A Study on Predicting the Stock Prices of Banking and Non- Banking Financial Institutions.

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ABSTRACT

The study delves into the comparative analysis of banking and non-banking financial institutions (NBFI), focusing on prominent entities such as HDFC, SBI, ICICI (banking) and BAJAJ FINANCE, MAHINDRA AND MAHINDRA FINANCE LTD, SHRIRAM FINANCE

(NBFI). Utilizing the ARIMA (Auto Regressive Integrated Moving Average) and ARMA (Auto Regressive Moving Average) models, the research aims to forecast and analyze the financial performance of these institutions over a specified period.

I.INTRODUCTION

Predicting stock prices of banking and non-banking financial institutions (NBFIs) like HDFC, ICICI, SBI, Bajaj Finance, Mahindra and Mahindra Financial Services, and Shriram Transport Finance Company is a multifaceted challenge influenced by a variety of factors. These institutions play crucial roles in the financial ecosystem, offering a range of services from traditional banking to specialized lending and financial products. Banking financial institutions (BFIs) such as HDFC, ICICI, and SBI are integral components of India's financial sector. HDFC is renowned for its robust mortgage lending business, ICICI for its extensive retail and corporate banking services, and SBI is the largest public sector bank with a broad customer base. These entities are affected by factors like interest rates, loan quality, regulatory policies, and overall economic health, influencing their stock performance.

On the other hand, NBFIs like Bajaj Finance, Mahindra and Mahindra Financial Services, and Shriram Transport Finance Company operate in specialized niches within the financial market. Bajaj Finance excels in consumer finance, Mahindra and Mahindra Financial Services focuses on rural and agricultural financing, and Shriram Transport Finance specializes in commercial vehicle loans. These institutions often experience different growth trajectories and risk profiles compared to traditional banks, impacting their stock prices differently.

Stock market price is most concerned about the stock open, low, high, close, and volume. In nature, a trading day closing price is not only associated with the previous trading day closing price. In this paper, considering banking and non-banking sectors of Nifty closing stock price (in Rs.) data was used i.e BAJAJ FINANCE, MAHINDRA&MAHINDRA FINANCE, SHRIRAM FINANCE, HDFC BANK, SBI BANK, ICICI BANK. The Data period between

2019 to 2023, with 84 observations for predicting the 2024 January to 2025 December data. Data is obtained from the part nseindia.com and the computations are done by using the ARIMA model.

II. COMPANY PROFILE

1. **HDFC BANK:** HDFC Bank, established in 1994, is a leading private sector bank in India and a subsidiary of the Housing Development Finance Corporation (HDFC) Group. It offers acomprehensive range of banking and financial services including retail banking, corporate banking, wholesale banking, treasury services, loans and advances, payment services, and investment banking. With a strong presence both domestically and internationally, HDFC Bankoperates through a network of branches, representative offices, and subsidiaries in multiple countries.
2. **SBI BANK:** The State Bank of India (SBI) is India's largest public sector bank, founded in 1955. With a rich history and extensive network, SBI serves as the backbone of India's banking sector. Offering a comprehensive range of banking and financial services, SBI caters to diverse customer needs across the country and globally. The bank operates through a vast network of branches, ATMs, and digital platforms, ensuring convenient access for customers. SBI provides retail banking services including savings accounts, loans, credit cards, and wealth management solutions.
3. **ICICI BANK:** ICICI Bank, headquartered in Mumbai, India, is one of the country's largest private sector banks. Established in 1994, it has grown into a comprehensive financial institution offering a diverse range of banking and financial services to individuals, businesses, and corporations. Its services span retail banking, corporate banking, investment banking, wealth management, insurance, and asset management.
4. **BAJAJ FINANCE:** Bajaj Group, established in 1926 by Jamnalal Bajaj, is a prominent Indian conglomerate with diversified interests spanning automobiles, financial services, consumer products, and more. Bajaj Auto, a flagship company, is one of the world's largest manufacturers of motorcycles and three-wheelers, renowned for its innovation and robust product lineup. Bajaj Finserv, another key entity, excels in financial services including lending, insurance, and wealth management, serving millions across India.
5. **MAHINDRA & MAHINDRA FINANCE:** Mahindra & Mahindra Ltd. (M&M) is a prominent Indian multinational conglomerate founded in 1945. It is renowned for its leadership in automotive manufacturing, producing a diverse range of vehicles from utility vehicles and commercial trucks to two-wheelers and electric vehicles. Beyond automobiles, M&M has a strong presence in agribusiness, aerospace, hospitality, and information technology sectors through its various subsidiaries and joint ventures.
6. **SHRIRAM FINANCE:** Shriram Group, founded in 1974, is a diversified conglomerate based in India with a strong presence across the financial services, infrastructure, and consumer products sectors. Shriram Transport Finance Company (STFC), a flagship entity, is one of the largest asset-financing non-banking financial companies (NBFCs) in India, specializing in financing pre-owned commercial vehicles.

III. RESEARCH METHODOLOGY:

REVIEW OF LITERATURE:

1. Using the Box Jenkins technique, Bircan and Karagöz (2003) investigated the best practical estimating model for the monthly exchange rate series over the years 1991– 2002. The estimate process led to the conclusion that ARIMA (2,1,1) was the most appropriate model for the exchange rate series. The model's eligibility for exchange rate estimate at the five percent significance level was determined by calculating the Q statistics.

2. Nyoni (2018) employed yearly time series data from 1960 to 2017 to simulate inflation in Kenya using ARIMA and GARCH models. He found that the ARIMA (2, 2, 1), ARIMA (1, 2, 0), and AR (1) - GARCH (1, 1) models are the
three mosteffective models for predicting inflation.

3. According to Uma Devi and colleagues, the stock market's seasonal tendency and flow are its main features. Investors and the stock broking firm will eventually notice and record the fluctuations as the index continues to rise. This will support strategic decision-making for both new and current investors. Experience and investors' ongoing observation are the keys to achieving it.

4. Wang, J.J., and colleagues recently said that hybrid techniques have also been used to enhance stock price forecasting models by utilizing their special strengths. ARIMA models have been developed from a statistical modeling standpoint. In general, predictions may be made using two approaches: statistical and artificial intelligence techniques, which are documented in their respective kinds of literature.

5. According to Merh, N., Sterba, J., et al. [11], and Javier, C., et al. [12], ARIMA models are robust and efficient in financial time series forecasting, particularly for short-term prediction compared to the widely used ANN techniques. They are widely used in the fields of finance and economics, and other statistical models such as regression method, exponential smoothing, generalized autoregressive, andconditional heteroskedasticity (GARCH) are also discussed.

6. Dhyani et al. (2020) used the Arima Model to research the Stock Market Forecasting Technique. They discovered that the ARIMA (1,0,1) model demonstrates how the model may be used to predict and estimate future demand in the food production industry.

