0.1073 & 0.4383 & 0.2767 & 0.1237 & 0.0288 \\ 0.0249 & 0.1073 & 0.4383 & 0.2767 & 0.1237 & 0.0288 \\ 0.0249 & 0.1073 & 0.4383 & 0.2767 & 0.1237 & 0.0288 \end{pmatrix}$$

so that $v_2 = (0.0249, 0.1073, 0.4383, \ 0.2767, \ 0.1237, 0.0288)$

For ***Model (3)***:

$$T_3 = \begin{pmatrix} 0.5648 & 0.4351 \\ 0.5 & 0.5 \end{pmatrix}$$

$$T_3^5 = \begin{pmatrix} 0.5346 & 0.4653 \\ 0.5346 & 0.4653 \end{pmatrix}$$

indicating that $v_3 = (0.5346, 0.4653)$.

For ***Model (4)***:

$$T_4 = \begin{pmatrix} 0 & 0 & 0.5 & 0.3333 & 0.1667 & 0 \\ 0 & 0.2308 & 0.5769 & 0.1154 & 0.0385 & 0.0385 \\ 0.0105 & 0.0842 & 0.4 & 0.3474 & 0.1158 & 0.0421 \\ 0.0465 & 0.0814 & 0.3721 & 0.407 & 0.0698 & 0.0233 \\ 0.0435 & 0.087 & 0.3043 & 0.3913 & 0.087 & 0.087 \\ 0 & 0.2222 & 0.1111 & 0.4444 & 0.2222 & 0 \end{pmatrix}$$

$$T_4^8 = \begin{pmatrix} 0.0245 & 0.1013 & 0.3909 & 0.3522 & 0.0942 & 0.0367 \\ 0.0245 & 0.1013 & 0.3909 & 0.3522 & 0.0942 & 0.0367 \\ 0.0245 & 0.1013 & 0.3909 & 0.3522 & 0.0942 & 0.0367 \\ 0.0245 & 0.1013 & 0.3909 & 0.3522 & 0.0942 & 0.0367 \\ 0.0245 & 0.1013 & 0.3909 & 0.3522 & 0.0942 & 0.0367 \\ 0.0245 & 0.1013 & 0.3909 & 0.3522 & 0.0942 & 0.0367 \end{pmatrix}$$

indicating that $v_4 = (0.0245, 0.1013, 0.3909, 0.3522, 0.0942, 0.0367)$

Transition matrix and diagram for individual stocks

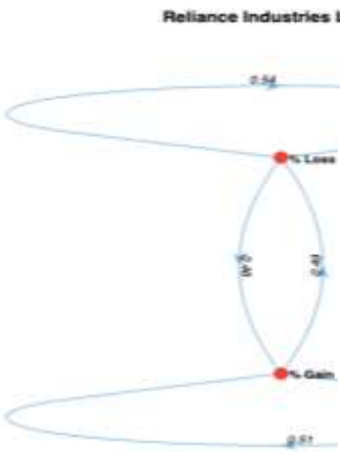
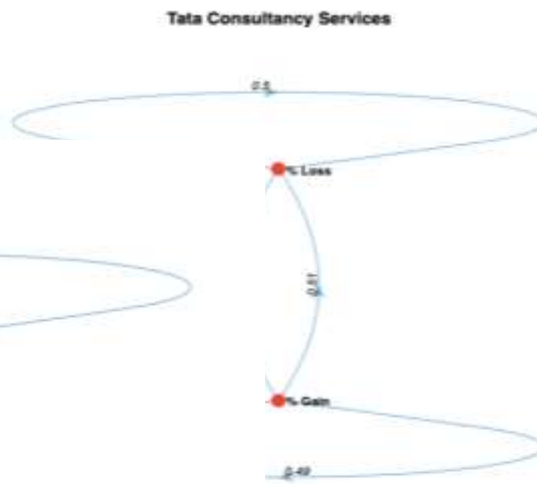


