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

Mr. P. Gayathri,
Student of II MBA
Department of Management Studies. Madanapalle Institute of Technology & Science

Dr. K.V. GEETHA DEVI, MBA, Ph.D.

Associate Professor, Department of Management Studies. Madanapalle Institute of Technology & Science

ABSTRACT

This study examines the prediction of stock prices for Indian banking and non-banking financial companies (NBFCs) from 2015 to 2024 using ARMA models. It analyses ten leading institutions—five banks such as SBI and HDFC, and five NBFCs including Muthoot Finance and Kotak Mahindra—to evaluate the ARMA model's effectiveness in capturing stock price behaviour. After testing for stationarity with the Augmented Dickey-Fuller test and selecting optimal ARMA structures, forecasts were generated to assess trend alignment and accuracy. Results show that banking stocks exhibited more stable and predictable patterns, with strong autoregressive components in institutions like SBI and HDFC. In contrast, NBFC stocks were generally more volatile, leading to inconsistent forecasting results, though Muthoot Finance stood out by aligning well with its historical growth trends. The study acknowledges limitations of the ARMA model, particularly its assumption of linearity and inability to incorporate external shocks or market sentiments. Nevertheless, it highlights ARMA's value as a foundational forecasting tool and recommends future research integrating macroeconomic variables to enhance prediction, ultimately supporting more informed investment decisions in the Indian financial sector.

Key words: stock prices of banking and non-banking of financial institution.

INTRODUCTION:

The stock market mirrors a nation's economic health, with the banking and NBFC sectors in India playing vital roles in credit distribution and financial inclusion. Over the past decade, these sectors have expanded rapidly, driven by reforms, technology, and shifting consumer demands. Predicting stock prices here is critical yet challenging, as prices respond to macroeconomic trends, regulatory shifts, investor sentiment, and geopolitical risks. This project employs ARMA models-a straightforward, statistically robust time series method—to forecast stock prices, emphasizing interpretability and suitability for linear, stationary data. It analyses monthly data from 2015 to 2024 for five banks and five NBFCs, testing for stationarity via the ADF test before building ARMA models. The study compares price dynamics across sectors, revealing generally stable trends for banks like SBI and HDFC, versus higher volatility in NBFCs such as Muthoot Finance and IIFL. These differences underscore the need for sector-specific models. Overall, this sets the stage for evaluating ARMA's effectiveness in navigating the complexities of forecasting stock prices in India's dynamic financial landscape.

Review of Literature

Joshi & Patel (2017): This study applied correlation and factor analysis to assess the key determinants of stock prices in financial firms. Asset quality and return on equity (ROE) emerged as significant factors influencing investor sentiment and valuation. The researchers highlighted that strong ROE and healthy assets provide confidence to investors and result in higher stock valuations. They

ISSN: 2583-6129
DOI: 10.55041/ISJEM04819

also found that these factors are more influential in long-term investment decisions. The study thus supports the use of multivariate statistical tools in stock price analysis.

Sharma and Mehta (2016): Sharma and Mehta demonstrated the efficacy of using ARMA models for stock price forecasting based on financial ratios. Their research indicated that historical ratios like debt-equity and return on assets can provide insights into future price movements. The ARMA models captured underlying time dependencies in financial variables. They concluded that statistical forecasting methods, when combined with financial metrics, enhance prediction accuracy. The study supports the integration of quantitative and qualitative data for better market analysis.

Verma & Arora (2021) Found that lagged stock prices significantly influence current banking stock movements in India. Showed strong momentum effects, especially in well-capitalized banks, supporting short-term trend forecasting using ARMA models.

Nair & Thomas (2022) Explored investor perceptions of NBFC stocks, revealing they are viewed as high-risk, high-reward, leading to increased trading activity and volatility. Suggested behavioural factors play a bigger role in NBFC stock price movements than in traditional banking stocks.

Mukherjee et al. (2023) Advocated for sector-specific ARMA/ARIMA models, noting that banks and NBFCs have distinct volatility patterns. Recommended frequent updates to model parameters to better capture evolving market behaviours.

Real-Time Data & High-Frequency Forecasting 2024–25 research emphasizes using high-frequency intraday data (minute-to-minute) and alternative sources like sentiment indicators, to refine short-term forecasts. These models often feature automatic recalibration and model drift detection mechanisms.