7. Vijay Pandey and Abhishek Bajpai (2019) look for better combinations in the ANN andARIMA models to forecast the NSE Nifty 50 daily data over a ten-year period, which represents the Indian stock market.

8. A study by Patel et al. (2019) highlighted the use of SVM for predicting the stock pricesof Indian financial institutions. The research demonstrated that SVM could effectivelycapture the non-linear relationships in stock price movements, resulting in accurate predictions for banks like HDFC and ICICI.

9. A study by Choudhury and Jones (2019) explored ensemble learning methods, such as

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Random Forest and Gradient Boosting Machines, for stock price prediction. Their research indicated that ensemble methods could capture diverse market conditions and improve prediction robustness, especially for volatile stocks like those of Bajaj Finance.

10. A study by Verma et al. (2021) highlighted the efficacy of SVM in predicting the stockprices of Indian financial institutions. The research demonstrated that SVM, with its capability to manage non-linear data patterns, provided reliable predictions for banks such as HDFC and ICICI.

11. Jain and Kumar (2021) discussed the application of ANN for stock price prediction. They emphasized that ANNs, with their deep learning capabilities, could outperform traditional statistical models for predicting prices of banking stocks like SBI and non-banking financial stocks such as Bajaj Finance.

12. Kumar and Mehta (2021) applied Vector Autoregression (VAR) models to forecast stock prices. Their findings suggested that VAR models could effectively account for interdependencies among stock prices of different financial institutions, enhancing prediction accuracy for both banking and non-banking stocks.

13. Kumar and Rao (2022) proposed a hybrid model combining SVM and Genetic Algorithms (GA) for feature selection. This hybrid approach optimized input features,resulting in improved prediction accuracy for stocks of both banking institutions (e.g.,ICICI) and non-banking institutions (e.g., Mahindra & Mahindra Financial Services).

14. In 2022, a study by Li et al. analyzed the influence of social media sentiment on stock prices. They found that integrating Twitter sentiment analysis with ML models significantly enhanced prediction accuracy for financial stocks, including those of ICICI and Mahindra & Mahindra Financial Services.

15. A study by Patel and Sharma (2023) examined the effectiveness of SVM in predictingstock prices for Indian financial institutions. They found that SVM models were particularly effective in capturing non-linear patterns in stock prices for banks such as HDFC and ICICI.

16. A study by Bose and Dey (2023) investigated the impact of news sentiment on stock prices of financial institutions. They used natural language processing (NLP) techniques to extract sentiment from financial news and integrated it with ML models to predict stock prices of banks such as SBI and non-banking entities like Shriram Finance.

17. Gupta and Banerjee (2023) utilized ARIMA (Auto-Regressive Integrated Moving Average) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models to predict stock prices. Their research demonstrated that these models effectively captured volatility and trends in stock prices of financial institutions like HDFC and Bajaj Finance.

18. Sharma and Patel (2023) conducted a comprehensive comparison of various ML and econometric models for stock price prediction. They found that DL models like LSTMprovided the highest accuracy for volatile stocks, while hybrid models offered a good balance between complexity and performance for a range of financial stocks, includingthose of HDFC and Shriram Transport Finance.

The method used in this study to develop the ARIMA model for stock price forecasting is explained in detail below. The tool used for implementation is E-views software version 12. Stock data used in this research work are historical monthly stock prices obtained from banking and non-banking financial institutions stock prices. The data comprised four elements: open price, low price, high price, and close price. In this research, the closing price is chosen to represent the price of the index to be predicted. The closing price is chosen because it reflects all the activities of the index in trading. To determine the best ARIMA model among several experiments performed, the following criteria are used in this study for each stock index.

- Unit root test.
- Correlogram.
- Estimate equation.
- Q-statistics and correlogram show that there is no significant pattern left in the autocorrelation functions (ACFs) and partial autocorrelation functions (PACFs) of the residuals, it means the residual of the selected model are white noise. The subsections below described the processes of ARIMA model-development.
- By using 84 observations from the time period of 2019 to 2023 and predicting the 2024and 2025 data.
- Relatively high of adjusted R2.
- BANKING FINANCIAL INSTITUTIONS:
  - HDFC BANK
  - SBI BANK
  - ICICI BANK
- NON-BANKING FINANCIAL INSTITUTIONS:
  - BAJAJ FINANCE
  - MAHINDRA & MAHINDRA FINANCE ltd
  - SHRIRAM FINANCE

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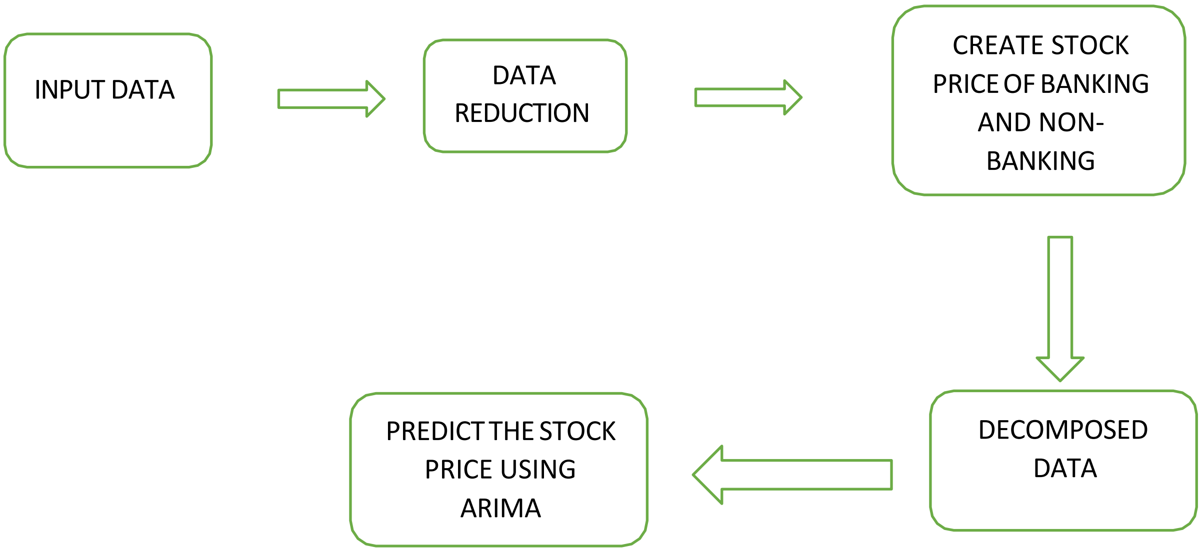


STATEMENT OF THE PROBLEM:

An ARIMA model is a hybrid of a moving average and an auto-regressive model usedin time series analysis. These models are fitted to time series data to forecast future points in the series or to better identify with the data. Another name for it is the Box-Jenkins technique. If it is discovered that the data is non-stationary, it is decreased usingthe differencing approach.

