Universe Scientific Publishing

Analysis and Prediction of Stock Prices for China's Big Four Banks Based on Markov Chain

YAN JIAWEI

Department of Economics and Management, Guangzhou College of Applied Science and Technology, Guangdong Province 511370, China

Abstract: Predicting stock trends is a social hotspot and choosing a proper model is crucial for stock research. This paper uses the daily closing prices of the china's big four banks on the Shanghai Stock Exchange from January 2019 to June 2025 and calculates daily returns via the logarithmic return method. Then, it analyzes returns and volatility, and applies the Markov chain to predict the return changes of these banks. The results show that the four banks have different risk characteristics. Only the predicted returns of the Construction Bank are accurate, while the actual returns of the other three banks are higher than the predicted ones. This indicates that the Markov chain method can effectively predict the minimum returns of the big four banks and that its prediction accuracy are related to the risk characteristics of the predicted stocks.

Keywords: Markov Chain; Return; China's Big Four banks

1 Introduction

The stock market, as a critical avenue for corporate financing, plays a pivotal role in the financial market. It has also become a vital financial instrument for individuals to manage investments and hedge risks. The Chinese stock market, with its emerging market characteristics, exhibits significant volatility and complexity, making accurate stock price prediction crucial for investors. Among the various methods for stock price prediction, Markov chains stand out for their ability to capture the stochasticity and nonlinear dynamics of stock price changes. Unlike traditional methods based on historical data and time series analysis, Markov chains focus on the transition probabilities between the current state and the next state, independent of past states. This unique feature enables them to more flexibly model the inherent randomness of financial markets.

In recent years, numerous researchers have applied Markov chains to predict different financial markets and asset types. However, most existing studies either group stocks from various industries together for prediction, compare predictions of individual stocks' short-term performance with actual results, or predict stock index instead of individual stocks. Despite these efforts, limitations persist. For instance, the sample selection is often broad, lacking a deep focus on specific industries or markets. Moreover, the impact of different risk characteristics of stocks on the prediction accuracy of Markov chains has not been thoroughly explored.

This study focuses on the stocks of China's big four banks, which hold a significant position in China's financial system. The "Big Four" in China are the Industrial and Commercial Bank of China (ICBC), China Construction Bank (CCB), Agricultural Bank of China (ABC), and Bank of China (BOC). Their massive asset size and substantial influence on financial markets make them crucial for investment and risk management.

Previous research has insufficiently examined the use of Markov chains for predicting stock prices of China's big four banks. This study addresses this gap by applying Markov chain analysis to forecast these banks' stock prices. Concentrating on the big four banks allows for control over variables like industry, issuance market, and time period, facilitating a more accurate assessment of Markov chains' predictive effectiveness across varying risk profiles. By exploring these underexamined areas, this study not only enhances the literature on Markov chain applications but also provides practical insights into the dynamic behavior of bank stock prices in the Chinese market.

1.1 statement of the problem

Price volatility in equities poses significant investment risks. Understanding the positioning of stock prices is essential for informed investment decisions. Investors rely on market information to determine optimal stock selection, timing for buying, selling, or holding. This study seeks to assess the returns and risks associated with China's big four banks and forecast their stock price fluctuations through the application of the Markov chain methodology.Concurrently, under controlled industry, market, and temporal conditions, the study examines whether the accuracy of Markov chain predictions varies for stocks with different risk profiles.

1.2 Empirical literature review

The application of Markov chains in financial market analysis has gained significant traction due to their ability to model stochastic processes with state-dependent transitions. Various studies have explored the use of Markov chains in different contexts. For instance, Nhung (2025) applied discrete-time Markov chains to optimize stock portfolios on the Vietnamese Stock Exchange. By categorizing daily returns into three states (decrease, stable, increase), the study derived transition probability matrices (TPMs) and limiting distributions to identify stocks with higher probabilities of entering high-return states. However, this research focused on portfolio optimization rather than stock price prediction and overlooked risk factors.