OBJECTIVES OF THE STUDY:

- To find out which factors affect stock prices the most.
- To compare stock behaviour between banks and NBFCs.
- To predict the stock price for the future of BANKING & NON-BANKING financial institutions.
- To recommend the best industry to the investor for making the investment decision.

The model does not include external factors like interest rates or economic policies.

RESEARCH AND METHODALAGY

The study collected historical stock price data of Muthoot Money Bank from 2015 to 2024 using secondary sources such as NSE and Money control. To prepare the data for time series analysis, it was tested for stationarity with the Augmented Dickey-Fuller (ADF) test, and non-stationary series were differenced. An ARMA model was then developed using the differenced stock prices, selecting appropriate autoregressive (AR) and moving average (MA) lags based on their statistical significance. The model was employed to forecast future stock prices from 2025 to 2030, projecting a steady upward trend that reflects strong company fundamentals and positive market sentiment. Finally, model evaluation indicated high accuracy, with significant coefficients and no autocorrelation in residuals, confirming its suitability for investment analysis and strategic planning.

This study was conducted based on the secondary data collected from DSE'S websites. Only companies associated with the financial sector (banking &non-banking financial institution) were selected for study. A total of 10 financial companies (5 banking &5 non-banking financial institution) were selected and their data on variables were collected from 2015 to 2024.

ISSN: 2583-6129
DOI: 10.55041/ISJEM04819

PREDICTING THE STOCK PRICES OF MULTIPLE REGRESSION ANALYSIS FOR BANKING

1.STATE BANK OF INDIA (SBI):

Table: UNTITLED Workfile: SBI,142::Untitled\

Augmented Dickey-Fuller Unit Root Test on PRICE

Null Hypothesis: PRICE has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.163912	0.9692
Test critical values:	1% level	-3.486064	
	5% level	-2.885863	
	10% level	-2.579818	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(PRICE)
Method: Least Squares
Date: 06/10/25 Time: 19:04
Sample (adjusted): 2015M02 2024M12
Included observations: 119 after adjustments

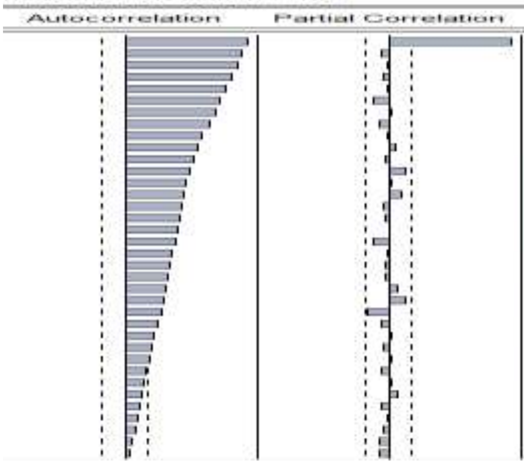
Variable	Coefficient	Std. Error	t-Statistic	Prob.
PRICE(-1)	0.002843	0.017345	0.163912	0.8701
C	2.985840	7.397380	0.403635	0.6872

R-squared	0.000230	Mean dependent var	4.084034
Adjusted R-squared	-0.008316	S.D. dependent var	34.06515
S.E. of regression	34.20649	Akaike info criterion	9.918372
Sum squared resid	136899.9	Schwarz criterion	9.966080
Log likelihood	-588.2026	Hannan-Quinn criter.	9.938339
F-statistic	0.026867	Durbin-Watson stat	2.139659
Prob(F-statistic)	0.870083		

The test statistic (0.1639) is greater than all the critical values (less negative) The p-value (0.9692) is much greater than 0.05, meaning we fail o reject the null hypothesis**.**

CORRELATION:

Date: 06/10/25 Time: 19:05
Sample: 2015M01 2030M12
Included observations: 120



	AC	PAC	Q-Stat	Prob
1	0.962	0.962	113.81	0.000
2	0.921	-0.053	219.07	0.000
3	0.881	-0.012	316.19	0.000
4	0.840	-0.033	405.24	0.000
5	0.799	-0.016	486.61	0.000
6	0.762	-0.118	559.20	0.000
7	0.708	0.030	624.14	0.000
8	0.661	-0.075	681.24	0.000
9	0.614	-0.016	730.99	0.000
10	0.575	0.064	774.95	0.000
11	0.535	-0.024	813.38	0.000
12	0.507	0.128	848.22	0.000
13	0.482	0.019	880.02	0.000
14	0.466	0.099	909.97	0.000
15	0.449	-0.045	938.08	0.000
16	0.430	-0.024	964.15	0.000
17	0.416	0.008	988.79	0.000
18	0.395	-0.117	1011.2	0.000
19	0.375	-0.005	1031.6	0.000
20	0.355	-0.032	1050.0	0.000
21	0.332	-0.026	1066.3	0.000
22	0.316	0.072	1081.2	0.000
23	0.306	0.139	1095.3	0.000
24	0.287	-0.165	1107.9	0.000
25	0.260	-0.058	1118.2	0.000
26	0.235	0.022	1126.8	0.000
27	0.211	-0.045	1133.8	0.000
28	0.190	0.029	1139.6	0.000
29	0.168	-0.051	1144.2	0.000
30	0.149	0.023	1147.8	0.000
31	0.137	0.071	1150.9	0.000
32	0.120	-0.054	1153.3	0.000
33	0.103	-0.016	1155.1	0.000
34	0.084	-0.047	1156.3	0.000
35	0.060	-0.080	1156.9	0.000
36	0.035	-0.077	1157.1	0.000

Table: UNTITLED Workfile: SBI,142::Untitled\

Dependent Variable: D(PRICE)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 06/11/25 Time: 09:46
Sample: 2015M02 2024M12
Included observations: 119
Convergence achieved after 30 iterations
Coefficient covariance computed using outer product of gradients

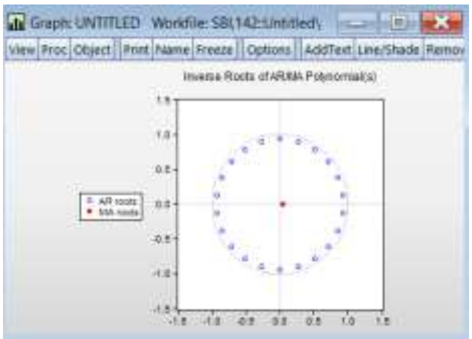
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.036055	2.402399	1.680011	0.0957
AR(22)	-0.232491	0.108547	-2.141844	0.0343
MA(1)	-0.044299	0.117560	-0.376823	0.7070
SIGMASQ	1082.679	119.3053	9.074863	0.0000

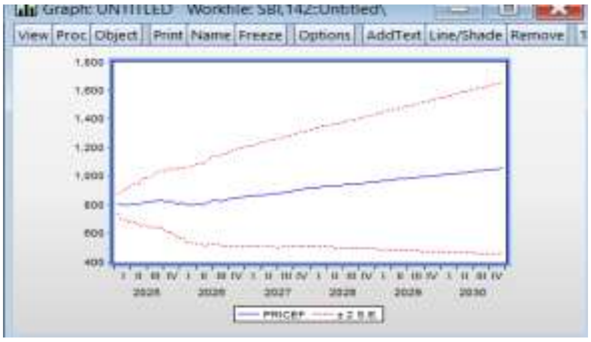
R-squared	0.059099	Mean dependent var	4.084034
Adjusted R-squared	0.034554	S.D. dependent var	34.06515
S.E. of regression	33.47145	Akaike info criterion	9.902588
Sum squared resid	128838.8	Schwarz criterion	9.996003
Log likelihood	-585.2040	Hannan-Quinn criter.	9.940521
F-statistic	2.407748	Durbin-Watson stat	1.977875
Prob(F-statistic)	0.070770		

Inverted AR Roots	.93-.13i	.93+.13i	.85-.39i	.85+.39i
	.71+.61i	.71-.61i	.51-.79i	.51+.79i
	.26-.90i	.26+.90i	.00+.94i	-.00-.94i
	-.26-.90i	-.26+.90i	-.51+.79i	-.51-.79i
	-.71+.61i	-.71-.61i	-.85-.39i	-.85+.39i
	-.93+.13i	-.93-.13i		
Inverted MA Roots	.04			

The model is applied to the monthly change in PRICE, not the original price (since PRICE was non-stationary).AR (22) is significant (p-value = 0.0343), meaning that the change in price is influenced by its value 22 months ago.MA (1) is not significant (p-value = 0.7070), so the 1-month moving average term doesn't add much value.

ARAMA STRUCTURE: **FORECASTING:**





PREDICTING GRAPH:

The model expects SBI's price to keep rising steadily in the future. However, the forecast looks smoother and less volatile than actual past prices, which means the model may not fully capture market fluctuations**.** From the chart, we observe that SBI's price has shown a strong upward trend historically, with notable fluctuations and a steep rise between periods 20 to 25.