FIGURE 4.1: RIL equity transiti



ransition matrix and diagram

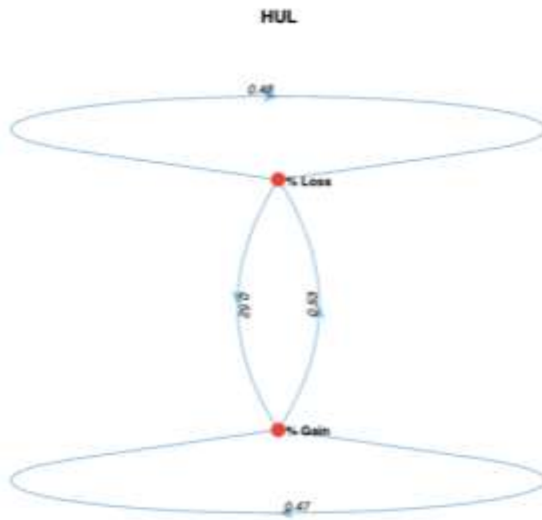


FIGURE 4.5: HUL equity transition matrix and diagram

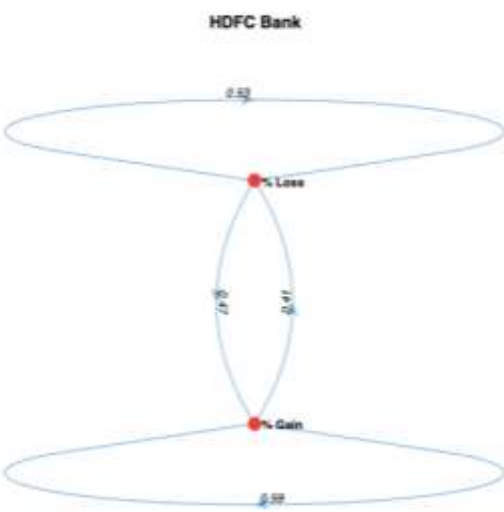


FIGURE 4.3: HDFC equity transition matrix and diagram

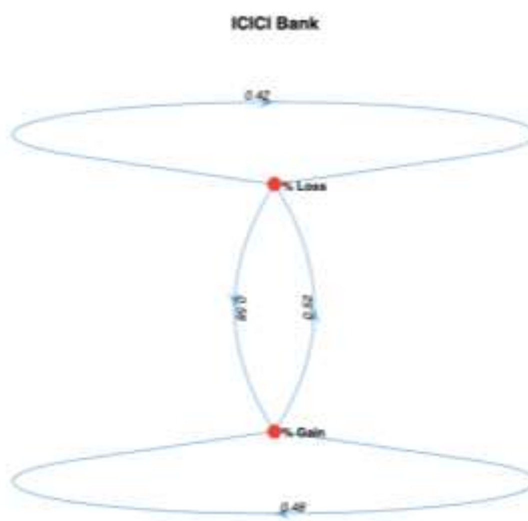


FIGURE 4.4: ICICI equity transition matrix and diagram

TABLE 4.1: Summary statistics for steady-state distributions and mean recurrent time for equities.

	Steady State Distributions		Mean Recurrent time
Equities	Loss	Gain	
RIL	0.5123	0.4877	2.0504
TCS	0.5041	0.4959	2.0165
HDFC	0.4626	0.5374	1.8608
ICICI	0.4717	0.5283	1.8929
HUL	0.5043	0.4957	2.0178

TABLE 4.2: Chi-square test for goodness of fit for the Markov chain model

Equity	calculated	df	tabulated
RIL	4.094	1	6.635
TCS	4.004	1	6.635
HDFC	4.629	1	6.635
ICICI	4.420	1	6.635

Transition matrix S_1 for ***model (a)*** composed of a random sample of 50 days was found to be:

$$S_1 = \begin{pmatrix} 0.655 & 0.345 \\ 0.5 & 0.5 \end{pmatrix}$$

$$S_1^6 = \begin{pmatrix} 0.582 & 0.418 \\ 0.582 & 0.418 \end{pmatrix}$$

indicating that $v_5 = (0.582, 0.418)$.

Transition matrix S_2 for ***model (b)*** composed of a random sample of 50 days was found to be:

$$S_2 = \begin{pmatrix} 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0.5 & 0.17 & 0.33 & 0 \\ 0.06 & 0.11 & 0.33 & 0.39 & 0.11 & 0 \\ 0 & 0.13 & 0.4 & 0.33 & 0.13 & 0 \\ 0.14 & 0.29 & 0.14 & 0.14 & 0.14 & 0.14 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}$$

$$S_2^6 = \begin{pmatrix} 0.041 & 0.122 & 0.367 & 0.306 & 0.143 & 0.02 \\ 0.041 & 0.122 & 0.367 & 0.306 & 0.143 & 0.02 \\ 0.041 & 0.122 & 0.367 & 0.306 & 0.143 & 0.02 \\ 0.041 & 0.122 & 0.367 & 0.306 & 0.143 & 0.02 \\ 0.041 & 0.122 & 0.367 & 0.306 & 0.143 & 0.02 \\ 0.041 & 0.122 & 0.367 & 0.306 & 0.143 & 0.02 \end{pmatrix}$$

so that $v_6 = (0.041, 0.122, 0.367,\ 0.306,\ 0.143, 0.02)$

5. DISCUSSION AND CONCLUSION

The TPMs for both ***Sensex*** (T_1) and the ***portfolio*** (T_3) reveal a notable trend: there is a greater likelihood of transitioning to a state of gain than a state of loss. This is a positive indicator for investors, as the steady state probabilities suggest that days of gains are more probable than days of losses in both Sensex and the portfolio.

