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Accuracy of ARIMA Model for Individual Stocks of Nifty 50 – Sector Wise

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Abstract
The Autoregressive Integrated Moving Average (ARIMA) model stands out as a robust tool for stock price prediction within the Nifty 50 index, a pivotal gauge of the Indian stock market.This research delves into the efficacy of the ARIMA model within the Nifty 50 index framework. Specifically, an exhaustive analysis is conducted on historical price dynamics exhibited by constituent equities of the index over a four-year period from January 1, 2018, toFebruary 28, 2023. Our findings indicate that ARIMA offers the most precise predictions for shorter timeframes, notably the 30-day forecast, followed by the 60-day forecast, and subsequently the 180-day forecast. Moreover, an evaluation of ARIMA model accuracy acrossvarious industries is carried out through metrics such as root mean square error (RMSE), MeanAbsolute Error (MAE), and mean absolute percentage error (MAPE). In summary, this study suggests the viability of employing ARIMA models to forecast future values of Nifty50 stockswithin specific sectors, especially for short-term predictions. It also underscores the need for further exploration in tailoring forecasting methodologies to suit the distinctive attributes of diverse industries.

Keywords: ARIMA, Stock Prices, Prediction, Time series analysis

Introduction

One of the main supports of the international financial system is the stock market. It serves asa consolidated marketplace for the purchase and sale of securities by investors, mostlyownership shares in publicly traded corporations. These shares, also referred to as stocks, constitute a portion of a company's ownership. Investing in stocks allows a person to get ownership stake in a firm and potentially benefit from growth in the form of dividend paymentsand rising stock values.
The economy is influenced by the stock market in many ways. It gives businesses a platform to raise money for innovation, growth, and acquisitions. Businesses can raise money for expansion by issuing new shares, which will draw in investors. On the other hand, investors use the stock market to increase their wealth by buying stock in businesses they think have potential in the future. Price discovery is made easier by the market, which guarantees a just exchange of goods and services between buyers and sellers depending on variables such as corporate performance, market dynamics, and general economic sentiment.

The Nifty 50 serves as a vital indicator of India's stock market health. Maintained by the National Stock Exchange of India (NSE), this index tracks the performance of the 50 largest and most actively traded companies listed on the exchange. These companies span various sectors like consumer goods, energy, banking, finance, technology, and infrastructure. By analysing the Nifty 50, investors gain valuable insights into the current state and future prospects of the Indian economy.
Selection of companies in the Nifty 50 is based on stringent criteria, including trading liquidity,which refers to how easily shares can be bought and sold, and market capitalization, which reflects the total value of all outstanding shares. This

ensures the index accurately captures theperformance of leading businesses across sectors and provides a reliable gauge of Indian corporate health.

Accurately estimating stock values is a never-ending challenge in finance. The AutoregressiveIntegrated Moving Average (ARIMA) model is an effective tool for analysing and forecastingtime series data, such as Nifty 50 stock movements. The use of ARIMA in modelling and predicting the performance of Nifty 50 equities is examined in this research study.A statistical method called the ARIMA model uses patterns found in historical data to forecastvalues in the future. It blends three elements together:

- Autoregressive (AR): This part takes into account how the time series' historical valueshave affected its current value. In essence, it expresses the degree to which the presentprice is impacted by its historical pricing.
- Integrated (I): Any differencing used to attain stationarity—the constancy of the data's statistical features throughout time is referred to as integration. For precise forecasting,this is essential.
- Moving Average (MA): This component takes into account how previous random errors, or noise, have affected the current value. It aids in data smoothing and helps eliminate sporadic swings.

The historical price data of a Nifty 50 stock can be fitted with an ARIMA model to reveal trends, seasonality, and cyclical patterns. We are able to forecast future stock values and their possible volatility with this knowledge. The precise procedures involved in creating and utilizing ARIMA models on Nifty 50 data will be examined in this research study. We shall evaluate ARIMA's predicting efficacy and contrast its results with those of other forecasting methods. We hope to further our understanding of this useful tool for financial modelling andinvestment decision-making by examining the advantages and disadvantages of ARIMA.