Luwang et al. (2024) examined intraday order dynamics and market capitalization effects by analyzing high-frequency NASDAQ order data through first-order Markov chains. They revealed time-dependent transition patterns and found that small-cap stocks exhibited a higher frequency of limit-order modifications. Nevertheless, their research concentrated on order dynamics rather than stock price prediction.

Kiplangat (2024) applied a 5-state Markov chain model to analyze stocks in the Nairobi Securities Exchange (NSE) in frontier markets. The research confirmed the presence of first-order Markov properties and observed convergence to steady states within 12–23 trading days. However, this study focused on a different market context and did not specifically address bank stocks.

Mu & Li (2024) investigated the efficacy of Markov chains in short-term index forecasting within developed markets using China's CSI 300 Index. The model demonstrated notable accuracy in predicting index movements over a span of 1–2 days. Yet, its application was limited to index forecasting rather than individual bank stocks.

McQueen & Thorley (1991) conducted pioneering research on stock return predictability using Markov chains, providing foundational insights into the potential of this method. Doubleday & Esunge (2011) further investigated the application of Markov chains to stock trends, demonstrating their utility in capturing the stochastic nature of financial markets. Agwuegbo et al. (2010) proposed a random walk model for stock market prices, which shares similarities with Markov chain models. Mettle et al. (2014) developed a methodology for stochastic analysis of share prices as Markov chains with finite states, contributing to the understanding of stock price dynamics in discrete state spaces.

Zhang et al. (2009) explored the use of Markov chains for stock market trend prediction, while Zhou (2014) applied weighted Markov chains to forecast stock prices. These studies highlight the versatility of Markov chain models in financial market analysis but often focus on general market trends or specific indices rather than individual bank stocks.

Despite these advancements, several research gaps persist. Most studies employ a broad sample selection that includes stocks from various industries, lacking a deep focus on specific sectors such as banking stocks, which exhibit distinct volatility patterns. Notably, no studies have specifically focused on China's "Big Four" banks (ICBC, CCB, ABC, BOC), despite their systemic importance. Additionally, most research uses a limited number of states (usually ≤6), suggesting that finer partitions could enhance prediction accuracy for bank stocks. Furthermore, the potential of hybrid approaches combining Markov chains with risk metrics remains unexplored for banking portfolios.

This study addresses these gaps by focusing on the application of Markov chains to predict the stock prices of China's big four banks. It provides a more targeted analysis by controlling for the same industry, market, and time period. Moreover, it explores the prediction effectiveness of Markov chains under different risk characteristics of the banks, offering new insights into the prediction accuracy of Markov chains for stocks with varying risk profiles.

2 Methodology

2.1 Markov Chains

The Markov chain, a stochastic process exhibiting the Markov property, was developed based on the theory proposed by the Russian mathematician Andrey Markov in1906. This property stipulates that the probability distribution of the future state depends solely on the current state, irrespective of the past states. Consequently, the present state probabilistically determines the future state, while the historical states are inconsequential for predicting the future.

A stochastic process exhibits the Markov property if and only if it satisfies:

$P(X_{t+1} = j|X_t = i, X_{t-1} = k_{t-1}, \dots, X_0 = K_0) = P(X_{t+1} = j|X_t = i)$ for $t = 0,1,2,\dots,n$

The conditional probability below is the transition probability from state $X_t = i$ to $X_{t+1} = j$:

$P(X_{t+1} = j|X_t = i) = P_{ij}$

If the value of X_{t+1} depends solely on the current state X_t and the transition probability P_{ij} , and is independent of past states $X_{t-1}, X_{t-2}, \dots$, then such a discrete-state, discrete-time stochastic transition process is termed a Markov Chain. Markov Chains model conditional transition probability distributions through:

(1) A state space $S = s_1, s_2, \dots, s_k$

(2) A transition probability matrix P

where the matrix elements represent the conditional probabilities:

$P(X_{t+1} = s_j|X_t = s_i) = P_{ij}$ for $i, j = 1,2,3, \dots, k$

When P_{ij} is time-independent, the Markov chain is called a homogeneous Markov Chain.