NEED OF THE STUDY:

- Investors seek to forecast stock prices of HDFC, ICICI, SBI, Bajaj Finance, Mahindra and Mahindra Financial Services, and Shriram Transport Finance for informed investment decisions.
- Predicting stock prices helps mitigate financial risks associated with holdings in these banking and non-banking financial institutions (NBFIs).
- Insights gained from stock price predictions aid in understanding market dynamics and sector-specific performance trends.
- Accurate predictions provide a competitive advantage to investors and financial institutions by enabling proactive portfolio management.
- Regulators rely on stock price forecasts to monitor market stability and ensure compliance within the banking and NBFI sectors.
- Predictions guide strategic planning for these institutions, influencing decisions on capital deployment, mergers and acquisitions, and expansion strategies.

OBJECTIVES:

- To examine the stock price of BANKING & NON-BANKING financial institutions.
- To predict the stock price for the future of BANKING & NON-BANKING financial institutions by using ARIMA (autoregressive integrated moving average) model.
- To identify and choose the best among the BANKING & NON-BANKING financial institutions.
- To recommend the best industry to the investors for making investment decisions.

SCOPE OF THE STUDY:

- The study analyzes the data from the past five years of the Banking and Non- Banking financial institutions.
- Use technical analysis to study stock price trends of Bajaj Finance, Mahindra & Mahindra, and Shriram Transport Finance.
- Consider market sentiment and investor behavior towards BANKING AND NON-BANKING financial institutions for sentiment analysis.
- Monitor sector-specific factors influencing HDFC, ICICI, and SBI such as loan growth and asset quality, and Bajaj Finance, Mahindra and Mahindra, Shriram Transport Finance market positioning.
- Assess regulatory changes affecting HDFC, ICICI, SBI operations and BAJAJ FINANCE, MAHINDRA, AND MAHINDRA, SHRIRAM Transport Finance compliance.

LIMITATIONS:

- It is not the best option for data that is weak or non-stationary.
- Overfitting issues may arise as the model's complexityrises.
- There may not be much use for the ARIMA model in long-term forecasting.
- One drawback is that it ignores outside variables like weather and day of the week that might affect load demand.
- Financial data inconsistencies and missing values can affect the accuracy of predictive models.

IV. ANALYSIS

BANKING FINANCIAL INSTITUTIONS

1. HDFC

BEST EQUATION-1

Date: 05/29/24 Time: 17:44
Sample (adjusted): 2019M01 2023M12
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.025	-0.025	0.0399	
		2	-0.030	-0.031	0.0972	
		3	0.035	0.034	0.1794	0.672
		4	-0.058	-0.057	0.3990	0.819
		5	-0.097	-0.098	1.0375	0.792
		6	0.078	0.070	1.4591	0.834
		7	0.063	0.066	1.7337	0.885
		8	-0.176	-0.170	3.9393	0.685
		9	-0.078	-0.103	4.3804	0.735
		10	-0.018	-0.033	4.4041	0.819
		11	-0.090	-0.066	5.0126	0.833
		12	-0.132	-0.160	6.3536	0.785
		13	0.129	0.068	7.6717	0.742
		14	0.114	0.133	8.7141	0.727
		15	-0.046	-0.016	8.8878	0.781
		16	-0.021	-0.088	8.9257	0.836
		17	-0.073	-0.118	9.3833	0.857
		18	-0.016	0.031	9.4054	0.896
		19	-0.147	-0.187	11.354	0.838
		20	0.169	0.058	14.016	0.728
		21	0.117	0.132	15.332	0.701
		22	-0.146	-0.102	17.408	0.626
		23	0.147	0.136	19.588	0.547
		24	-0.015	-0.038	19.611	0.607
		25	-0.002	0.080	19.611	0.665
		26	0.008	-0.014	19.618	0.718
		27	0.074	-0.070	20.244	0.734
		28	0.055	0.104	20.594	0.763

GRAPH-4.1
(This graph shows the stock price of HDFC BANK)

INTERPRETATION:

R-Squared and Adjusted R-Squared: Higher values indicate a better fit. ARIMA (1,1) has the highest R-squared value of 0.835759.

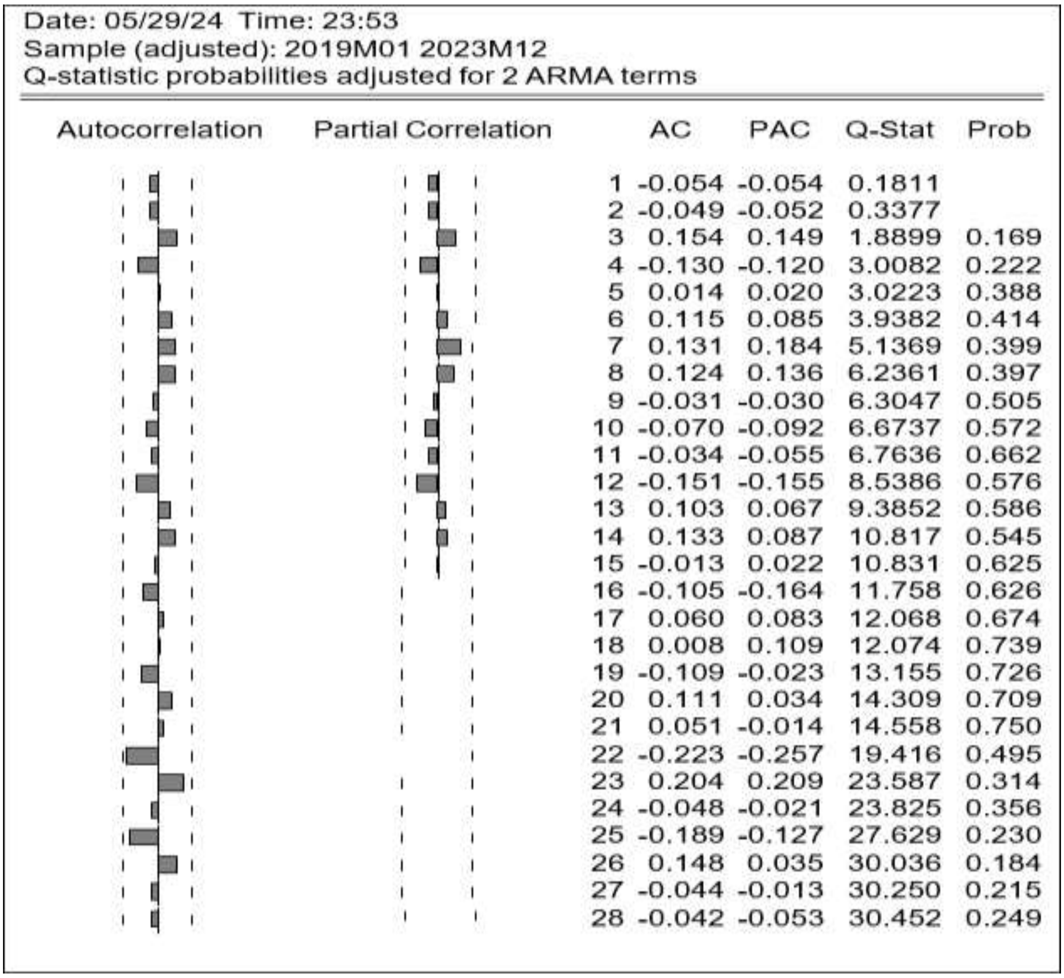
Akaike Information Criterion (AIC): Lower values indicate a better fit. The Model with the lowest AIC is ARIMA (1,1), with a value of 11.92938.

