International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 11 | Nov - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

Predicting Bank Nifty Movements Based on ICICI, HDFC, and Axis Bank Returns

Dr. Manita D Shah*, M L Anushree**, Tarun Suvindran**, Disha G**, Vasantha GP**, Thejaswini SM**

*Professor, Faculty of Management Studies, Jain (Deemed-to-be University), Bangalore.

**MBA, 2023-25, Faculty of Management Studies, Jain (Deemed-to-be University), Bangalore.

Abstract

This study investigates the link between the returns of ICICI Bank, HDFC Bank, and Axis Bank and the overall performance of the Bank Nifty index, which is a crucial measure of the Indian banking sector's health on the National Stock Exchange. Using five years of historical data, regression analysis and descriptive statistics evaluate trends, correlations, and prediction accuracy in anticipating Bank Nifty returns based on the performance of these large banks. The study finds that while Bank Nifty displays stability as it aggregates multiple bank stocks, individual banks like Axis Bank and HDFC exhibit distinct volatility patterns, with Axis Bank showing significant fluctuations due to firm-specific and external factors.Regression results show a little association between individual bank returns and the Bank Nifty, indicating that the index has limited predictive value for single equities. Nonetheless, knowing these patterns may help investors manage risk, anticipate market changes, and develop portfolio diversification methods. The findings emphasize the relevance of sector-specific patterns, implying that although Bank Nifty captures broad market movements, other elements have a distinct influence on each bank's performance, providing insights for more sophisticated investment and risk management methods.

INTRODUCTION

Over the past few decades, the Indian stock market has grown significantly and fluctuated, attracting the interest of both domestic and foreign investors. Investors, analysts, and traders have paid close attention to Bank Nifty, one of its many indexes that represents the performance of the banking industry on the National Stock Exchange (NSE) of India. Major Indian banking stocks are included in the Bank Nifty index, also referred to as the NIFTY Bank Index. It is a vital gauge of the state of the financial industry and the overall state of the economy. Changes in investor mood, credit conditions, and India's economic stability are frequently reflected in changes in the Bank Nifty since the banking industry is essential to capital allocation, liquidity provisioning, and credit supply.

Because of their significant market capitalization, profitability, and impact on the index as a whole, ICICI Bank, HDFC Bank, and Axis Bank stand out among the banks that make up the Bank Nifty index. These banks collectively account for a sizeable portion of the index, and the movement of the Bank Nifty is greatly influenced by the performance of their stocks. Axis Bank, HDFC Bank, and ICICI Bank make up a sizable portion of India's private banking industry, which is renowned for its longevity, inventiveness, and consistent growth trajectory. Because of their size and market significance, the returns of these banks' stocks frequently follow the trends in the banking industry; hence, examining their returns can provide information about the direction of the Bank Nifty. Gaining insight into this link may help investors create winning trading plans, predict changes in the market, and better control risks.

Analyzing financial data and examining intricate interdependencies are necessary for forecasting the Bank Nifty index using the returns of ICICI Bank, HDFC Bank, and Axis Bank. Trends and prognostic indicators can be found by looking at historical price patterns, volatility metrics, and statistical correlations between these banks and the index. These interactions can be modeled using a range of analytical approaches, from contemporary machine learning algorithms to more conventional statistical techniques. For example, financial modeling frequently uses time-series analysis to account for seasonality and other cyclical patterns as well as to capture trends across time. Regression analysis, neural networks, and decision trees are examples of machine learning approaches that have gained popularity for examining intricate, non-linear patterns in financial data. These models seek to quantify the connections between Bank Nifty and bank results in order to provide a basis for trading signal generation and well-informed investment choices.

Furthermore, by assisting investors in anticipating downturns or volatility in the banking industry, predictive models can play a crucial role in risk management. The profitability of banks, particularly those with sizable loan portfolios like ICICI, HDFC, and Axis, can be impacted by variables like credit risk, interest rate swings, and regulatory changes during difficult economic times. Investors can keep ahead of market volatility by modifying their portfolios to reduce future losses by using models that forecast the movement of the Bank Nifty based on the returns of these banks. These models also shed light on the potential effects of external variables on specific banks and, consequently, the banking index, such as changes in domestic fiscal policies, monetary policy decisions, and worldwide economic conditions. When developing strategies that complement investor goals and market conditions, this knowledge can be quite helpful.

Further understanding of the characteristics of the Indian stock market can also be gained by examining Bank Nifty in connection to ICICI, HDFC, and Axis Bank. Given the growing interconnectedness of financial markets, examining particular industries, like banking, provides important insights about the market overall. The success of the Bank Nifty affects not just the banking industry but also industries like consumer goods, real estate, and infrastructure that depend on bank lending. Thus, knowing how the stock returns of top banks relate to the Bank Nifty can help us better comprehend the market and economy as a whole

Objective

- **To analyze the historical relationship** between the returns of ICICI Bank, HDFC Bank, and Axis Bank and the overall Bank Nifty index to determine any correlation or causative trends.
- **To evaluate the predictive accuracy** of different modeling approaches (e.g., regression analysis, time-series analysis, machine learning algorithms) in forecasting Bank Nifty based on individual bank returns.
- **To provide insights for investors** and analysts on the potential application of the model in making informed investment decisions, risk management, and portfolio diversification.