PREDICTING THE STOCK PRICES OF NON- BANKING FINANCIAL INSTITUTION

1.MUTHOOT FINANCES BANK:

UNIT ROOT TEST:

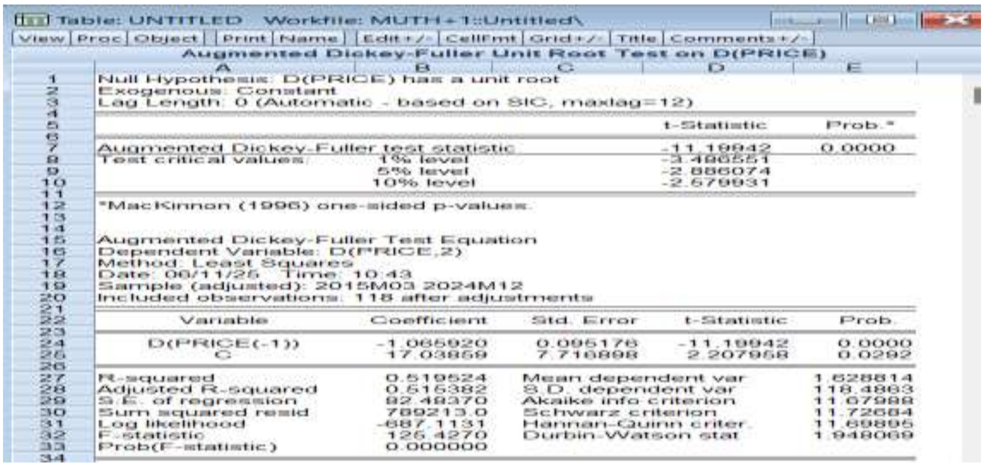


Table: UNTITLED Workfile: MUTH+1::Untitled\

Augmented Dickey-Fuller Unit Root Test on D(PRICE)

Null Hypothesis: D(PRICE) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.19942	0.0000
Test critical values:	1% level	-3.486551	
	5% level	-2.886074	
	10% level	-2.579931	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(PRICE,2)
Method: Least Squares
Date: 06/11/25 Time: 10:43
Sample (adjusted): 2015M03 2024M12
Included observations: 118 after adjustments

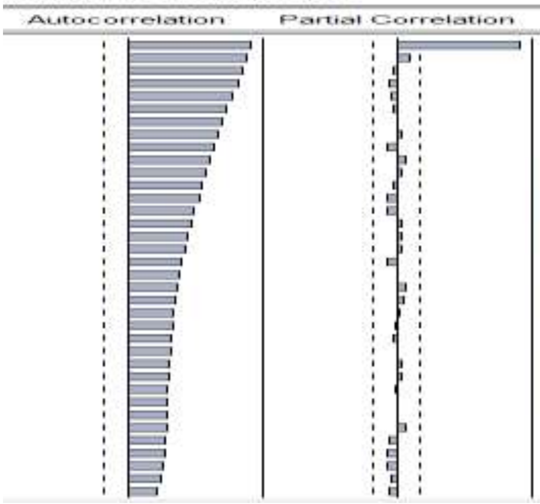
Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(PRICE(-1))	-1.065920	0.095176	-11.19942	0.0000
C	17.03859	7.718898	2.207958	0.0292

R-squared	0.519524	Mean dependent var	1.628814
Adjusted R-squared	0.515382	S.D. dependent var	118.4883
S.E. of regression	82.48370	Akaike info criterion	11.67988
Sum squared resid	789213.0	Schwarz criterion	11.72684
Log likelihood	-687.1131	Hannan-Quinn criter.	11.69895
F-statistic	125.4270	Durbin-Watson stat	1.948069
Prob(F-statistic)	0.000000		

Since the test statistic (-11.19942) is much lower than all the critical values, and the p-value is 0.0000, We reject the null hypothesis that there is a unit root (non-stationarity).