This study conducts a thorough examination of the past price movements demonstrated by theNifty 50 index's component equities between January 1, 2018, and Feb 28, 2023. Over the course of the year, our research will carefully examine the daily stock price data of each component, paying close attention to their variations and patterns. In addition, our research intends to use this extensive information to predict these constituents' future stock prices, witha focus on the period between March 1, 2023, and September 1, 2023. Using the AutoregressiveIntegrated Moving Average (ARIMA) model, our goal is to produce forecasts on the directionof these company values. Moreover, our research aims to assess the accuracy and reliability ofour projections by a comprehensive mapping exercise, going beyond basic forecasting. This entails calculating the tracking error between the prices predicted by the ARIMA model and the actual stock prices observed during the previously specified period of time. By examiningand evaluating these tracking errors, we intend to shed light on the efficiency and robustness of our forecasting approach and determine which industry it works best in.

Literature Review:

“ARIMA Model for Accurate Time Series Stocks Forecasting”, by Shakir Khan, Hela Alghulaiakh (2021) aims to get an accurate stock forecasting model by using Netflix stock historical data for five years. The research used Netflix stocks historical data for the past five years from 7 April 2015 to 7 April 2020. The methodology involved applying ARIMA modelsto the data and comparing the accuracy of the results using MAPE (Mean Absolute PercentageError). The conclusion of the research is that ARIMA (1,1,33) model showed better accuracy in calculating the MAPE and holdout testing, which shows the potential of using the ARIMA model for accurate stock forecasting.

“A Predictive Analysis of Indian Automobile Sector Stocks: An Application of Arima Model”,by Dr Vishweswarsastry V N, Dr Guruprasad Desai D R, Dr. C G Manjunatha, Pavan V (2023)intends to quantify the compound annual growth rate (CAGR) of foreign direct investment (FDI) inflows into the Indian automobile sector, estimate market prices of chosen Indian automobile securities, and examine conditional heteroskedasticity on prices using the GARCHmodel. The research method adopted was descriptive and analytical. The authors used the Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models for prediction. According to the analysis, FDI inflows into the Indian automobile sector increased at a compound annual growth rate (CAGR) of 19.87% between 2010 and 2021.

“A Comparative Research of Stock Price Prediction of Selected Stock Indexes and the Stock Market by Using Arima Model”, by Nayab Minhaj, Roohi Ahmed, Irum Abdul Khalique, Mohammad Imran (2022) aims to examine how well the ARIMA time series model predicts stock prices for a certain index and the overall market. The researchers tested the ARIMA model's ability to forecast stock prices and other volatile variables by comparing its performance in projecting a single stock index to the entire stock market. They discovered thatthe ARIMA model was more effective at forecasting the closing price of a single stock (Johnson& Johnson) than the S&P 500 index, most likely due to the latter's higher volatility. The procedure involved collecting historical data from Johnson & Johnson and the S&P 500 to construct ARIMA models, and then testing the accuracy of the models' forecasts.

"An Effective Time Series Analysis for Stock Trend Prediction Using ARIMA Model for NiftyMidcap-50", by B. Uma Devi, D.Sundar and Dr. P. Alli (2013) aims to determine the best strategy for forecasting stock prices using time series analysis. The authors evaluated various statistical methods and discovered that the ARIMA (Autoregressive Integrated Moving Average) model was the most accurate. The analysis examined historical closing prices for theNifty 50 index and the top four companies in the Nifty Midcap 50 index. The research concludes that the ARIMA model can be used to forecast stock prices with a reasonable level of accuracy.

"An Analysis on Tesla's Stock Price Forecasting Using ARIMA Model", by Aishwariya Subakkar, Graceline Jasmine and L. Jani Anbarasi (2023) aims to Create an ARIMA model forforecasting stock prices. The research methodology entails gathering data on Tesla's daily stockprices, categorizing it into training and testing sets, and then fitting an ARIMA model to the training data. The data used was Tesla's daily stock prices from July 10, 2015 until July 10, 2020. The article concludes that ARIMA models offer a promising future for predicting stockcosts. The proposed model obtained an R-Squared value of 99% for ARIMA, suggesting greatpredicting accuracy.