LITERATURE REVIEW

Prakash, B., & Saleena, B. (2024) Literature on stock market prediction highlights the effectiveness of machine learning (ML) and deep learning (DL) approaches, such as Support Vector Machines, Random Forest, XGBoost, and LSTM networks, in capturing complex financial patterns. Hybrid models and advanced methodologies are essential for addressing market volatility and enhancing predictive performance for informed investment strategies.

S. Banik, N. Sharma and K. Sharma (2021) This paper analyzes historical share price data of three major Indian banks—AXIS Bank, HDFC Bank, and ICICI Bank—using various forecasting models, including Support Vector Regression, Extreme Gradient Boosting, and Long Short-Term Memory. Results indicate that linear regression outperforms other models, significantly enhancing accuracy and reducing prediction errors compared to moving averages.

P. Ukhalkar, R. Zirmite and S. Hingane (2023) This study develops a sentiment analysis model for the Indian Bank Nifty Index to enhance decision-making for traders and investors. By analyzing data from news articles and social media, it evaluates various sentiment analysis approaches, identifies strengths and weaknesses, and addresses research gaps, contributing to practical applications and advancements in stock prediction.

Bhardwaj, M., & Adane, D. (2021, November 2) This paper explores Bank Nifty Index trend prediction, emphasizing the integration of Wave Analysis, Market Sentiment, and Fibonacci Retracements. Utilizing published stock data from the National Stock Exchange of India, the findings indicate that the proposed model demonstrates significant potential for short-term trend prediction, outperforming similar methodologies.

Mohan, B. R. (2022) The paper emphasizes the importance of crisis prediction in stock markets, particularly hybrid feature selection for identifying crucial financial characteristics. It examines multiple categorization models and finds that XGBoost and Deep Neural Networks perform better in stock predicting. In addition, regime-switching models outperform GARCH models in terms of volatility estimates.

Dr. Rao K. Mallikarjuna (2021) This study examines the volatility of the Nifty, Sensex, Nifty Bank index, and five important Indian banking stocks from January 2019 to January 2021 using GARCH, EGARCH, and GARCH models. It demonstrates the asymmetric impact of positive and negative shocks, emphasizing how negative news dramatically increases volatility, notably during the COVID-19 epidemic.

Subburayan, B. (2023) This article examines the causal linkages and volatility spillovers between the BSE Bankex index and five large Indian banks using data from January 2018 to March 2023. It identifies bidirectional causation and strong volatility spillovers, allowing investors and policymakers to improve financial stability and influence investment strategies in the Indian market.

Anupama, J., & Tribhuvana, L. (2021) This study examines the performance of select public and private sector banks in the Mutual Funds area before and after the pandemic, utilizing beta coefficients to assess risk and correlation with the NIFTY50 index. Findings reveal that HDFC, ICICI, and SBI are the top performers in their respective categories.

Sen, J., Waghela, H., & Rakshit, S. (2024, May 28) This research examines developments in stock price prediction, focusing on the shift from traditional methods to machine learning and deep learning approaches, namely LSTM models. It underlines the potential of these algorithms to improve portfolio construction and investing strategies by exploiting historical data for better forecast accuracy and sector profitability assessments.

Francis Punitha Sahaya Mary (2019) This research examines technical analysis as an important tool for investors in determining stock value and market movements, particularly in the banking industry. It emphasizes the use of indicators such as Beta, Relative Strength Index, and Simple Moving Average to assist investment decisions, appealing to risk-averse investors looking for safer stocks.

RESEARCH METHODOLOGY:

This study's research technique employs regression analysis and descriptive statistics to investigate the relationship between Bank Nifty and the returns of ICICI Bank, HDFC Bank, and Axis Bank. Reputable financial sources will be used to gather historical stock price data for these banks and the Bank Nifty index over a reasonable time frame in order to identify noteworthy trends. To compute daily or weekly returns, the gathered data will be preprocessed. Extra cleaning procedures will be carried out to deal with outliers and missing values. A preliminary comprehension of the data will next be provided by descriptive statistics, which will look at correlations between the Bank Nifty index and the banks' returns as well as metrics like mean, standard deviation, skewness, and kurtosis. Metrics like R-squared and Mean Absolute Error (MAE) will be used to evaluate the regression model's efficacy and provide a thorough assessment of its predictive accuracy. For analysis, 5 year data for all HDFC,ICICI,Axis bank and bank nifty have been taken and consists of 800 samples.