Markov chain models offer significant theoretical and practical utility in elucidating the evolutionary dynamics of systems observed over successive time periods. These repeated observation periods often correspond to continuous-time cycles, wherein the precise state of the system in each cycle cannot be definitively determined and must be characterized probabilistically through transition probabilities. The Transition Probability Matrix (TPM) provides a means to accurately calculate the probability of the system occupying a particular state at a given time point. Such Markov models can be constructively applied to the return series of diverse financial assets.

2.2 Chapman-Kolmogorov Equations

The Chapman-Kolmogorov equation is the foundational expression governing Markov chain dynamics, delineating the transition laws between states over multiple time steps. Fundamentally, it is a theorem of decomposition for multi-step transition probabilities, enabling the calculation of transition probabilities over arbitrary time intervals through single-step transition probabilities.

Given that P_{ij} is the one-step transition probability matrix, $P_{ij}^{(n+m)}$ is the (n+m)-step transition probability matrix, $P_{ij}^{(n)}$ is the n-step transition probability matrix and $P_{ij}^{(m)}$ is the m-step transition probability matrix.

$$P_{ij}^{(n+m)} = \sum_{k \in S} P_{ik}^{(n)} P_{kj}^{(m)}$$

For all $i = 0,1,2, \dots, n; j = 0,1,2, \dots, m; m = 1,2, \dots, m$ and $n = 1,2, \dots, n$

This equation describes the transition probability from state to state through an intermediate state ,which first transitioning from to in steps, then from to in steps. This expression reveals how to recursively compute n-step probabilities from one-step transition probabilities.

3 Results

This study utilizes daily closing price data from 1,568 trading days (January 2, 2019 to June 23, 2025) of China's four major banks. Logarithmic returns are calculated to derive daily stock returns, and price trends are predicted by constructing state spaces and transition probability matrices based on these returns.

Table 1 summarizes the descriptive statistics of the daily returns for the following banks during the period covered in this report:

Table 1 Summary statistics for returns

statistics	ABC	BOC	CCB	ICBC
No.of observations	1568	1568	1568	1568
Mean	0.0004	0.0004	0.0003	0.0003
Minimum	-0.0391	-0.0387	-0.0592	-0.0371
Maximum	0.0503	0.0649	0.0619	0.0545

Std.dev	0.0066	0.0067	0.0083	0.0065
Skewness	0.2781	0.7845	0.2733	0.6466
Kurtosis	10.1868	14.2618	9.3495	10.4475

Table 1 indicates that the four major banks exhibit highly similar average returns, all approaching zero, with their return distributions displaying leptokurtic and heavy-tailed characteristics. However, significant differences emerge in their risk profiles. CCB demonstrates the highest volatility, exemplifying high-risk exposure. ICBC shows the lowest volatility and other risk metrics, representing stability. BOC registers the highest positive skewness and kurtosis, indicating heightened event risk exposure. ABC maintains moderate values across indicators, reflecting balanced risk-return characteristics.