ISSN: 2583-6129
DOI: 10.55041/ISJEM04819

CORRELATION:



Date: 06/11/25 Time: 10:43
Sample: 2015M01 2030M12
Included observations: 120

	AC	PAC	Q-Stat	Prob
1	0.956	0.956	112.42	0.000
2	0.922	0.091	217.80	0.000
3	0.886	-0.023	316.01	0.000
4	0.847	-0.058	406.55	0.000
5	0.807	-0.038	489.52	0.000
6	0.768	-0.018	565.30	0.000
7	0.731	0.001	634.47	0.000
8	0.698	0.041	698.18	0.000
9	0.660	-0.073	755.62	0.000
10	0.631	0.072	808.65	0.000
11	0.606	0.040	857.95	0.000
12	0.580	-0.016	903.49	0.000
13	0.549	-0.073	944.76	0.000
14	0.518	-0.072	981.52	0.000
15	0.488	0.038	1014.7	0.000
16	0.464	0.046	1045.1	0.000
17	0.443	0.043	1072.9	0.000
18	0.417	-0.075	1097.8	0.000
19	0.395	0.012	1120.4	0.000
20	0.379	0.073	1141.5	0.000
21	0.367	0.051	1161.4	0.000
22	0.357	0.020	1180.4	0.000
23	0.348	-0.012	1198.7	0.000
24	0.338	-0.027	1216.2	0.000
25	0.329	0.004	1232.8	0.000
26	0.320	0.035	1248.8	0.000
27	0.315	0.036	1264.4	0.000
28	0.311	-0.009	1279.8	0.000
29	0.306	0.002	1294.9	0.000
30	0.301	0.005	1309.6	0.000
31	0.300	0.067	1324.5	0.000
32	0.295	-0.060	1338.9	0.000
33	0.287	-0.066	1352.7	0.000
34	0.275	-0.068	1365.5	0.000
35	0.259	-0.041	1377.1	0.000
36	0.237	-0.050	1386.9	0.000

Table: UNTITLED Workfile: MUTH+1::Untitled\

Dependent Variable: D(PRICE)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 06/11/25 Time: 10:45
Sample: 2015M02 2024M12
Included observations: 119
Convergence achieved after 45 iterations
Coefficient covariance computed using outer product of gradients

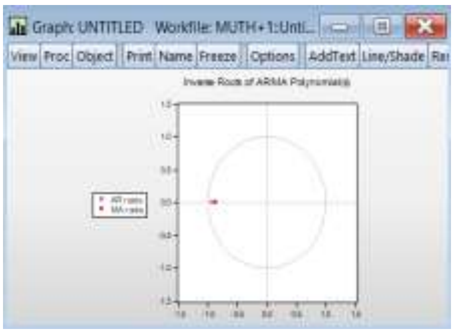
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	16.13900	7.463014	2.162531	0.0326
AR(1)	-0.910249	0.192767	-4.722021	0.0000
MA(1)	0.871664	0.222451	3.918445	0.0002
SIGMASQ	6600.225	677.5871	9.740778	0.0000

R-squared	0.009041	Mean dependent var	16.17647
Adjusted R-squared	-0.016810	S.D. dependent var	81.95662
S.E. of regression	82.64259	Akaike info criterion	11.70026
Sum squared resid	785426.8	Schwarz criterion	11.79368
Log likelihood	-692.1656	Hannan-Quinn criter.	11.73819
F-statistic	0.349735	Durbin-Watson stat	1.984622
Prob(F-statistic)	0.789405		

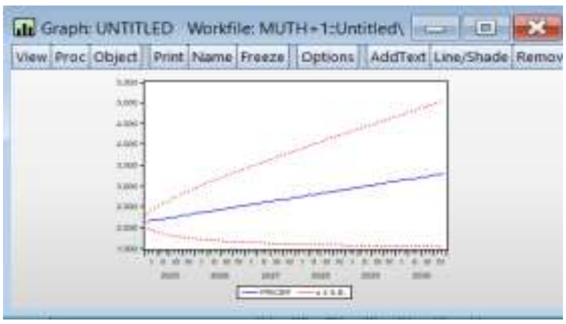
Inverted AR Roots	-.91
Inverted MA Roots	-.87

The ADF test statistic (-11.19942) is much lower than all critical values The p-value is 0.0000, which is less than 0.05, indicating strong evidence against the null hypothesis this means the differenced price series is stationary (i.e., it does not have a unit root anymore). This is essential for using ARIMA models in forecasting because they require the data to be stationary.

ARAMA STRUCTURE:



FORECASTING:



International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 07 | July – 2025 DOI: 10.55041/ISJEM04819
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

PREDATING GRAPH:

The model forecasts a stable and strong rise in stock price from 2025 to 2030.The forecasted trend aligns well with historical growth patterns, indicating model reliability. No major fluctuation is shown in the forecasted period, implying market stability or steady company performance. Useful for investment planning or risk management, assuming economic and company conditions remain stable.