Findings and discussion

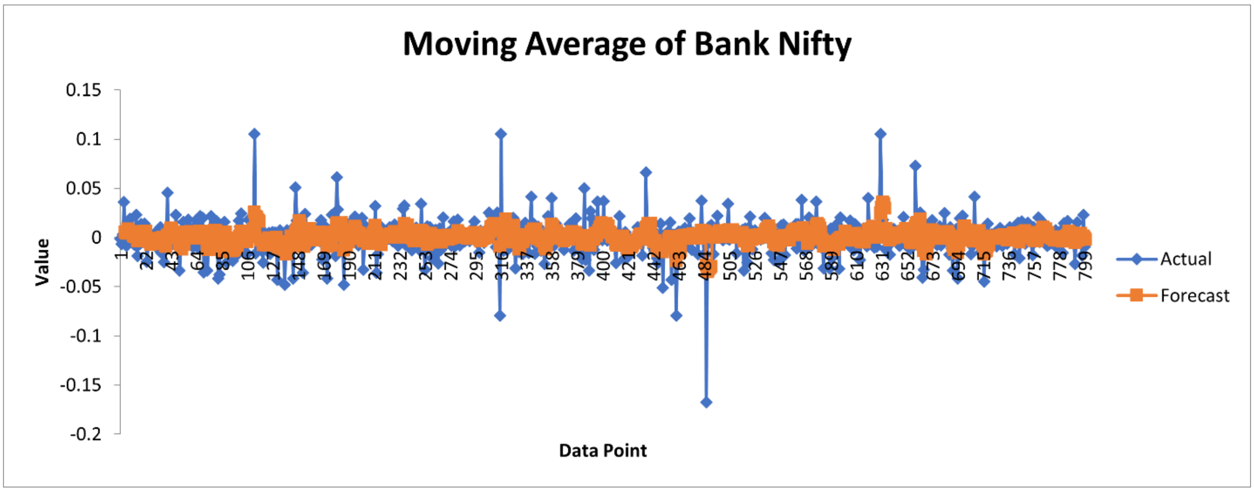


Fig 1.1

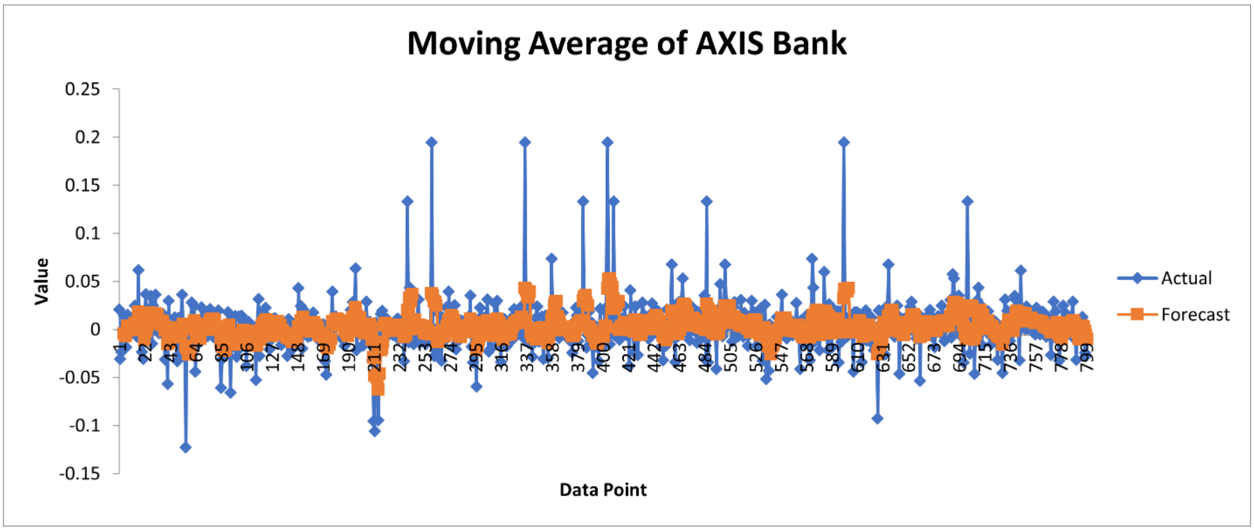


Fig 1.2

The two graphs compare actual values (blue dots) and predicted values (orange line) over a certain period to show the moving averages of Bank Nifty and Axis Bank. Although there are noticeable variations in volatility and deviation between the two datasets, both graphs demonstrate that the predicted moving average values generally follow the actual values' general direction. With fewer, smaller spikes, the predicted moving average on the Bank Nifty graph closely matches the actual values, suggesting a generally stable trend. This implies that abrupt, significant swings are less likely to occur in the banking stocks index as a whole. Since Bank Nifty aggregates several banks to balance out the volatility of individual stocks, the sporadic surges in actual Bank Nifty values most likely reflect larger market occurrences or outside economic effects. In comparison to the Bank Nifty graph, the Axis Bank graph shows more volatility in the actual numbers, with bigger and more frequent spikes. This suggests that Axis Bank's results are more volatile and more susceptible to particular occurrences or company-level variables. Although the model captures broad patterns, it might not adequately account for Axis Bank's more pronounced swings, as evidenced by the predicted values being relatively stable around the core trend. With the moving average projection nearly matching the actual values and exhibiting little variance, the research shows that the Bank Nifty is comparatively more stable. Since the volatility of individual banks is probably balanced by one another, this stability is anticipated for an index that reflects a larger sector. However, Axis Bank exhibits more noticeable departures from the predicted values, suggesting greater volatility and susceptibility to factors unique to the organization. Because of this, forecasting with a simple moving average becomes more difficult because the model is unable to adequately account for the sharp fluctuations in Axis Bank's returns.

Sample AX	
Mean	0.0030601
Standard Errc	0.00093188
Median	0.00194309
Mode	0.13312034
Standard Dev	0.02635752
Sample Varia	0.00069472
Kurtosis	17.7471857
Skewness	2.24211103
Range	0.31767794
Minimum	-0.1228708
Maximum	0.19480719
Sum	2.44807976
Count	800

Sample BN	
Mean	0.0006808
Standard Errc	0.0006
Median	0.00108802
Mode	-0.0417657
Standard Dev	0.01697043
Sample Varia	0.000288
Kurtosis	18.7480042
Skewness	-0.5364711
Range	0.27245745
Minimum	-0.1673401
Maximum	0.10511731
Sum	0.5446422
Count	800

Correlation	*Sample AX*	*Sample BN*
Sample AX	1	
Sample BN	-0.110669454	1

Covariance	*Sample AX*	*Sample BN*
Sample AX	0.00069385	
Sample BN	-4.94404E-05	0.00028764