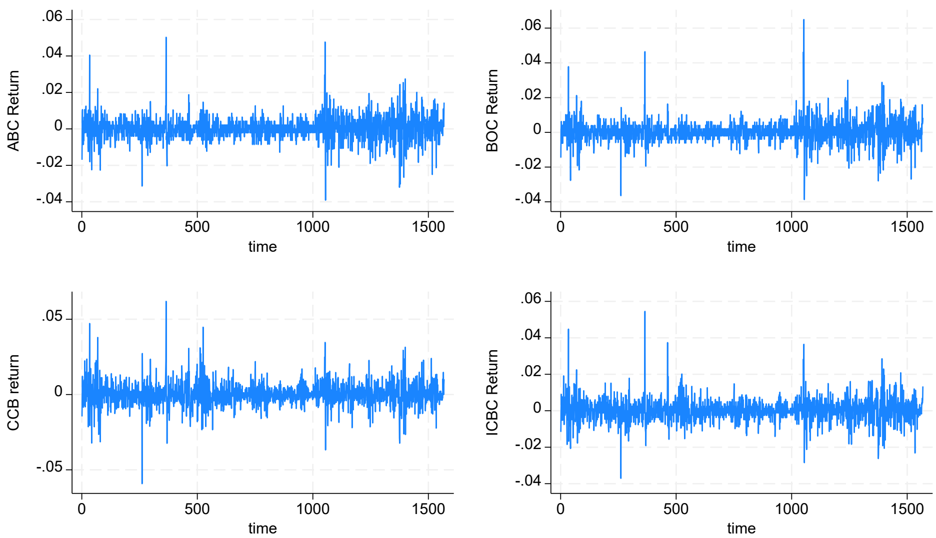

Figure 1 Plots of the time series for the four bank's daily returns

Graph 1 shows that the returns of the four banks are subject to variation due to factors such as policy changes, industry dynamics, and market sentiment, while exhibiting volatility clustering characteristics.

3.1 Constructing the Return Transition Probability Matrix

The state space partitioning is based on daily return movements. Given the implementation of a price limit mechanism in China's stock market—where daily price fluctuations are constrained within a 10% limit—returns are categorized into six discrete states: ⍰⍰⍰⍰, as detailed in Table 2.

Table 2 Summary of state space division

S_1	S_2	S_3	S_4	S_5	S_6
[-10%, -1%)	[-1%, -0.5%)	[-0.5%, 0)	[0, 0.5%)	[0.5%, 1%)	[1%, 10%)

Using Excel, we empirically generated state transition matrices for each of the four major banks, obtaining both transition frequency matrices and transition probability matrices for their respective return series, as presented in Table 3.

As shown in Table 3, during the research period, the state transition frequency matrix indicates that most of the four banks' state transitions start from S_4, and their final states are mostly in S_4, followed by S_3. For ABC, the probabilities of being in S_1, S_2, S_3, S_4, S_5, and S_6 are 0.104, 0.113, 0.198, 0.455, 0.098, and 0.119, respectively, which are also the probabilities of staying in the same state. For BOC, the return probability from S_3 to S_4 is 0.499, the highest among the four banks, while the return probability from S_4 to S_4 is 0.476. The probabilities of returns transferring from S_3 and S_4 to S_6 are low. For CCB, the return probabilities from any state to S_2 are similar. The return probability from S_3 to S_4 is 0.393. For ICBC, the return probability from S_3 to S_4 is 0.423.