SCHWARZ Criterion: Similar to AIC, a lower value indicates a better fit. Again, ARIMA (1,1)has the lowest value of 12.06900.

Hannan-Quinn Criterion: Similar to AIC and Schwarz Criterion indicates a better fit. ARIMA (1,1) has the lowest value of 11.98399.

2. SBI BANK

BEST EQUATION-2

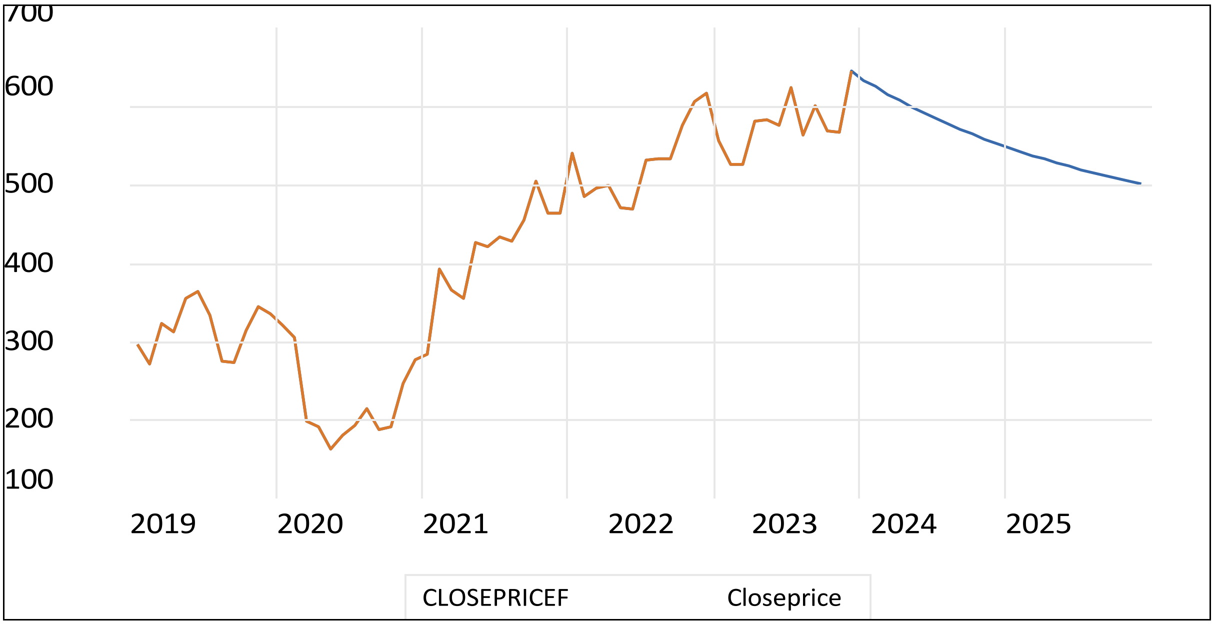


Date: 05/29/24 Time: 23:53
Sample (adjusted): 2019M01 2023M12
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.054	-0.054	0.1811	
		2	-0.049	-0.052	0.3377	
		3	0.154	0.149	1.8899	0.169
		4	-0.130	-0.120	3.0082	0.222
		5	0.014	0.020	3.0223	0.388
		6	0.115	0.085	3.9382	0.414
		7	0.131	0.184	5.1369	0.399
		8	0.124	0.136	6.2361	0.397
		9	-0.031	-0.030	6.3047	0.505
		10	-0.070	-0.092	6.6737	0.572
		11	-0.034	-0.055	6.7636	0.662
		12	-0.151	-0.155	8.5386	0.576
		13	0.103	0.067	9.3852	0.586
		14	0.133	0.087	10.817	0.545
		15	-0.013	0.022	10.831	0.625
		16	-0.105	-0.164	11.758	0.626
		17	0.060	0.083	12.068	0.674
		18	0.008	0.109	12.074	0.739
		19	-0.109	-0.023	13.155	0.726
		20	0.111	0.034	14.309	0.709
		21	0.051	-0.014	14.558	0.750
		22	-0.223	-0.257	19.416	0.495
		23	0.204	0.209	23.587	0.314
		24	-0.048	-0.021	23.825	0.356
		25	-0.189	-0.127	27.629	0.230
		26	0.148	0.035	30.036	0.184
		27	-0.044	-0.013	30.250	0.215
		28	-0.042	-0.053	30.452	0.249

GRAPH-4.2

(This graph shows the stock prices of SBI BANK)



INTERPRETATION:

R-Squared and Adjusted R-Squared: Higher values indicate a better fit. ARIMA (2,1) has the highest R-squared value of 0.922281.

Akaike Information Criterion (AIC): Lower values indicate a better fit. The Model with the lowest AIC is ARIMA (2,1), with a value of 10.32953.

SCHWARZ Criterion: Similar to AIC, a lower value Indicates a better fit. Again, ARIMA (2,1) has the lowest value of 10.4695.

Hannan-Quinn Criterion: Similar to AIC and Schwarz Criterion indicates a better fit. ARIMA (2,1) has the lowest value of 10.38414.