Fig 1.3

Axis bank descriptive analysis

The descriptive data for Axis Bank (Sample AX) show a right-skewed distribution with a somewhat lower median of 0.0019 and a positive mean return of roughly 0.0036, indicating an average daily gain. The mode, which is approximately 0.133, indicates that the mean is pulled upward by a few days with strong returns. The data exhibits strong volatility with a standard deviation of 0.0264, and the range of 0.3177 (from -0.1228 to 0.10948) demonstrates both notable gains and losses. A leptokurtic distribution with frequent extreme values is implied by the high kurtosis value of 17.75, yet a propensity toward sporadic high positive returns is suggested by the positive skewness of 2.24.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 11 | Nov - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

According to this analysis, Axis Bank has unusual return patterns that include sporadic spikes, little correlation with the daily returns of the Bank Nifty, and high volatility all around.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.11066945
R Square	0.01224773
Adjusted R Sc	0.01100994
Standard Errc	0.02621202
Observations	800

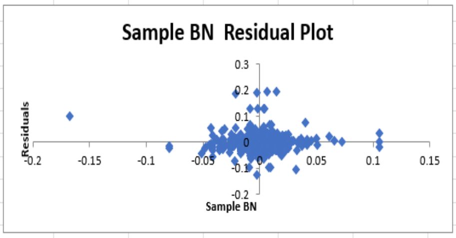
ANOVA

	df	SS	MS	F	Significance F
Regression	1	0.00679847	0.00679847	9.89487679	0.00171886
Residual	798	0.54828182	0.00068707		
Total	799	0.55508029			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.00317712	0.00092748	3.42553567	0.00064494	0.00135653	0.00499771	0.00135653	0.00499771
Sample BN	-0.1718856	0.05464298	-3.1456123	0.00171886	-0.2791466	-0.0646247	-0.2791466	-0.0646247

RESIDUAL OUTPUT

Observation	dicted Sample	Residuals	ndard Residuals
1	0.00335719	0.01757731	0.67100214
2	0.00432359	-0.0349901	-1.3357229
3	0.00264536	-0.0258421	-0.9865061



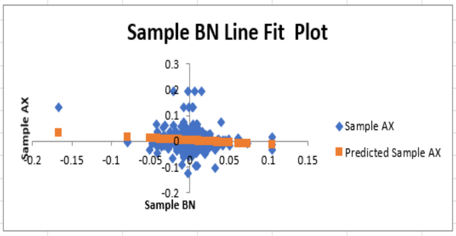


Fig 1.4

Axis bank regression

Some information about their relationship may be gleaned from the regression study of Axis Bank (Sample AX) vs Bank Nifty (Sample BN). With a low R-squared value of roughly 0.012 in the regression output, Bank Nifty's returns barely account for 1.2% of the variability in Axis Bank's returns. A weak linear relationship between the two variables is suggested by this low R-squared. The statistically significant p-value of 0.0017 and the coefficient for Sample BN of -0.1719 show that Bank Nifty has a marginally adverse effect on Axis Bank's returns. This suggests that, assuming all other variables remain same, Axis Bank's return should alter by roughly -0.1719 units for every unit change in the Bank Nifty's return. The low R-squared value, however, suggests that this association might not be robust or consistent. A statistically significant F-value is displayed in the ANOVA table, indicating that the regression model outperforms a model without any predictors. The residual plot, which shows significant scatter with dots widely scattered around zero, further implies that the model's capacity for prediction is constrained. Furthermore, the model does not closely match the actual values of Axis Bank returns, as seen by the line fit figure, suggesting possible underfitting.

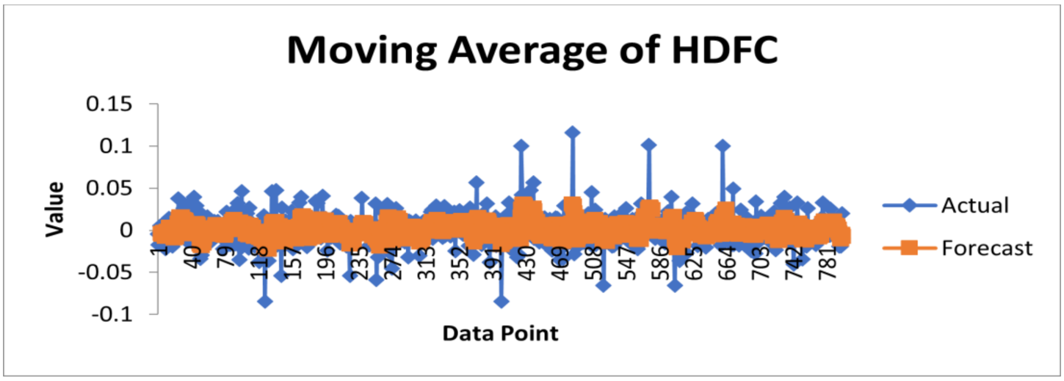


Fig 2.1

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 11 | Nov - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