FINDINGS:

(SBI) STATE BANK OF INDIA (BANKING &FINANCIAL INSTITUTION):

The original stock price was non-stationary, but the differenced series was suitable for ARMA modelling.AR (22) was statistically significant, showing that past prices (22 months prior) influence current price changes. The MA (1) term was not significant, contributing little to model accuracy.

AXIS BANK (BANKING &FINANCIAL INSTITUTION):

The differenced stock price series was confirmed to be stationary through the ADF test (p-value = 0.0000) The ARMA model had a very low explanatory power (R^2 = 0.0116), indicating it explains only about 1.2% of the variation in the price. Adjusted R^2 was negative, suggesting overfitting or inclusion of unnecessary parameters.

HDFC BANK (BANKING &FINANCIAL INSTITUTION):

The first-differenced stock price series is stationary, as confirmed by the ADF test ($p < 0.05$). The ARIMA (17,1,1) model used is statistically valid but shows limited explanatory power. The MA (1) term is significant, helping to adjust for short-term fluctuations.

NON -BANKING FINCIAL INSTITUTION:

MUTHOOT FINANCE (NON-BANKING FINANCIALINSTITUTION):

The stock price became stationary after differencing (ADF test p-value = 0.0000). The ARMA model forecasted a strong and stable upward trend from 2025 to 2030.The model aligns well with historical performance and shows no major fluctuations, indicating reliable company fundamentals.

IIFL Finance (NON-BANKING FINANCIAL INSTITUTION):

The differenced series is stationary and well-suited for ARMA modelling (R^2 = 0.559294). The model captured historical volatility well but showed a drop in predicted prices toward the end of the forecast period. The trend was upward but highly volatile, suggesting sensitivity to market conditions.

ISSN: 2583-6129
DOI: 10.55041/ISJEM04819

KOTAKMAHINDRA FINANCE (NON-BANKING FINANCIAL INSTITUTION):

The model had very poor fit, with no significant AR or MA terms. R /² was extremely low, and AR (26) suggests overfitting. Forecast shows smooth growth, but it lacks real predictive strength due to weak model structure.

SUGGESTIONS:

BANKING STOCK PRICES

STATE BANK OF INDIA (SBI) (BANKING &FINANCIAL INSTITUTION):

Focus on improving digital banking services to attract tech-savvy users. Use data-driven tools to predict stock movements more accurately. Maintain stable performance to keep stock prices less volatile.

AXIS BANK (BANKING &FINANCIAL INSTITUTION):

Since the model showed low predictability, the bank should communicate financial results clearly to improve investor trust. Improve public awareness of growth strategies to boost investor sentiment. Consider reducing exposure to volatile sectors to stabilize stock performance.

HDFC BANK (BANKING &FINANCIAL INSTITUTION):

HDFC has a strong forecast model -continue its consistent financial performance. Include more external macroeconomic variables (like inflation, interest rates) in analysis for better forecasting. Maintain a diversified loan portfolio to manage risks effectively.

NON-BANKING FINANCIAL COMPANIES (NBFCS)

MUTHOOT FINANCE (NON-BANKING FINANCIAL INSTITUTION):

Continue strengthening the gold loan segment, which gives steady performance Expand to rural and tier-2 cities. For untapped market potential. Invest more in digital loan services and customer support tools.

IIFL FINANCE (NON-BANKING FINANCIAL INSTITUTION):

Address stock price volatility by stabilizing income sources. Communicate long-term plans to investors to reduce market uncertainty. Improve credit risk analysis systems to minimize future losses.

KOTAK MAHI NDRA FINANCE (NON-BANKING FINANCIAL INSTITUTION):

Model showed poor accuracy -simplify ARMA structure and avoid overfitting. Use hybrid models or include external variables (e.g. economic indicators) for better prediction. Focus on transparent reporting and improving public investor relations.