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2. ICICI BANK

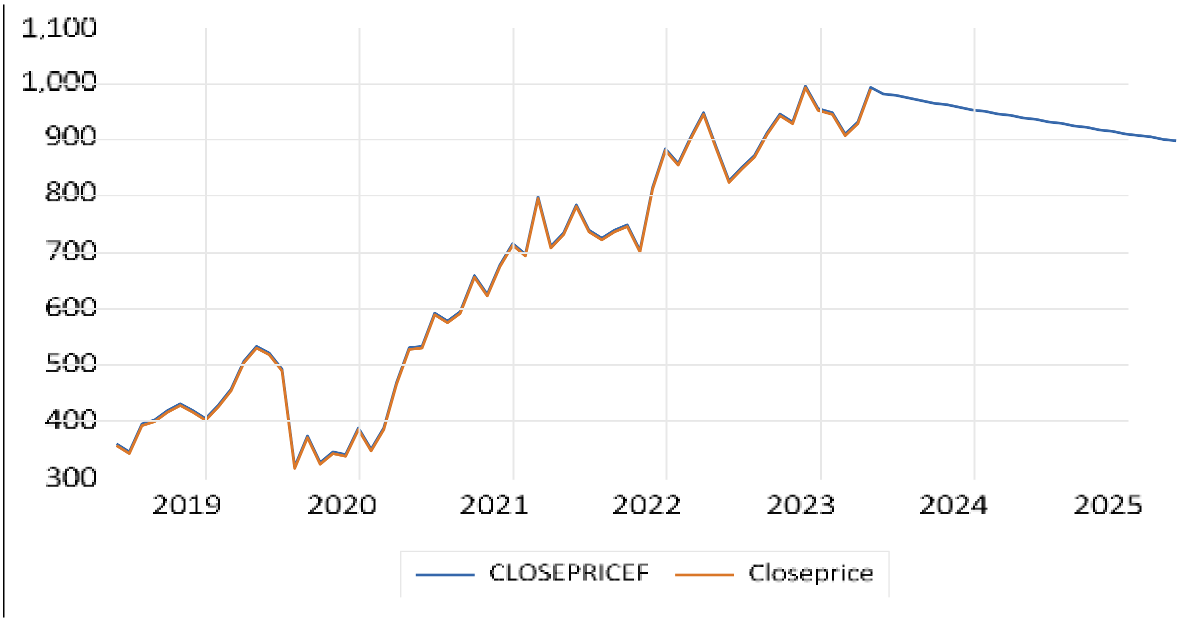
BEST EQUATION:

Date: 05/30/24 Time: 11:43
Sample (adjusted): 2019M01 2023M12
Q-statistic probabilities adjusted for 2 ARMA terms

	AC	PAC	Q-Stat	Prob
1	-0.052	-0.052	0.1732	
2	0.012	0.010	0.1831	
3	0.080	0.082	0.6030	0.437
4	-0.147	-0.140	2.0371	0.361
5	-0.165	-0.186	3.8819	0.275
6	0.022	0.001	3.9147	0.418
7	0.069	0.108	4.2498	0.514
8	-0.026	-0.010	4.2975	0.636
9	-0.026	-0.097	4.3473	0.739
10	0.028	-0.021	4.4065	0.819
11	-0.123	-0.087	5.5482	0.784
12	-0.020	0.001	5.5794	0.849
13	0.056	0.039	5.8258	0.885
14	0.053	0.057	6.0489	0.914
15	-0.042	-0.071	6.1918	0.939
16	-0.043	-0.109	6.3508	0.957
17	-0.053	-0.064	6.5901	0.968
18	0.087	0.167	7.2662	0.968
19	-0.114	-0.084	8.4507	0.956
20	0.148	0.076	10.500	0.914
21	0.146	0.108	12.529	0.862
22	-0.173	-0.156	15.450	0.750
23	0.115	0.100	16.788	0.724
24	0.015	0.045	16.811	0.774
25	-0.121	-0.036	18.357	0.738
26	-0.025	-0.066	18.424	0.782
27	0.041	-0.027	18.611	0.815
28	-0.066	-0.047	19.122	0.831

GRAPH-4.3

(This graph shows the stock prices of ICICI BANK)



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INTERPRETATION:

R-Squared and Adjusted R-Squared: Higher values indicate a better fit. ARIMA (1,1) has the highest R-squared value of 0.948287.

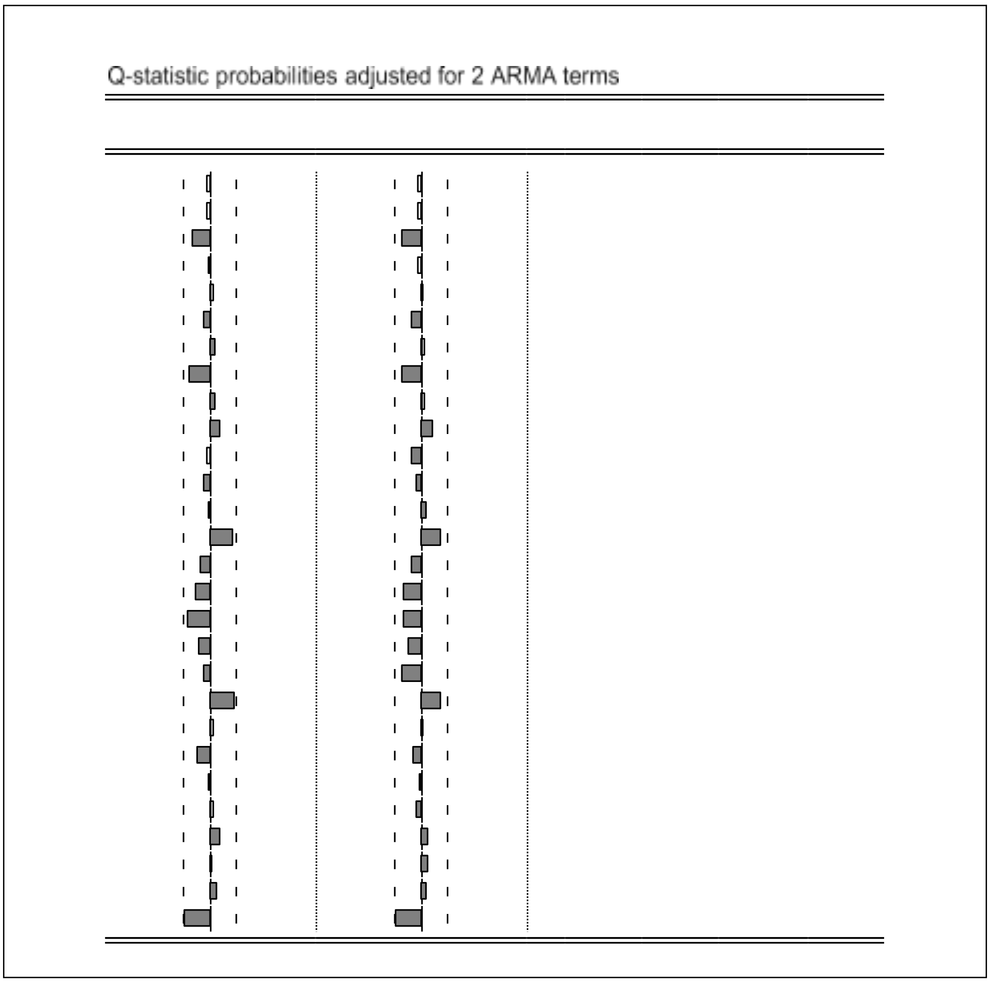
Akaike Information Criterion (AIC): Lower values indicate a better fit. The Model with the lowest AIC is ARIMA (1,1), with a value of 10.8745.

SCHWARZ Criterion: Similar to AIC, lower value Indicate a better fit. Again, ARIMA (1,1) has the lowest value of 10.95437.

Hannan-Quinn Criterion: Similar to AIC and Schwarz Criterion indicates a better fit. ARIMA (1,1) has the lowest value of 10.86936.