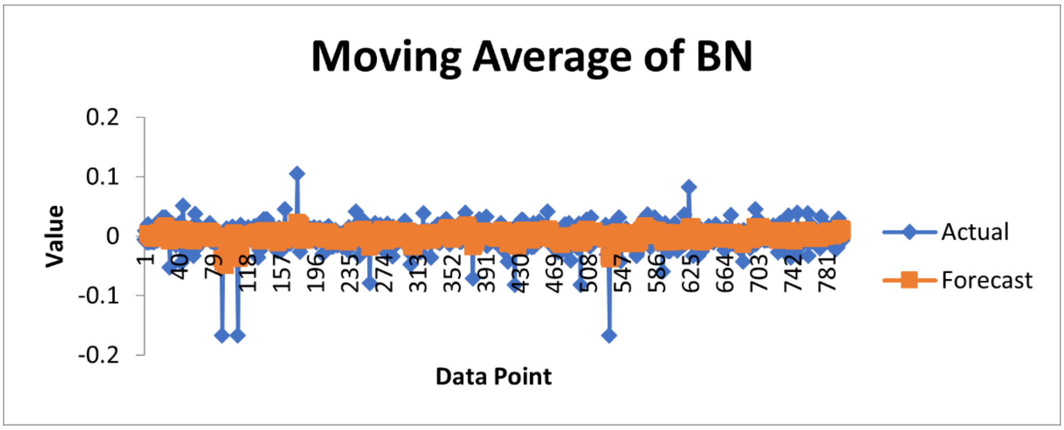


Fig 2.2

The "BN" graph shows real values (blue diamonds) over a sequence of data points coupled with a moving average trend line (orange). The actual values exhibit significant volatility, fluctuating between roughly -0.2 and 0.2. This suggests that "BN" fluctuates frequently and irregularly, most likely as a result of transient changes or data noise. The predicted moving average line, which is centered at zero, stays comparatively stable in spite of these variations. This consistency implies that the moving average strategy successfully evens out the short-term fluctuations, establishing a baseline trend that mirrors "BN"'s general long-term patterns. With actual values frequently varying around the predicted trend without a clear directional trend over time, the discrepancy between actual and forecasted values emphasizes the erratic nature of "BN."

The moving average forecast line (orange) in the "HDFC" graph is likewise constant, remaining near 0 throughout the data points. Although they fall within a more constrained range of roughly -0.1 to 0.15, the actual values (blue diamonds) likewise oscillate around the predicted line, indicating considerably less volatility than that shown in the "BN" data. Although the actual numbers' periodic spikes show some short-term variability, they are not as noticeable as those in the "BN" graph. This may indicate that the tendency for "HDFC" is marginally more predictable than that of "BN." Despite the short-term noise, the projected line's steady closeness to the actual values suggests that the moving average is successfully catching the main trend and offering a trustworthy foundation for comprehending "HDFC"'s long-term pattern.

Both plots show how the moving average approach provides a steady baseline for each item by mitigating short-term changes. But compared to "HDFC," the "BN" graph exhibits greater real value volatility, indicating that "BN" is more prone to transient fluctuations. The moving average is a useful tool for spotting broad patterns in both situations, but the variations in volatility imply that "HDFC" might perform more consistently than "BN." Understanding each entity's behavior in relation to stability and long-term forecasting may be made easier with this insight.

HDFC	
Mean	0.0006409
Standard Errc	0.00061408
Median	0.00033282
Mode	-0.0038126
Standard Dev	0.01736872
Sample Varia	0.00030167
Kurtosis	8.01329464
Skewness	0.77821897
Range	0.20035399
Minimum	-0.0843582
Maximum	0.11599583
Sum	0.5127203
Count	800

BANKNIFTY	
Mean	-0.0002187
Standard Errc	0.00066436
Median	0.00068327
Mode	0.03174852
Standard Dev	0.01879095
Sample Varia	0.0003531
Kurtosis	25.386139
Skewness	-2.6949401
Range	0.27245745
Minimum	-0.1673401
Maximum	0.10511731
Sum	-0.1749603
Count	800

Correlation

	HDFC	BANKNIFTY
HDFC	1	
BANKNIFTY	-0.013111133	1

Covariance

	HDFC	BANKNIFTY
HDFC	0.000301295	
BANKNIFTY	-4.27379E-06	0.00035266

Fig 2.3

Descriptive statistics of HDFC

The HDFC descriptive statistics shed light on how this dataset behaves over 800 observations. Although the tiny size reflects relatively low daily returns, the mean value of 0.0006409 indicates that HDFC's average return is marginally positive. The data's moderate volatility, which reflects some degree of price unpredictability over time, is indicated by the standard deviation of 0.01736872. The central tendency is around zero, according to the median (0.00033822) and mode (-0.0038126) values. The median is positive, which is consistent with the somewhat positive mean.In contrast to a normal distribution, the data appears to have heavy tails and a greater probability of extreme values (outliers), as indicated by the kurtosis value of 8.01329464, which is much higher than 3. According to the range (0.20035399), there is a wide variation between the lowest (-0.0843582) and highest (0.11599583) values. The distribution appears to have a right skew, with more positive returns than negative returns, while there are sporadic big positive deviations, according to the positive skewness of 0.77821897. The standard error of 0.00061408 and sample variation of 0.00030167 provide additional evidence that HDFC's returns are comparatively steady over time. A balanced return pattern with a small upward bias is reflected in the low total sum of returns (0.5127203) over 800 observations, which further suggests that return variations tend to cancel out over time.All things considered, HDFC's descriptive statistics show low average returns, moderate volatility, and a propensity for extreme positive and negative values. The data's positive skewness and high kurtosis point to a distribution that is not quite normal, with sporadic significant positive returns.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.0131111
R Square	0.0001719
Adjusted R Sc	-0.001081
Standard Erri	0.0173781
Observation:	800