"Application of Auto ARIMA Model for Forecasting Returns on Minute Wise AmalgamatedData in NSE", by Lakshmi Yermal and Balasubramanian P (2017) aims to investigate the use of the Automatic ARIMA function for projecting stock returns based on minute-by-minute datafor 50 equities on the National Stock Exchange in India. The research technique entails applying ARIMA models to minute-by-minute data on the stock returns of 50 companies (NIFTY 50) listed on the National Stock Exchange of India from July 2014 to June 2015. Thedata used is tick by tick data obtained from the NSE and then converted to minute-by-minute aggregated data using the big data tool Spark. The study concludes that Auto ARIMA appliedto the sample produces satisfactory forecasts indicated by low Mean Absolute Percentage Error(MAPE) for only three companies, while forecasts for the others were found to be weak.

“ARIMA Time Series Analysis in Forecasting Daily Stock Price of Chittagong Stock Exchange (CSE)”, by Tasnim Uddin Chowdhury, Md. Shahidul Islam (2021) aims to considerthe applicability of a time series model for forecasting the daily share price of the Chittagong Stock Exchange (CSE). The research method involved gathering closing prices for 60 randomly selected corporations from the CSE website between January 2019 and December 2019. The Durbin-Watson test was used to check for autocorrelation in share prices, and the Augmented Dickey-Fuller test was used to check for stationarity. An ARIMA model was then built utilizing the autocorrelation function (ACF) and the partial autocorrelation function
(PACF). The model's goodness-of-fit was determined using the Ljung-Box Test Q, Root MeanSquare Error (RMSE), Mean Absolute Percentage Error (MAPE), and R-squared value. The study revealed that the ARIMA model can predict the daily share price of the CSE.

"Forecasting Nifty Using Autoregressive Integrated Moving Average Model", by Arup Bramha Mohapatra (2022) aims to determine how well the Autoregressive Integrated MovingAverage Model (ARIMA) predicts the Nifty 50 stock market index in India over short periodsof time. The research technique comprises obtaining data on the Nifty 50 from June 15, 2020 to January 28, 2022. The data is then differenced to make it stationary, and the Nifty 50 is forecasted using the ARIMA model from January 18, 2022 to January 28, 2022. The study concludes that, while the ARIMA model can predict the Nifty 50 for short periods of time, it lags behind other technical analysis methods.

"Forecasting Nigerian Stock Exchange Returns: Evidence from Autoregressive Integrated Moving Average (ARIMA) Model", by Emenike Kalu O. aims to create a model to forecast stock returns in Nigeria using the ARIMA model. The methodology entails using monthly NSEAll-Share Indices from January 1985 to December 2008 as data. The ARIMA (1,1,1) model was found to outperform the naïve model. However, the variances from the real data show thatthe global economic downturn disrupted the correlation relationship that existed between the NSE All-Share Index and its history.

"Forecasting of Indian Stock Market using Time-series ARIMA Model", by Debadrita Banerjee (2014) aims to create a model for predicting future unobserved values of Indian stockmarket indexes. The research method involved collecting data on the Sensex's monthly closingstock indices for six years (2007-2012) and using time-series ARIMA analysis to establish thebest model for predicting the data. The study examined data from the Sensex's monthly closingstock indices during a six-year period (2007-2012). The article indicated that the ARIMA (1,0,1) model was the best at forecasting Indian stock market indexes. This model was chosenbecause it met all of the goodness-of-fit criteria and accurately predicted the monthly indices in 2013.