3. BAJAJ FINANCE:

BEST EQUATION:



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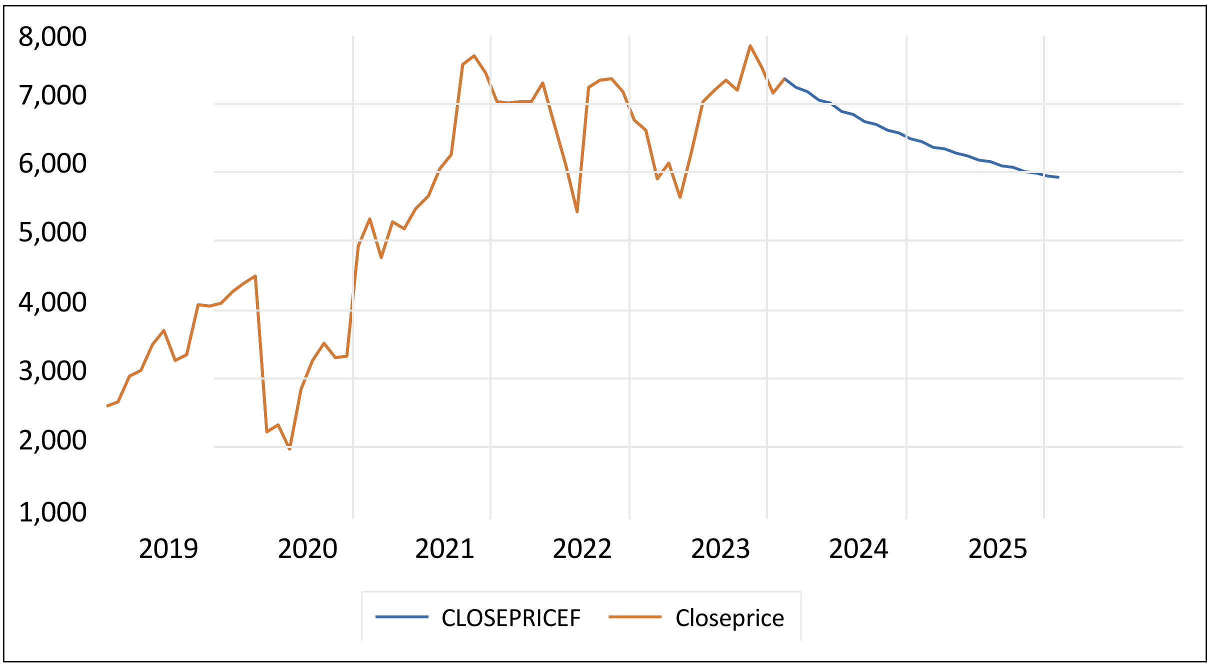
GRAPH-4.4

(This graph shows the stock prices of BAJAJ FINANCE)



INTERPRETATION:

R-Squared and Adjusted R-Squared: Higher values indicate a better fit. ARIMA (2,1) has the highest R-squared value of 0.891939.

Akaike Information Criterion (AIC): Lower values indicate a better fit. The Model with the lowest AIC is ARIMA (2,1), with a value of 15.72918.

SCHWARZ Criterion: Similar to AIC, lower value Indicate a better fit. Again, ARIMA (2,1) has the lowest value of 15.86943.

Hannan-Quinn Criterion: Similar to AIC and Schwarz Criterion indicates a better fit. ARIMA (2,1) has the lowest value of 15.78443.

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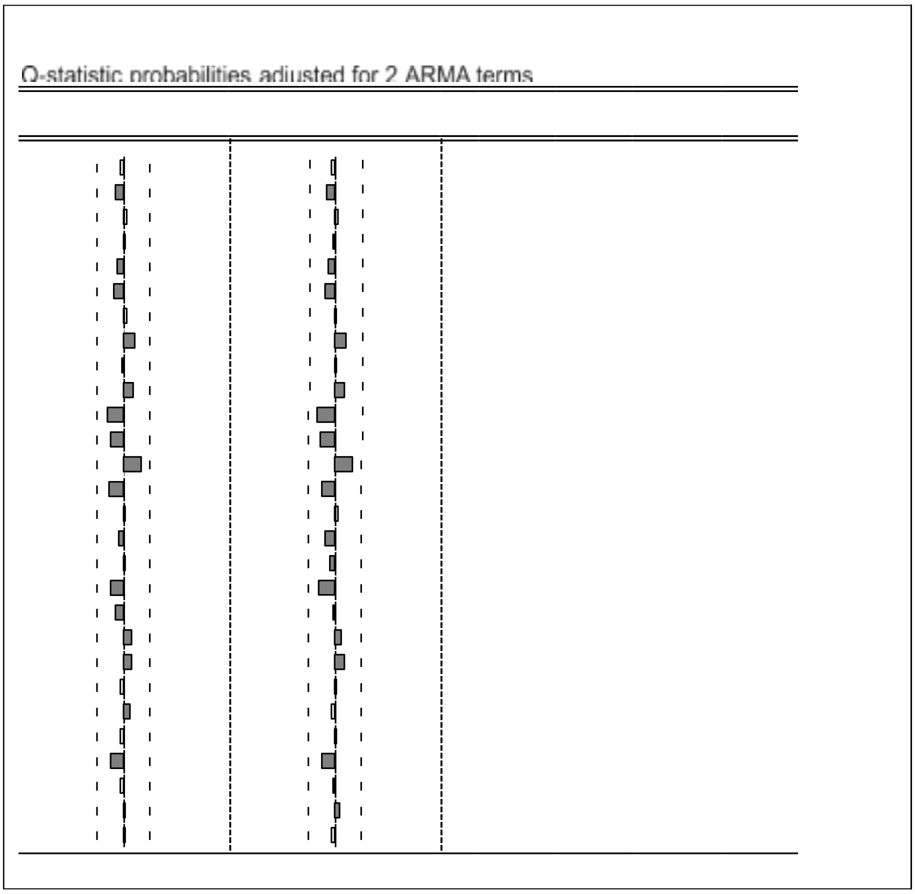
3. **MAHINDRA & MAHINDRA FINANCE BEST EQUATION:**



GRAPH-4.5

(This graph shows the stock prices of MAHINDRA & MAHINDRA FINANCE)

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INTERPRETATION:

R-Squared and Adjusted R-Squared: Higher values indicate a better fit. ARIMA (1,1) has the highest R-squared value of 0.836404.