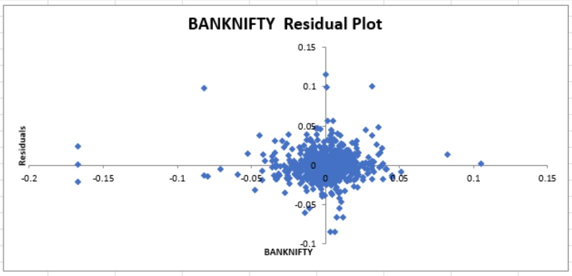
ANOVA

	df	SS	MS	F	Significance F
Regression	1	4.143E-05	4.143E-05	0.1372012	0.7111777
Residual	798	0.2409947	0.000302		
Total	799	0.2410361			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.0006382	0.0006145	1.0387333	0.2992434	-0.0005679	0.0018444	-0.0005679	0.0018444
BANKNIFTY	-0.0121188	0.0327175	-0.3704068	0.7111777	-0.0763413	0.0521037	-0.0763413	0.0521037

RESIDUAL OUTPUT

Observation	Predicted HDFC	Residuals	Standard Residuals
1	0.0007029	-0.0053178	-0.3061994
2	0.000527	-0.0179457	-1.0333111
3	0.0005294	-0.004342	-0.250012
4	0.000762	0.0044847	0.258227
5	0.000398	0.0003563	0.0205175
6	0.0007701	-0.0104595	-0.6022543
7	0.0006494	-0.01984	-1.1423837
8	0.0006441	0.0073488	0.4231399
9	0.0007546	0.0035109	0.202159
10	0.000577	-0.0226953	-1.3067874
11	0.0007132	0.0103444	0.5956286
12	0.0007654	-0.0107619	-0.6196657



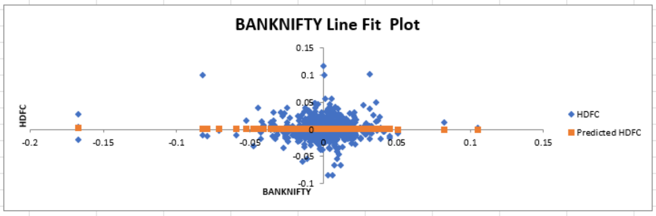


Fig 2.4

Regression analysis of HDFC

The low R-squared value of 0.0001719 indicates a very weak relationship in the HDFC regression study with BANKNIFTY as the independent variable. This implies that BANKNIFTY accounts for an insignificant 0.017% of the variation in HDFC's returns. At standard confidence levels, BANKNIFTY's returns are not statistically significant in forecasting HDFC's returns, as indicated by the company's coefficient of -0.0121 and high p-value of 0.7118. The model's lack of statistical significance is further supported by the low F-statistic, which has a significance value of 0.711177. There is no discernible pattern in the residual plot, which indicates a random scatter around zero. This frequently indicates that the regression model may not be a good match. BANKNIFTY is a poor predictor of HDFC returns, as further evidenced by the line fit figure, which shows little alignment between actual and forecasted HDFC values. All things considered, this regression model indicates that BANKNIFTY's performance has virtually little effect on HDFC, rendering it useless for forecasting HDFC returns.

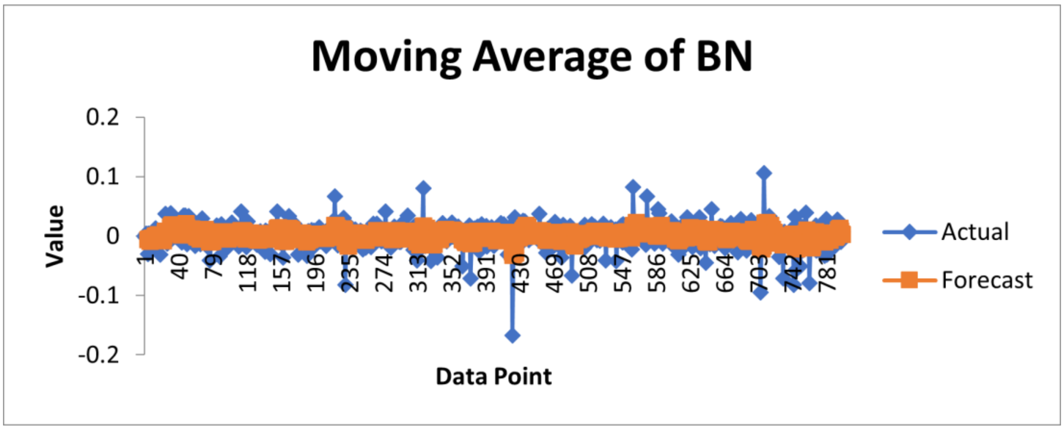


Fig 3.1

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 11 | Nov - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