"Forecasting stock market prices using mixed ARIMA model: a case study of Indian pharmaceutical companies", by Bharat Kumar Meher, Iqbal Thonse Hawaldar, Cristi Spulbar and Ramona Birau aims to create a mixed Auto-Regressive Integrated Moving Average (ARIMA) model to forecast the share prices of pharmaceutical companies included on India's NIFTY 100 index. The research methodology entails obtaining daily closing prices of pharmaceutical companies listed on India's NIFTY 100 from January 1, 2017 to December 31,2019. An ARIMA model was then used to forecast share values from October 1 to December 31, 2019. The study shows that the ARIMA model can be used to forecast pharmaceutical company share prices in India, with the ARIMA (131, 1, 47) model having the lowest volatility,SIGMASQ, and R-squared and modified R-squared. However, the authors warn that there is apotential that some residuals were not incorporated in the aforementioned models, and that more research is needed to increase the model's accuracy.

"Forecasting Stock Market Series with ARIMA Model", by Fatai Adewole Adebayo, Ramysamy Sivasamy and Dahud Kehinde Shangodoyin (2014) aims to Find the most accurateARIMA model for forecasting stock market prices in Botswana and Nigeria. The Box-Jenkinsmethodology is used to find, estimate, and diagnose ARIMA models for stock market data. Thedata used are quarterly stock market data from Botswana and Nigeria between 2002 and 2012.The article concludes that the best model for forecasting stock market prices in Botswana is ARIMA (3,1,1), whereas the best model for forecasting stock market prices in Nigeria is ARIMA (1,1,4).

"Forecasting NIFTY 50 benchmark Index using Seasonal ARIMA time series models", by AmitTewari aims to Examine how Time Series Analysis techniques can be used to track the behaviorof an exchange-traded index in a stock market. The research technique included the use of Seasonal ARIMA (SARIMA) models to capture the movement of the Nifty 50 index, which isone of the most actively traded exchange-traded contracts globally. Data for the previous 11 years (2009-2019) were downloaded from the NSE website. The data post-2008 was utilized because the Indian economy was emerging from a massive financial slump in 2008 and undergoing systematic and structural adjustments. The study concludes that SARIMA (2,2,1) x (2,2,1,12) is a viable model for forecasting the Nifty 50 index, however there may be some uncertainty associated with forecasting stock and index price changes due to macroeconomic and microeconomic factors.

"Forecasting Stock Index Price in the Indian Stock Market Using the ARIMA Model", by Anurag Verma and Anupam Verma (2020) aims to Test the ARIMA model's ability to predictthe Nifty-50 index price in the Indian stock market. The research technique entails fitting an ARIMA model to historical monthly Nifty-50 index data from April 1996 to December 2018,followed by forecasting the index price for January 2019 to December 2019. The data used is the closing price of the Nifty-50 index. The research concludes that the ARIMA model can beutilized to create reasonable short-term forecasts of stock prices.

"Indian Stock Market Predictive Efficiency using the ARIMA Model", by Manish R Pathak and Jimmy. M. Kapadia (2021) aims to forecast the closing stock price of the Nifty 50 on the National Stock Exchange. The research methodology entails analyzing secondary financial data from the Nifty 50 over the last five years and utilizing Eviews software to establish the optimum ARIMA model. The data used are the closing stock prices of the Nifty 50 over the last five years. In conclusion, the ARIMA (1,1,2) model is the best model for short-term prediction of the Nifty 50 index, and adjusted ARIMA can increase forecasting accuracy.

"Predicting the Stock Market Index using Stochastic Time Series ARIMA Modelling: The Sample of BSE and NSE", by Dr. C. Viswanatha Reddy aims to using time series analysis, develop a forecasting model for the stock market index. The research approach includes determining the stationarity of time series data and predicting with the ARIMA model. The study's data is derived from the weekly closing indices of the BSE and NSE, which can be obtained on Yahoo Finance. The study concludes that the ARIMA model can forecast stock market indexes in the short run. However, the authors acknowledge that the stock market is volatile and difficult to foresee.

"Prediction of Market Capitalization Trend through Selection of Best ARIMA Model with Reference to Indian Infrastructural Companies", by Kapil Shrimal and Hanuman Prasad (2016)aims to create a model to estimate the market capitalization of infrastructure businesses in India. The research technique includes employing ARIMA analysis on quarterly market capitalization data of 21 infrastructural companies listed on the S&P BSE-200 Index. The datawas obtained from the BSE India website. The research concludes that ARIMA models can beused to predict the market capitalization of infrastructure companies in India. The report also discovered that companies with solid dividend distribution policies, expanding sales and assets,and exciting future investment programs are more likely to experience an increase in market capitalization.