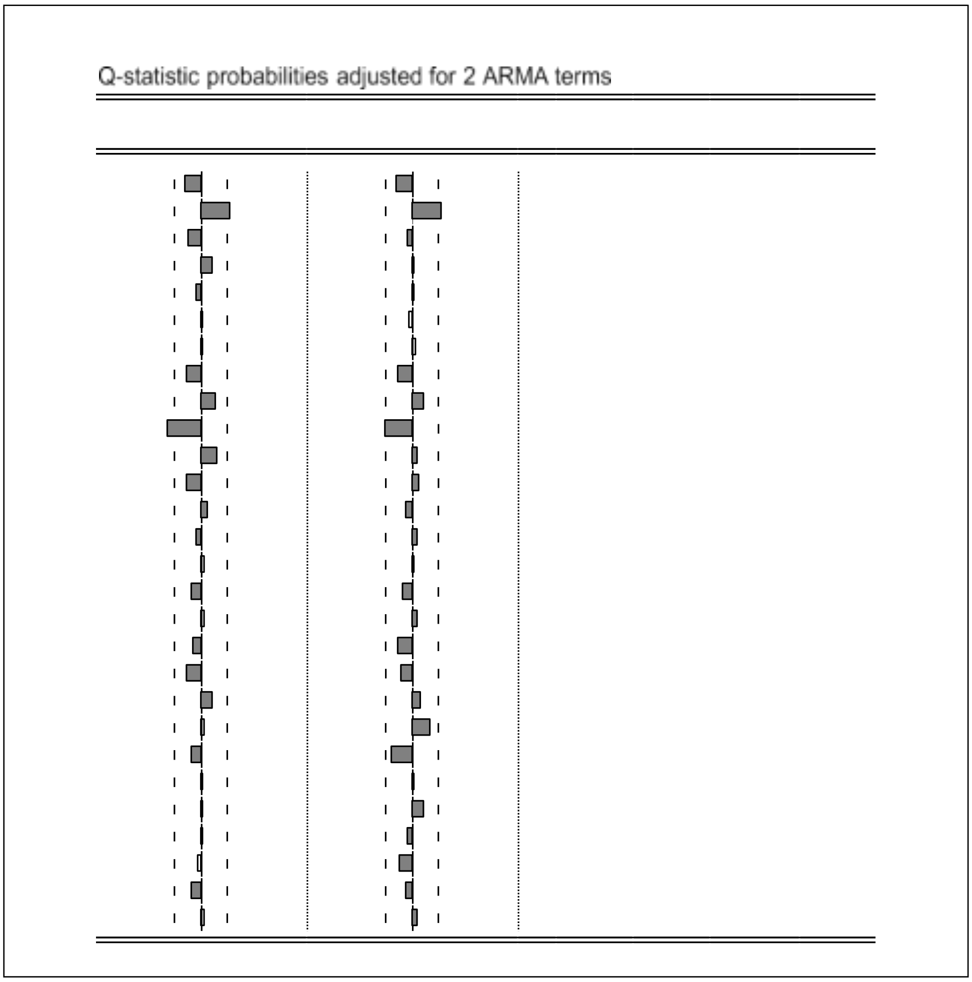
Akaike Information Criterion (AIC): Lower values indicate a better fit. The Model with the lowest AIC is ARIMA (1,1), with a value of 10.14599.

SCHWARZ Criterion: Similar to AIC, lower value Indicate a better fit. Again, ARIMA (1,1) has the lowest value of 10.28561.

Hannan-Quinn Criterion: Similar to AIC and Schwarz Criterion indicates a better fit. ARIMA (1,1) has the lowest value of 10.20060.

4. SHRIRAM FINANCE

BEST EQUATION:



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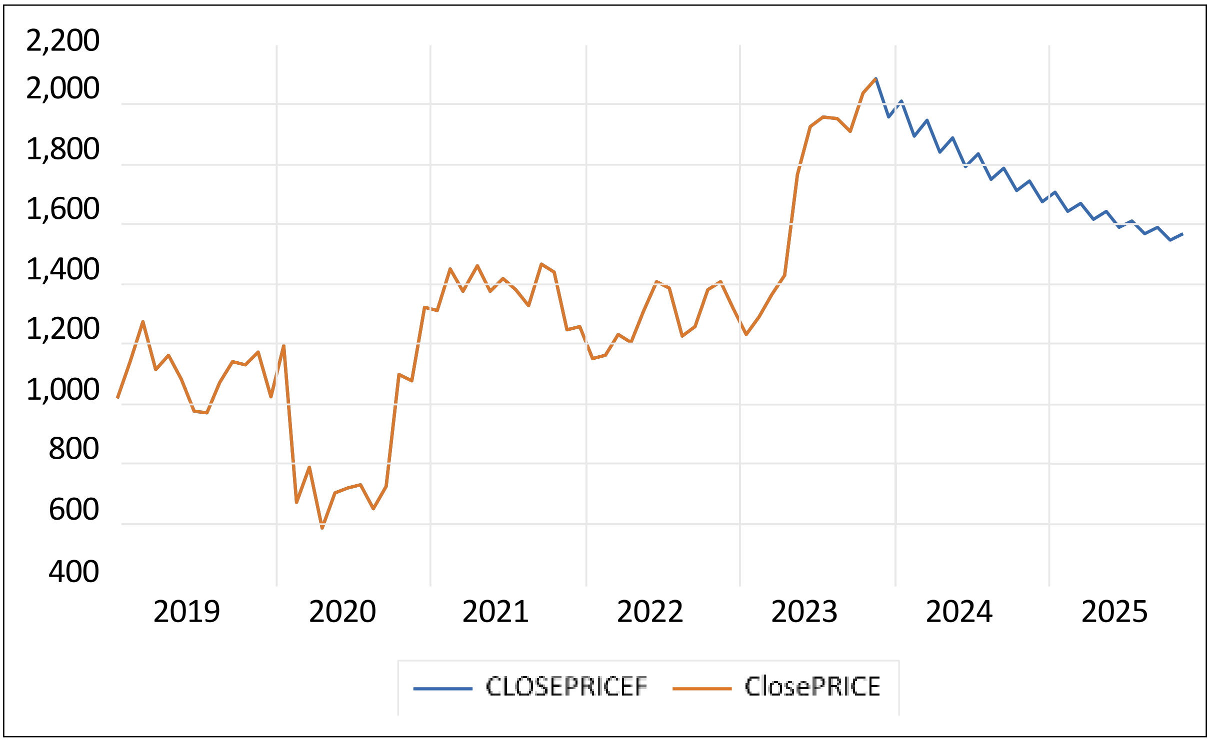
GRAPH-4.6

(This graph shows the stock prices of SHRIRAM FINANCE)



INTERPRETATION:

R-Squared and Adjusted R-Squared: Higher values indicate a better fit. ARIMA (2,1) has the highest R-squared value of 0.847177.

Akaike Information Criterion (AIC): Lower values indicate a better fit. The Model with the lowest AIC is ARIMA (2,1), with a value of 12.78339.

SCHWARZ Criterion: Similar to AIC, lower value Indicate a better fit. Again, ARIMA (2,1) has the lowest value of 12.92301.

Hannan-Quinn Criterion: Similar to AIC and Schwarz Criterion indicates a better fit. ARIMA (2,1) has the lowest value of 12.83800.