In the TPMs for Model (2) and (4), the analysis shows that regardless of the current state, there is a high probability of the next day being one of small loss or small gain. This indicates a market that is not prone to large, sustained swings, which is encouraging for investors focusing on long-term growth and stability.

Stock Behaviour

The transition matrix for ***RIL*** *(FIGURE 4.1)* indicates a 53.6% chance of staying in a % loss state and a 46.54% chance of switching from % loss to % gain. Additionally, there is a 48.7% chance of transitioning from a gain state to a loss state, and a 51.2% chance of maintaining a gain state. The mean recurrent time to return to a gain state is 2.05 weeks (*TABLE 4.1)*

The ***TCS*** stock shows an equal chance (50%) of moving to a loss or gain state from a loss state (*FIGURE 4.2*). In the long run, the stock has a 50% chance of decreasing in price and 49% chance of increasing. This indicates a balanced but slightly volatile nature of TCS stock.

HDFC Bank's transition probabilities favour an increase in stock prices, with a higher likelihood of the stock price increasing than decreasing (*FIGURE 4.3*) The mean recurrent time for the HDFC stock to return to a gain state is approximately 1.86 weeks, making it the most efficient stock in terms of transitioning to a gain state among the ones studied.

The behaviours of ***ICICI*** (*FIGURE 4.4*) and ***HUL*** *(FIGURE 4.5)* are consistent with the patterns observed in RIL and TCS but differ in the magnitude of their transition probabilities. Their long-run distribution and mean recurrent times, however, are similar.

Statistical Validation

The *chi-square test* results (*TABLE 4.2*) confirm the goodness of fit for the Markov chain model. With the calculated values for all five equities being less than the critical values at a 99% Confidence Interval, it suggests that the steady-state probabilities of the states are stable and consistent, validating the reliability of the Markov chain model in financial analysis.

A sample of 50 days was carefully chosen out of a total of 244 trading days. The similarity between the TPM from this small sample and the TPM from the entire year's data shows that the technique of selecting the sample was effective and helped in accurately capturing the main trends of the Sensex during the year.

In summary, the study demonstrates that a diversified portfolio tends to replicate the overall market's behaviour, with a tendency towards small gains and losses.

HDFC Bank emerges as the most efficient stock in the portfolio, characterized by the shortest mean recurrence time to a state of gain and the highest steady-state probability for gain.

This detailed analysis not only reinforces the utility of Markov chain models in stock market analysis but also provides actionable insights for investors and portfolio managers. The consistency and stability of these models, as evidenced by the chi-square test, further solidify their applicability in financial market prediction and analysis.

6. REFERENCES

[1] M. I. Kaya and M. E. Karsligil, "Stock price prediction using financial news articles," in 2010 2nd IEEE International Conference on Information and Financial Engineering, pp. 478– 482, Chongqing, 2009.

[2] Kevin J. Doubleday and Julius N. Esunge, 2010, Application of Markov Chains to Stock Trends, Journal of Mathematics and Statistics, ISSN 1549- 3644

[3] Agwuegbo, S.O.N., A. P. Adewole and A. N. Maduegbuna, 2010. A random walk model for stock market prices. J. Math. Stat., 6: 342-346. DOI:10.3844/jmssp.2010.342.346

[4] Jones, P.W. and P. Smith, 2009. Stochastic Processes: An Indroduction. 2nd Edn., Chapman and all/CRC, Spain, ISBN: 13: 9781420099607, pp: 221.

[5] D. N. Choji, S. N. Eduno, and G. T. Kassem, "Markov chain model application on share price movement in stock market," Journal of Computer Engineering and Intelligent Systems, vol. 4, no. 10, 2013.

[6] D. Zhang and X. Zhang, "Study on forecasting the stock market trend based on stochastic analysis method: international," Journal of Business and Management, vol. 4, no. 6, 2009.

[7] S. Otieno, E. O. Otumba, and R. N. Nyabwanga, "Application of Markov chain to model and forecast stock market trend: a study of Safaricom shares in Nairobi Securities Exchange," Kenya: International Journal of Current Research, vol. 7, no. 4, pp. 14712–14721, 2015.

[8] Gabriel Kallah-Dagadu , Victor Apatu, Felix Okoe Mettle , Dennis Arku , and Godwin Debrah, 2022, Application of Markov Chain Techniques for Selecting Efficient Financial Stocks for Investment Portfolio Construction. Hindawi, Journal of Applied Mathematics, Aritcle ID 2863302

WEBSITES

[1] https://www.google.com/finance/?hl=en