Table 3 State transition frequency matrix and transition probability matrix

Stock	State transition frequency matrix	Transiton probability matrix
ABC	$F_{ABC} = \begin{pmatrix} 8 & 7 & 14 & 18 & 17 & 13 \\ 7 & 18 & 37 & 60 & 26 & 12 \\ 13 & 41 & 74 & 186 & 43 & 17 \\ 24 & 63 & 184 & 309 & 69 & 30 \\ 11 & 20 & 49 & 75 & 18 & 11 \\ 13 & 11 & 16 & 31 & 11 & 11 \end{pmatrix}$	$P_{ABC} = \begin{pmatrix} 0.104 & 0.091 & 0.182 & 0.234 & 0.221 & 0.168 \\ 0.044 & 0.113 & 0.231 & 0.375 & 0.163 & 0.074 \\ 0.035 & 0.110 & 0.198 & 0.497 & 0.115 & 0.045 \\ 0.035 & 0.093 & 0.271 & 0.455 & 0.102 & 0.044 \\ 0.060 & 0.109 & 0.266 & 0.408 & 0.098 & 0.059 \\ 0.140 & 0.118 & 0.172 & 0.333 & 0.118 & 0.119 \end{pmatrix}$
BOC	$F_{BOC} = \begin{pmatrix} 4 & 8 & 11 & 20 & 6 & 13 \\ 10 & 14 & 30 & 62 & 26 & 11 \\ 11 & 29 & 100 & 202 & 39 & 18 \\ 19 & 58 & 194 & 331 & 63 & 25 \\ 9 & 29 & 46 & 48 & 20 & 11 \\ 8 & 15 & 18 & 28 & 9 & 7 \end{pmatrix}$	$P_{BOC} = \begin{pmatrix} 0.063 & 0.127 & 0.175 & 0.317 & 0.095 & 0.223 \\ 0.065 & 0.092 & 0.196 & 0.405 & 0.170 & 0.072 \\ 0.027 & 0.072 & 0.247 & 0.499 & 0.096 & 0.059 \\ 0.027 & 0.083 & 0.279 & 0.476 & 0.091 & 0.044 \\ 0.055 & 0.177 & 0.280 & 0.293 & 0.122 & 0.073 \\ 0.093 & 0.174 & 0.209 & 0.326 & 0.105 & 0.093 \end{pmatrix}$
CCB	$F_{CCB} = \begin{pmatrix} 11 & 15 & 22 & 30 & 14 & 16 \\ 21 & 28 & 43 & 73 & 22 & 20 \\ 16 & 49 & 96 & 155 & 47 & 31 \\ 34 & 64 & 152 & 168 & 62 & 44 \\ 11 & 28 & 45 & 52 & 18 & 24 \\ 14 & 23 & 36 & 46 & 15 & 22 \end{pmatrix}$	$P_{CCB} = \begin{pmatrix} 0.102 & 0.139 & 0.204 & 0.278 & 0.130 & 0.147 \\ 0.101 & 0.135 & 0.208 & 0.353 & 0.106 & 0.097 \\ 0.041 & 0.124 & 0.244 & 0.393 & 0.119 & 0.079 \\ 0.065 & 0.122 & 0.290 & 0.321 & 0.118 & 0.084 \\ 0.062 & 0.157 & 0.253 & 0.292 & 0.101 & 0.135 \\ 0.090 & 0.147 & 0.231 & 0.295 & 0.096 & 0.141 \end{pmatrix}$
ICBC	$F_{ICBC} = \begin{pmatrix} 5 & 6 & 19 & 15 & 12 & 8 \\ 8 & 18 & 49 & 63 & 19 & 14 \\ 15 & 50 & 120 & 193 & 57 & 21 \\ 18 & 61 & 189 & 273 & 74 & 23 \\ 11 & 29 & 54 & 70 & 23 & 8 \\ 7 & 7 & 25 & 24 & 10 & 5 \end{pmatrix}$	$P_{ICBC} = \begin{pmatrix} 0.077 & 0.092 & 0.292 & 0.231 & 0.185 & 0.123 \\ 0.047 & 0.105 & 0.287 & 0.368 & 0.111 & 0.082 \\ 0.033 & 0.110 & 0.263 & 0.423 & 0.125 & 0.046 \\ 0.030 & 0.101 & 0.314 & 0.394 & 0.123 & 0.038 \\ 0.056 & 0.149 & 0.277 & 0.359 & 0.118 & 0.041 \\ 0.090 & 0.090 & 0.321 & 0.308 & 0.128 & 0.063 \end{pmatrix}$

3.2 Estimate of the Steady State Probabilities

To investigate the long-horizon dynamics of stock prices across the four major banks, this study computes the -step transition probability matrix (where denotes the probability of transitioning from state to state in periods), thereby projecting the future state distribution of stock prices after cycles. As becomes sufficiently large, if the row vectors of converge to an identical probability distribution, this indicates that the Markov chain attains a stationary distribution, signifying the emergence of a long-run equilibrium in the system.

The research results indicate that for China's big four banks, after a certain number of trading days, their transition matrices show a tendency towards constant probabilities. As the matrix power increases further, all elements clearly converge, proving the stock price transition system reaches equilibrium. Specifically, ABC and CCB reach stability after a period of 6 trading days, while BOC and ICBC after 4 trading days. From a Markov chain theory perspective, this convergence to a steady - state system demonstrates ergodicity. That is, regardless of the initial state, the four banks' stock return states will eventually converge to a unified steady - state distribution.