"Predictive Efficiency of ARIMA and ANN Models: A Case Analysis of Nifty Fifty in IndianStock Market", by Vijay Shankar Pandey and Abhishek Bajpai (2019) aims to analyze the accuracy of ARIMA (p,d,q) and ANN models in predicting the Nifty Fifty in the Indian StockMarket. The research methodology involved using time series data of the closing index of the

Nifty Fifty for a period of ten years. The authors used statistical tools such as R-squared, Adjusted R-squared, Akaike Information Criterion (AIC), and Schwartz Bayesian Criterion (SBC) to compare the performance of the models. The conclusion of the paper was that ANN models were more accurate in predicting the Nifty Fifty than ARIMA models. Specifically, theauthors found that ARIMA (2,1,2) and ANN (4-10-1) with both train functions GDX and BFGwere the best predictors, with ANN models outperforming ARIMA models

"Selection of Best ARIMA Model for Forecasting Average Daily Share Price Index of Pharmaceutical Companies in Bangladesh: A Case Study on Square Pharmaceutical Ltd", by Dr. Jiban Chandra Paul, Md. Shahidul Hoque Mohammad Morshedur Rahman (2013) aims tofind the best ARIMA model for forecasting Square Pharmaceuticals Limited's average daily share price index (SPL). The process included assessing the data for stationarity using the ACFand PACF plots, followed by utilizing the Ljung-Box-Pierce Q-statistic and Dickey-Fuller teststatistic. The data used were SPL's average daily share price indexes for the year 2011. The analysis concluded that the ARIMA (2, 1, 2) model was the most effective at forecasting the SPL data series.

"Stock Market Index Prediction of SBI in India using ARIMA Models", by T. Sartitha and Dr.

M. Raghavender Sharma (2022) aims to forecast State Bank of India (SBI) stock values usingBox-Jenkins ARIMA models. The research technique entails collecting historical data on dailystock prices from the Bombay Stock Exchange (2-January-2017 to 29-October-2020). The Box-Jenkins methodology is used to develop and validate ARIMA models for forecasting stockprices. The study's data is based on SBI's daily stock prices from the Bombay Stock Exchange.The article concludes that the ARIMA (0,1,0) × (1,0,0)5 model is the best for projecting SBI stock values, based on error measures (MAE, MSE, MAPE, and RMSE).

Research Objective

Financial forecasting, particularly in the ever-volatile realm of the stock market, remains a complex and elusive pursuit. Investors and analysts constantly grapple with the challenge of predicting price movements to inform their decisions. While numerous forecasting models exist, ARIMA (Autoregressive Integrated Moving Average) stands as a well-established and widely used technique. This research delves into the effectiveness of ARIMA for predicting stock prices within individual sectors of the Nifty 50 index, a key benchmark for the Indian stock market.

The core objective of this study is to meticulously evaluate how well ARIMA captures the unique price movements that characterize different industries within the Nifty 50. This will involve a two-pronged approach. Firstly, we will construct separate ARIMA models for each sector, encompassing sectors like banking, technology, and infrastructure. By meticulously analyzing the accuracy of each sector's model, we can identify industries where ARIMA excelsat predicting price movements. For example, sectors with historically stable growth patterns might demonstrate superior alignment with ARIMA's capabilities. Conversely, sectors where ARIMA performs poorly might indicate limitations in the model itself or the presence of external factors that fall beyond ARIMA's scope. For instance, sudden policy changes specifically impacting a particular sector could throw off ARIMA's predictions.

This in-depth analysis will yield valuable insights into the applicability of ARIMA within the dynamic context of the stock market. By pinpointing sectors where ARIMA thrives and unveiling its limitations within others, we can empower investors and analysts to make informed decisions about using ARIMA for specific sectors within the Nifty 50. Imagine an investor interested in the technology sector; understanding how well ARIMA captures price movements in this specific industry would allow them to make a more strategic decision aboutincorporating ARIMA's forecasts into their overall investment strategy.