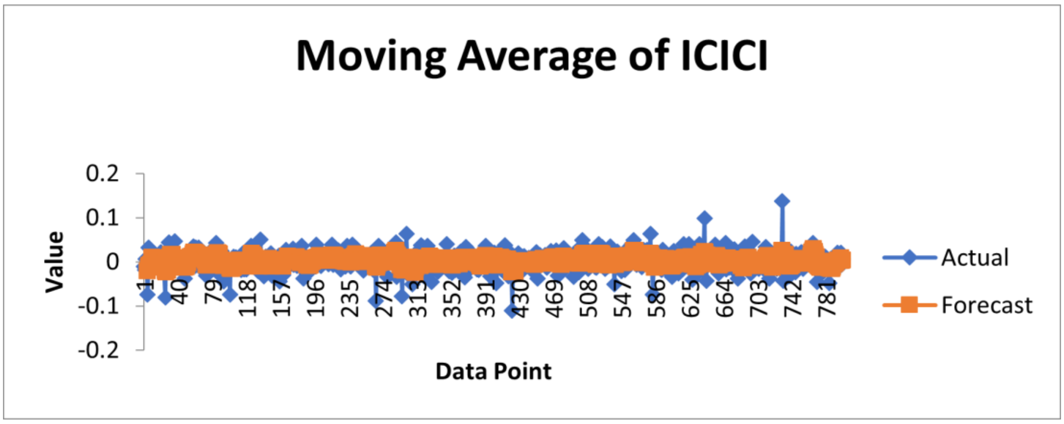


Fig 3.2

The actual values (blue line) in the "Moving Average of BN" graph exhibit minor oscillations around zero with sporadic spikes, indicating periodic instability in the data. Around zero, the predicted values (orange line) stay relatively constant, suggesting that the forecast model anticipates a steady trend with little departure from the mean. Overall, the model reflects the general trend with minimal divergence, while the spikes in the actual data points show several instances of unanticipated alterations. Comparably, the actual values in the "Moving Average of ICICI" graph exhibit slight oscillations around zero, along with a few spikes, albeit these are not as noticeable as they are in the BN graph.

ICICI	
Mean	0.001859906
Standard Error	0.00068641
Median	0.001940662
Mode	0.00729268
Standard Deviation	0.019414618
Sample Variance	0.000376927
Kurtosis	6.696632866
Skewness	-0.142438827
Range	0.248370039
Minimum	-0.110745758
Maximum	0.13762428
Sum	1.487925
Count	800

BANKNIFTY	
Mean	0.000647715
Standard Error	0.000616471
Median	0.000942479
Mode	0.007950304
Standard Deviation	0.017436422
Sample Variance	0.000304029
Kurtosis	16.8405997
Skewness	-1.397901179
Range	0.272457448
Minimum	-0.167340139
Maximum	0.105117309
Sum	0.518171753
Count	800

Correlation		*ICICI*	*BANKNIFTY*
	ICICI	1	
	BANKNIFTY	0.139190654	1

Covariance		*ICICI*	*BANKNIFTY*
	ICICI	0.000376456	
	BANKNIFTY	4.70601E-05	0.000303649

Fig 3.3

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 11 | Nov - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

ICICI Descriptive statistics

The ICICI descriptive statistics show a reasonably symmetric distribution with a moderate degree of volatility. The data appears to be roughly symmetric with no significant skew, as indicated by the mean return of 0.00186, which is around the median of 0.00194. Moderate return variability is shown by the standard deviation of 0.01941 and is further supported by the sample variance of 0.000376927. There are a few small outliers on the lower end, but they are not very noticeable, as indicated by the skewness of -0.1424, which has a modest leftward tilt. The distribution appears to have heavier tails than a normal distribution, implying sporadic extreme values, as indicated by the comparatively high kurtosis of 6.6966. Variability is confirmed by the range (0.2484), as well as by the minimum and greatest values (-0.1107 and 0.1376, respectively). Overall, ICICI’s returns display moderate volatility, slight negative skewness, and a tendency for more extreme outliers than a typical normal distribution.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.13919065
R Square	0.01937404
Adjusted R Sc	0.01814518
Standard Errc	0.01923767
Observations	800

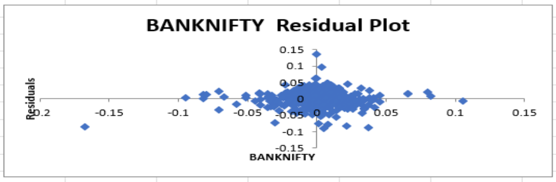
ANOVA

	df	SS	MS	F	Significance F
Regression	1	0.00583478	0.00583478	15.7659323	7.8153E-05
Residual	798	0.29533021	0.00037009		
Total	799	0.30116499			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.00175952	0.00068062	2.58515989	0.0099097	0.0004235	0.00309555	0.0004235	0.00309555
BANKNIFTY	0.1549821	0.03903208	3.97063374	7.8153E-05	0.07836442	0.23159979	0.07836442	0.23159979

RESIDUAL OUTPUT

Observation	Predicted ICIC	Residuals	Standard Residuals
1	0.00178142	-0.0128734	-0.6695975
2	0.0014388	-0.0196883	-1.024067



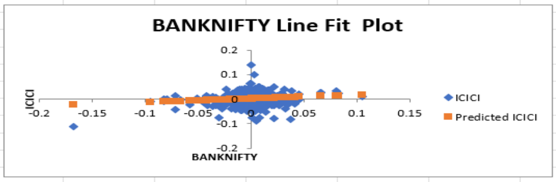


Fig 3.4

Idfc bank regression analysis

The BSE BANKNIFTY index (an independent variable) and the stock price of ICICI Bank (a dependent variable) are examined in the regression study. The correlation coefficient, also known as the Multiple R value, is roughly 0.139, suggesting a weakly positive relationship between the stock prices of ICICI Bank and BANKNIFTY. The R-Square score of 0.019 indicates that changes in BANKNIFTY only account for 1.9% of the variability in ICICI's stock price, suggesting that other factors probably have a greater influence. Despite only explaining a small portion of the variation, the model as a whole is statistically significant, according to the ANOVA findings, which indicate an F-statistic of 15.77 with a p-value of 7.81e-05. The BANKNIFTY coefficient is 0.154 and the intercept is 0.00176, both of which are statistically significant with p-values less than 0.05. This implies that ICICI's stock price should rise by an average of 0.154 units for every unit increase in BANKNIFTY. However, this model's predictive value is restricted due to its low R-Square, which means that BANKNIFTY by itself is not a reliable indicator of ICICI's price movements. Though the weak correlation suggests that this linear model does not capture much of the relationship between BANKNIFTY and ICICI's stock price, the residual and line fit plots show a scattered distribution of residuals, indicating no clear pattern, which suggests that the model's assumptions may be met.