From a Markov chain theoretical perspective, this convergence of transition matrices to a stationary system unequivocally demonstrates ergodicity. That is, irrespective of initial states, the return states of all four major banks' stock prices asymptotically stabilize into a unified stationary distribution.

$$ABC\ P_{ij}^{6} = \begin{pmatrix} 0.048 & 0.102 & 0.239 & 0.433 & 0.118 & 0.060 \\ 0.048 & 0.102 & 0.239 & 0.433 & 0.118 & 0.060 \\ 0.048 & 0.102 & 0.239 & 0.433 & 0.118 & 0.060 \\ 0.048 & 0.102 & 0.239 & 0.433 & 0.118 & 0.060 \\ 0.048 & 0.102 & 0.239 & 0.433 & 0.118 & 0.060 \\ 0.048 & 0.102 & 0.239 & 0.433 & 0.118 & 0.060 \end{pmatrix}$$

$$BOC\ P_{ij}^{4} = \begin{pmatrix} 0.039 & 0.099 & 0.254 & 0.440 & 0.104 & 0.064 \\ 0.039 & 0.099 & 0.254 & 0.440 & 0.104 & 0.064 \\ 0.039 & 0.099 & 0.254 & 0.440 & 0.104 & 0.064 \\ 0.039 & 0.099 & 0.254 & 0.440 & 0.104 & 0.064 \\ 0.039 & 0.099 & 0.254 & 0.440 & 0.104 & 0.064 \\ 0.039 & 0.099 & 0.254 & 0.440 & 0.104 & 0.064 \end{pmatrix}$$

$$CCB\ P_{ij}^{6} = \begin{pmatrix} 0.068 & 0.132 & 0.252 & 0.335 & 0.113 & 0.100 \\ 0.068 & 0.132 & 0.252 & 0.335 & 0.113 & 0.100 \\ 0.068 & 0.132 & 0.252 & 0.335 & 0.113 & 0.100 \\ 0.068 & 0.132 & 0.252 & 0.335 & 0.113 & 0.100 \\ 0.068 & 0.132 & 0.252 & 0.335 & 0.113 & 0.100 \\ 0.068 & 0.132 & 0.252 & 0.335 & 0.113 & 0.100 \end{pmatrix}$$

$$ICBC\ P_{ij}^{4} = \begin{pmatrix} 0.041 & 0.109 & 0.291 & 0.384 & 0.124 & 0.050 \\ 0.041 & 0.109 & 0.291 & 0.384 & 0.124 & 0.050 \\ 0.041 & 0.109 & 0.291 & 0.384 & 0.124 & 0.050 \\ 0.041 & 0.109 & 0.291 & 0.384 & 0.124 & 0.050 \\ 0.041 & 0.109 & 0.291 & 0.384 & 0.124 & 0.050 \\ 0.041 & 0.109 & 0.291 & 0.384 & 0.124 & 0.050 \end{pmatrix}$$

3.3 Estimate of the Future Expected Daily Returns

In this section, we aim to predict the state of returns for the four major banks on the next trading day, June 24, 2025. To achieve this, we need to define an initial state vector first. Then, we multiply this vector by the transition probability matrix to predict the state transition of the initial state vector after one trading day.

This study selects the actual initial states of the four banks as the initial state vector. The focus is on their returns' real - state on June 23, 2025. The initial state vector is shown in the table below.

Table 4 Initial distribution

Stock	Initial distribution
ABC	(0,0,0,0,0,1)
BOC	(0,0,0,0,1,0)
CCB	(0,0,0,0,0,1)
ICBC	(0,0,0,0,0,1)

Through the calculations, we can obtain the final distribution of the four banks' return probabilities on June 24, 2024. Table 5 presents the predictions based on using the actual initial states of the four banks as the initial state vector.

The forecast in Table 5 shows that on June 24, 2025, China's four major banks have the highest probability of being in return state S_4, with probabilities of 0.333, 0.428, 0.295, and 0.308. S_4 indicates their returns are in [0, 0.5%). On that day, the actual returns of ABC, BOC, CCB, and ICBC were 0.83%, 0.59%, 0.22%, and 0.99%. Except for CCB, the other three banks' returns were underestimated. This implies their actual returns are no less than the predicted values, demonstrating the Markov chain model's effectiveness in setting a return floor for investors.