Furthermore, the study paves the way for further research in tailoring forecasting models to better suit the unique characteristics of different industries. This could involve comparing ARIMA's performance with other forecasting models like GARCH or exploring the integrationof machine learning techniques. Additionally, investigating the impact of external factors likeeconomic indicators, news events, or regulations on the effectiveness of ARIMA in different sectors could prove highly valuable. Exploring advanced ARIMA variations like Auto ARIMAalso holds the potential to improve forecasting accuracy across the board.

In conclusion, this research not only contributes to a deeper understanding of ARIMA's strengths and weaknesses within the context of the Nifty 50, but also paves the way for the development of more sector-specific and effective financial forecasting models. By acknowledging the unique characteristics of different industries and their impact on forecasting models, we can move closer to achieving a more nuanced and accurate picture of the ever- evolving stock market landscape.

Hypothesis

Hypothesis 1:

Null Hypothesis (H0): There is no significant difference in accuracy of ARIMA model for different timeframes

Alternative Hypothesis (H1): There is a significant difference in accuracy of ARIMA model for differenttime frames.

Hypothesis 2:

Null Hypothesis (H0): Percentage change in daily stock price have no unit root. Alternative Hypothesis (H1): Percentage change in daily stock price have a unit root.Hypothesis 3:

Null Hypothesis (H0): The accuracy of ARIMA models for the industry with the highestnumber of companies is not greater than that of the remaining industries.

Alternative Hypothesis (H1): The accuracy of ARIMA models for the industry with the highest number of companies is superior to that of the remaining industries.

Research Methodology

This research explores the potential of using time series analysis, a technique well-suited for analyzing data points collected over time, to predict stock prices. We specifically focused on areadily available source of secondary data - the Nifty 50 index. This index, a benchmark for the Indian stock market, includes 50 companies listed on the National Stock Exchange (NSE) of India. To conduct our analysis, we collected historical price data for all 50 companies, encompassing a five-year period from January 2nd, 2018, to February 28th, 2023. This resultedin a dataset containing 1,277 data points for each company.

Before applying any forecasting models, we needed to ensure the data was suitable for such analysis. A statistical test called the Augmented Dickey-Fuller test was employed to check fora specific characteristic in the data called a "unit root." This essentially means the data has a trend or isn't inherently stable over time. Fortunately, ouranalysis revealed that the data, specifically the percentage changes in stock prices, did not exhibit a unit root, indicating stationarity. This makes the data ideal for using time series forecasting models like ARIMA.

Following this confirmation, we built an ARIMA model for each company within the Nifty 50.ARIMA is a powerful technique that considers past trends and fluctuations in the data to predictfuture values. To create the model, we analyzed two specific functions - autocorrelation and partial autocorrelation - which help identify patterns in the data that the ARIMA model can leverage for predictions. In simpler terms, these functions help us understand how past price changes might influence future movements.

The ARIMA model, defined as ARIMA (p, d, q),

It incorporates auto-regression with p lags (AR (p)) which is defined as (i):

$$y_t = \mu + \sum_{i=1}^{p} \gamma_i y_{t-i} + \epsilon_t \ \dots\dots\dots (i)$$

Where, yt is the share price at time t, μ is constant, γi is the coefficient of lag variable, $yt-i$ is the share price at time (t – i) and ϵt is the error term.

Moving average with q lags (MA (q)), where the parameters are determined by the analysis ofthe time series data which is defined as (ii):

$$y_t = \mu + \sum_{i=1}^{q} \theta_i y_{t-i} + \epsilon_t \ \dots\dots\dots (ii)$$

Where, yt is the share price at time t, μ is constant, θi is the coefficient of lag variable, $yt-i$

is the share price at time (t – i) and ϵt is the error term.
Now autoregressive moving average ARMA (p,q) model combines both p autoregressive terms with q moving average which can be termed as equation (iii):

$$y_t = \mu + \sum_{i=1}^{p} \gamma_i y_{t-i} + \sum_{i=1}^{q} \theta_i y_{t-i} + \epsilon_t \ldots (iii)$$