FINDINGS:

1. HDFC BANK (BANKING FINANCIAL INSTITUTION):

The ARIMA (1,1) model has the lowest AIC value of 11.92938. This suggests that, compared to other models, ARIMA (1,1) strikes the best balance between model complexity and goodness of fit.

The ARIMA (1,1) model has the lowest Schwarz criterion value of 12.06900, reinforcing the conclusion from the AIC that this model provides the best fit with an appropriate level of complexity.

The ARIMA (1,1) model has the lowest HQIC value of 11.98399, further supporting the selection of this model as the best fit for the data.

The ARIMA (1,1) model has the highest R-squared value of 0.835759. This indicates that the model explains

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approximately 83.5% of the variance in the data, suggesting a very strong fit.

2. SBI BANK (BANKING FINANCIAL INSTITUTION):

The ARIMA (2,1) model has the lowest AIC value of 10.32953. This suggests that, compared to other models, ARIMA (2,1) strikes the best balance between model complexity and goodness of fit.

The ARIMA (2,1) model has the lowest Schwarz criterion value of 10.46915, reinforcing the conclusion from the AIC that this model provides the best fit with an appropriate level of complexity.

The ARIMA (2,1) model has the lowest HQIC value of 10.38414, further supporting the selection of this model as the best fit for the data.

The ARIMA (2,1) model has the highest R-squared value of 0.922281. This indicates that the model explains approximately 9% of the variance in the data, suggesting a verystrong fit.

3. ICICI BANK (BANKING FINANCIAL INSTITUTION):

The ARIMA (1,1) model has the lowest AIC value of 10.82359. This suggests that, compared to other models, ARIMA (1,1) strikes the best balance between model complexity and goodness of fit.

The ARIMA (1,1) model has the lowest Schwarz criterion value of 10.95437, reinforcing the conclusion from the AIC that this model provides the best fit with an appropriate level of complexity.

The ARIMA (1,1) model has the lowest HQIC value of 10.86936, further supporting the selection of this model as the best fit for the data.

The ARIMA (1,1) model has the highest R-squared value of 0.948287. This indicates that the model explains approximately 94.8% of the variance in the data, suggesting a very strong fit.

4. BAJAJ FINANCE (NON-BANKING FINANCIAL INSTITUTION):

The ARIMA (2,1) model has the lowest AIC value of 15.72981. This suggests that, compared to other models, ARIMA (2,1) strikes the best balance between model complexity and goodness of fit.

The ARIMA (2,1) model has the lowest Schwarz criterion value of 15.86943, reinforcing the conclusion from the AIC that this model provides the best fit with an appropriate level of complexity.

The ARIMA (2,1) model has the lowest HQIC value of 15.78443, further supporting the selection of this model as the best fit for the data.

The ARIMA (2,1) model has the highest R-squared value of 0.891939. This indicates that the model explains approximately 89.19% of the variance in the data, suggesting avery strong fit. 5.MAHINDRA&MAHINDRA FINANCE (NON-BANKING FINANCIAL INSTITUTION):

The ARIMA (1,1) model has the lowest AIC value of 10.14599. This suggests that, compared to other models, ARIMA (1,1) strikes the best balance between model complexity and goodness of fit.

The ARIMA (1,1) model has the lowest Schwarz criterion value of 10.28561, reinforcing the conclusion from the AIC that this model provides the best fit with an appropriate level of complexity.

The ARIMA (1,1) model has the lowest HQIC value of 10.20060, further supporting the selection of this model as the best fit for the data.

The ARIMA (1,1) model has the highest R-squared value of 0.836404. This indicates that the model explains approximately 83.6% of the variance in the data, suggesting a very strong fit.

6. SHRIRAM FINANCE (NON-BANKING FINANCIAL INSTITUTION):

The ARIMA (2,1) model has the lowest AIC value of 0.898107. This suggests that, compared to other models, ARIMA (2,1) strikes the best balance between model complexity and goodness of fit.

The ARIMA (2,1) model has the lowest Schwarz criterion value of 12.92301, reinforcing the conclusion from the AIC that this model provides the best fit with an appropriate level of complexity.

The ARIMA (2,1) model has the lowest HQIC value of 12.83800, further supporting the selection of this model as the best fit for the data.

The ARIMA (2,1) model has the highest R-squared value of 0.844294. This indicates that the model explains approximately 84.4% of the variance in the data, suggesting a very strong fit.

SUGGESTIONS:

There is a potential investment opportunity for investors to invest in both Banking andNon- Banking financial institutions.

In Banking institutions among all three banks, there is an instant growth in HDFC bank and ICICI bank. In SBI & HDFC banks have more than 10% of returns. Investors can choose these two banks to invest. However, In SBI bank there are more fluctuations but it is predicted that it will have more returns in the future. ICICI has less than 10% of returns in the future.

In non-banking financial institutions among all the three companies MAHINDRA AND MAHINDRA company has less than 10% of returns. so, investors have better choose SHRIRAM FINANCE and BAJAJ FINANCE companies.

There is an explore opportunities for strategic partnerships or collaborations betweenBanking and Non-Banking financial institutions to capitalize on synergies and marketresearch. ICICI and MAHINDRA &MAHINDRA companies are better off making apartnership because from that they can overcome their risk and increase their returns.

Both Banking and Non-Banking Financial Institutions are better able to implementhedging techniques or diversification strategies to mitigate risks and enhance resilience. The hedging technique is DERIVATIVES. Most of the banks can use options and future derivatives. So, ICICI Bank and MAHINDRA & MAHINDRAcompanies need to use those DERIVATIVES to protect their balance sheets from volatility in financial markets.

CONCLUSION:

In conclusion, predicting stock prices of banking and non-banking financial institutions to requires a holistic understanding of both industry-specific dynamics and broader economic factors. This knowledge enables investors, analysts, and policymakers to make informed decisions, manage risks effectively, and capitalize on opportunities in the dynamic and interconnected financial markets. This paper presents for stock price prediction an extensive process of building an ARIMA model. Based on historical data Forecasting with ARIMA provides a prediction, in which data has been applied by first-order difference to remove random

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walk pattern problems. The experimental results on a short-term basis are obtained with the best ARIMA model to predict stock prices satisfactory. In the stock market, this could guide investors to make profitable investment decisions. With the results obtained, the ARIMA models with emerging forecasting techniques can compete reasonably well in short-term prediction. From the analysis, the different investors can choose different Financial institutions according to their returns of the companies. So, here SBI Bank, and HDFC Bank have more returns when compared with ICICI Bank. When coming to the NON-BANKING financial institutions SHRIRAM and BAJAJ companies have more than 10% of their returns when compared with MAHINDRA & MAHINDRA company. In conclusion, predicting stock prices of banking and non-banking financial institutions requires a holistic understanding of both industry-specific dynamics and broader economic factors. This knowledge enables investors, analysts, and policymakers to make informed decisions, manage risks effectively, and capitalize on opportunities in the dynamic and interconnected financial markets.

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