Table 5 Results of the predicted state and actual state

Stock	S_1	S_2	S_3	S_4	S_5	S_6	Predicted State	Actual State
ABC	0.140	0.118	0.172	0.333	0.118	0.119	S_4	S_5
BOC	0.044	0.102	0.245	0.428	0.111	0.070	S_4	S_5
CCB	0.090	0.147	0.231	0.295	0.096	0.141	S_4	S_4
ICBC	0.090	0.090	0.321	0.308	0.128	0.063	S_4	S_5

4 Conclusion

This study focuses on applying Markov chains to analyze and predict the stock prices of China's four major banks. It reveals that the daily returns of these banks are nearly zero and exhibit significant excess kurtosis, indicative of a heavy - tailed distribution. Despite comparable mean returns, the four major banks exhibit distinct risk profiles. CCB exemplifies high-risk exposure with elevated volatility. ICBC shows optimal stability through minimized volatility. BOC manifests the most pronounced event risk exposure, evidenced by extreme positive skewness and kurtosis. ABC maintains balanced risk-return characteristics with intermediate metric values.

By constructing the transition probability matrix, it clearly shows the probabilities of banks transitioning between different return states. Further analysis reveals that this matrix converges to a steady state after a certain number of trading days. Specifically, ABC, BOC, CCB, and ICBC reach equilibrium in their return states after the period of 6, 4, 6, and 4 trading days, respectively.

This study aims to build a Markov model for accurate stock - price prediction of the four major banks. Results show that, except for CCB, the other three banks' same - day returns were underestimated. This implies actual returns are no less than predicted. Interestingly, only BOC, with the highest "event risk", was predicted accurately. This indicates that the accuracy of the Markov chain method in prediction may be related to the risk characteristics of the stock being predicted. Overall, the Markov chain method can effectively assist investors in analyzing and predicting stock price states, thereby providing a basis for investment decisions.

References

[1] Agwuegbo, S. O. N. , Adewole, A. P. , & Maduegbuna, A. N. . (2010). A random walk model for stock market prices. Journal of Mathematics and Statistics, 6(3).

[2] Doubleday, K. J. , & Esunge, J. N. . (2011). Application of markov chains to stock trends. Journal of Mathematics & Statistics, 7(2), 103-106.

[3] Deju, Z. , & Xiaomin, Z. . (2009). Study on forecasting the stock market trend based on stochastic analysis method. International Journal of Business & Management(6).

[4] Dennis Cheruiyot Kiplangat .(2024).”Modelling selected stock prices at the Nairobi securities exchange using Markov Chains,International Journal of Science and Research Archive, 2024, 13(02), 1528–1542

[5] Dinh Thi Kim Nhung. (2025).”An Application of Markov Chains in Optimizing Stock Portfolios in the Vietnamese Stock Market”. ln:International Journal of Mathematics Trends and Technology. Volume 71 Issue 4, 1-7

[6] Foucault, T. . (1998). Order flow composition and trading costs in dynamic limit order markets. Thierry Foucault.

[7] Hollifield, B. , Miller, R. A. , & Sandas, P. . (2004). Empirical analysis of limit order markets. Review of Economic Studies, 71(4), 1027-1063.

[8] Luwang, S. R. , Rai, A. , Nurujjaman, M. , & Petroni, F. . (2025). Intraday order transition dynamics in high, medium, and low market cap stocks: a markov chain approach.

[9] M. Peterson, E. Sirri.. (2002). Order submission strategy and the curious case of marketable limit orders, Journal of Financial and Quantitative analysis 37 (2), 221–241.

[10] Mcqueen, G. , & Thorley, S. . (1991). Are stock returns predictable? a test using markov chains. The Journal of Finance.

[11] Mettle, F. , Quaye, E. , & Laryea, R. . (2014). A methodology for stochastic analysis of share prices as markov chains with finite states. SpringerPlus, 3(1), 657-657.

[12] Otieno, S. , Otumba, E. O. , & Nyabwanga, R. N. . (2015). Application of markov chain to model and forecast stock market trend: a study of safaricom shares in nairobi securities exchange, kenya.

[13] Svoboda, I. M. M. . (2012). Application of markov chain analysis to trend prediction of stock indices.

[14] Zhou, Q. X. . (2014). Application of weighted markov chain in stock price forecasting.