CONCLUSION

To sum up, the descriptive and regression studies shed important light on the correlations and trends in volatility between the different banking stocks (Axis Bank, HDFC, and ICICI) and the larger BSE BANKNIFTY index. According to the data, BANKNIFTY is generally a reliable indication of the performance of the banking industry. This is probably because it aggregates a number of companies, which reduces the volatility of individual stocks. While the different equities exhibit differing levels of volatility and variance, BANKNIFTY's moving average exhibits stability, highlighting the distinct elements influencing each bank's performance.

Given its high volatility and frequent, substantial increases, Axis Bank appears to be susceptible to both external events and company-specific factors. It is less predictable and more challenging to anticipate using basic models due to the high kurtosis and positive skew in its distribution, which suggest the presence of significant, irregular gains. While generally more steady than Axis Bank, HDFC has moderate volatility and a slightly positive return, with a distribution that suggests larger tails and occasional big values.

These results are further supported by the regression analysis. Low R-squared values demonstrate BANKNIFTY's limited impact on individual stock returns, suggesting that the index is not a reliable indicator of changes in individual bank stocks. In particular, Axis Bank, HDFC, and ICICI's low R-squared values imply that variables other than the general banking index have a major influence on each bank's performance. Even if there is a slight positive correlation between ICICI and BANKNIFTY according to the model's regression, it would be useless to use BANKNIFTY as the only forecasting tool for ICICI due to its low predictive potential.

Each bank behaves differently, is volatile, and responds to specific things differently, even while the banking sector index (BANKNIFTY) provides a consistent long-term trend for the industry. The necessity for more complex, multivariate models that consider more variables in order to generate more accurate projections of the movements of specific stocks is highlighted by the incapacity of BANKNIFTY-based predictive models to completely capture these intricacies. In order to make wise investment choices, stakeholders must understand how individual companies behave within the broader index context, as this analysis highlights.

REFERENCES

1. Prakash, B., & Saleena, B. (2024). Analysis and Prediction of Stock Market Price Movements using Machine Learning Techniques: A Comparative Study. *SSRN*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4940494

2. S. Banik, N. Sharma and K. Sharma (2021), "Analysis of Regression Techniques for Stock Market Prediction: A Performance Review," 2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), Noida, India, 2021, pp. 1-5, doi: 10.1109/ICRITO51393.2021.9596192. https://ieeexplore.ieee.org/abstract/document/9596192

3. P. Ukhalkar, R. Zirmite and S. Hingane (2023), "Sentiment Analysis Models for Bank Nifty Index: An Overview of Predicting Stock Market Sentiment in India," 2023 7th International Conference On Computing, Communication, Control And Automation (ICCUBEA), Pune, India, 2023, pp. 1-9, doi: 10.1109/ICCUBEA58933.2023.10392130. https://ieeexplore.ieee.org/abstract/document/10392130

4. Bhardwaj, M., & Adane, D. (2021, November 2). *Bank Nifty Index Trend Prediction using Historical Data, Wave Analysis, Market Sentiment, and Fibonacci Retracement for Dynamic Decision Making. | EBSCOhost*. https://openurl.ebsco.com/EPDB%3Agcd%3A10%3A26292202/detailv2?sid=ebsco%3Aplink%3Ascholar&id=ebsco%3Agcd%3A153947145&crl=c&link_origin=scholar.google.com

5. Mohan, B. R. (2022). *Stock price forecasting models during crisis and high volatility*. https://idr.l4.nitk.ac.in/jspui/handle/123456789/17413

6. Dr. Rao K. Mallikarjuna (2021) *Assessing volatility in the banking stocks in Indian stock market during the Covid-19 pandemic: Using arch/garch models*. (2021). https://www.indianjournals.com/ijor.aspx?target=ijor:ajrbf&volume=11&issue=9&article=003

7. Subburayan, B. (2023). Causality and volatility spillovers of banks' stock price returns on BSE Bankex returns. *Journal of Corporate Accounting & Finance*, *35*(1), 59–75. https://doi.org/10.1002/jcaf.22648

8. Anupama, J., & Tribhuvana, L. (2021). A Comparative study on performance of Mutual Funds of select Public and Private sector banks – pre and post pandemic. In Quest Journals, *Journal of Research in Business and Management* (Vol. 9, Issue 7, pp. 22–29) [Journal-article]. Quest Journals

9. Sen, J., Waghela, H., & Rakshit, S. (2024, May 28). *Exploring sectoral profitability in the Indian stock market using deep learning*. arXiv.org. https://arxiv.org/abs/2407.01572

10. Francis Punitha Sahaya Mary (2019) *Technical analysis on selected stocks of Indian banking sector*. https://www.indianjournals.com/ijor.aspx?target=ijor:ijmie&volume=9&issue=9&article=008