CONCLUSION:

This study explored the use of ARMA models to forecast stock prices of Indian financial institutions, covering both banks and NBFCs from 2015 to 2024. The results showed that ARMA models work well for short-term predictions in relatively stable stocks, such as banks, which exhibit more predictable patterns due to regulatory consistency. However, the models struggled with highly volatile or nonlinear data, often seen in NBFCs. While companies like Muthoot Finance could still be effectively modelled with proper data treatment, stocks such as Kotak Mahindra and Balaji Finance showed weaker forecasting results, underlining the need for customized approaches. The study also highlighted ARMA's limitations in capturing sudden economic shocks or sentiment-driven price changes. Despite these constraints, the research underscores the value of time series analysis in financial forecasting and sets a foundation for future work using hybrid, AI-driven, or multi-variable models, ultimately aiding investors and analysts in navigating India's dynamic financial markets.

REFERENCES:

1. Agarwal, V. & Tiwari, R. 2011. "Predicting stock prices using financial indicators: A regression approach." *International Journal of Financial Management*, 1(1): 11–18.
2. Bandyopadhyay, T. & Saha, A. 2019. "Impact of gold price fluctuations on NBFC stocks." *Journal of Commodity Studies*, 8(2): 22–30.
3. Box, G. E. P. & Jenkins, G. M. 1976. *Time series analysis: Forecasting and control*. Holden-Day.
4. Chakraborty, S. 2012. "Stock price volatility in NBFCs: A study on Indian firms." *Indian Journal of Finance*, 6(9): 29–35.
5. Chatterjee, A. & Dey, B. 2021. "Data preprocessing and forecast accuracy in ARMA models." *International Journal of Quantitative Analytics*, 9(2): 41–52.
6. Das, R. & Banerjee, S. 2015. "Credit disruptions and their impact on NBFC stock prices." *Finance India*, 29(2): 487–496.
7. Fama, E. F. 1970. "Efficient capital markets: A review of theory and empirical work." *The Journal of Finance*, 25(2): 383–417.
8. Gupta, R. & Basu, P. 2007. "Semi-strong form efficiency in Indian stock market." *International Journal of Management Practice*, 2(4): 341–353.
9. Joshi, M. & Patel, N. 2017. "Financial metrics and stock performance: An SPSS-based study." *Indian Journal of Applied Research*, 7(5): 12–16.
10. Kumar, P. & Singh, R. 2014. "Time series analysis of banking sector stocks in India." *Asian Journal of Research in Banking and Finance*, 4(6): 45–58.
11. Mukherjee, R., Thomas, J. & Reddy, K. 2023. "Sector-specific stock forecasting in India using ARMA models." *Journal of Financial Studies and Research*, 11(2): 88–102.
12. Nair, R. & Thomas, J. 2022. "Investor perception of risk in Indian NBFCs." *International Journal of Financial Risk Management*, 7(3): 59–70.
13. Patel, R. & Shah, D. 2018. "Stock forecasting of Indian private sector banks using ARMA models." *Financial Modelling Review*, 6(1): 33–45.
14. Ravikumar, R. & Viswanathan, S. 2017. "Consumer sentiment and NBFC stock volatility in India." *Indian Journal of Economics and Business*, 16(3): 55–70.
15. Reddy, V. & Prasad, L. 2022. "Tuning ARMA models for banking stock forecasts in India." *Asian Journal of Economics and Finance*, 10(1): 13–24.
16. Roy, S. & Malhotra, D. 2020. "A comparative study of statistical and hybrid models for stock price forecasting." *International Journal of Applied Finance*, 6(3): 19–28.
17. Sharma, A. & Mehta, D. 2016. "Use of SPSS in stock market forecasting using financial ratios." *Journal of Applied Management Research*, 4(2): 67–75.
18. Srinivasan, K. & Goel, M. 2020. "The impact of COVID-19 on stock prices of Indian financial institutions." *Journal of Financial Markets and Institutions*, 3(1): 44–58.
19. Tripathi, M., Mehra, K. & Banerjee, A. 2018. "Nonlinear patterns in NBFC stock movements in India." *International Journal of Research in Banking and Finance*, 5(4): 33–45.
20. Verma, S. & Arora, H. 2021. "Time series decomposition and predictability in Indian banks." *International Journal of Business Data Analytics*, 8(1): 25–38.
21. Money control. n.d. "Financial data and stock prices of companies." Retrieved June 23, 2025, from https://www.moneycontrol.com
22. National Stock Exchange of India. n.d. "Equity stock prices and corporate filings." Retrieved June 23, 2025, from https://www.nseindia.com
23. Yahoo Finance. n.d. "Historical stock prices and market trends." Retrieved June 23, 2025, from https://finance.yahoo.com