One of the fundamental requirements for building a reliable forecasting model using time seriesanalysis is stationarity. This essentially means the data exhibits stable statistical properties overtime, without any trends or seasonal fluctuations that might skew the results. In the context ofstock prices, raw price data itself often exhibits trends, making it unsuitable for directmodelling. To address this, we transformed the data by calculating the percentage change in stock prices for each company within the Nifty 50. This transformation essentially removes any long-term trends and focuses on the relative price movements, making the data more aligned with the assumptions of time series models.
To formally verify this, we employed a statistical test known as the Augmented Dickey-Fullertest. This test specifically checks for the presence of a "unit root," which indicates non- stationarity in the data. Fortunately, the results of the Augmented Dickey-Fuller test confirmedthat the percentage change in stock prices for each company did not exhibit a unit root. In simpler terms, this means the data displayed the desired level of stability over time, making itperfectly suited for our chosen forecasting model - the ARIMA model. With this crucial confirmation in hand, we were confident in proceeding with the construction of individual ARIMA models for each company within the Nifty 50 index. The ARIMA model itself is a powerful tool that takes into account historical trends and fluctuations in the data to generate forecasts for future values. To build these models, we delve into the data using two specific functions - autocorrelation and partial autocorrelation. These functions essentially help us identify patterns in how past price changes are statistically related to future movements. By incorporating this understanding of historical price behaviour, the ARIMA model can make more informed predictions about the potential direction of stock prices within the Nifty 50.

Having established the suitability of the percentage change data for modelling through stationarity tests, we were ready to construct the ARIMA model itself. ARIMA stands for Autoregressive Integrated Moving Average, and it's a powerful technique specifically designedfor time series forecasting. This model incorporates three key components:

- **Autoregressive (AR) dynamics with P-lag:** This component considers the impact of past price changes on future movements. In simpler terms, the AR part of the model analyzes how a stock's price movement today might be influenced by its price movements P days ago. We explore various values of P (called the lag) to determine the optimal number of past data points to consider for the model.
- **Differencing (D) to achieve stationarity:** As mentioned earlier, stationarity is crucialfor time series models. While our data transformation ensured a certain level of stability,the differencing (D) component might be necessary to completely eliminate anyremaining trends or seasonality. This step essentially involves taking the difference between subsequent data points in the time series, effectively removing any underlyingtrends and highlighting the relative changes. The value of D (the degree of differencing)is determined through statistical analysis to achieve the most stationary form of the data.
- **Moving Average (MA) with Q-lag components:** The final piece of the ARIMA puzzleis the Moving Average (MA) component. This part of the model considers the averageof past forecast errors (the difference between predicted and actual values) over the pastQ periods. By incorporating this average error, the model can adjust its future forecaststo account for any systematic biases it might have exhibited in the past Q predictions. The value of Q (the lag) is also chosen through statistical analysis to identify the optimalwindow of past errors to consider.

We meticulously constructed individual ARIMA models for each of the 50 stocks within the Nifty 50 index. This process involved analyzing 1,277 data points for each company, spanningfrom January 2018 to February 2023. The goal was to develop a model that could effectively capture the historical price movements and use that understanding to predict future share values.
To assess the effectiveness of each custom-built ARIMA model, we employed a battery of statistical metrics. These metrics, including Root Mean Square Error (RMSE), Mean AbsolutePercentage Error (MAPE), Mean Absolute Error (MAE), and R-Square value, provided valuable insights into how well the model's predictions aligned with the actual stock

prices. Byanalyzing these metrics, we could identify the strengths and weaknesses of each model and potentially refine them for better accuracy.

Finally, with the optimal ARIMA model selected for each company, we put them to the real test - forecasting future share prices. We tasked each model with predicting the share prices forthe next 60 days in April. Once we had these forecasts, we compared them with the actual market prices that occurred in April. This comparison again involved utilizing RMSE, MAPE,and Mean Square Error (MSE) to determine how closely the model's predictions mirrored reality. By evaluating the accuracy of these forecasts, we could gain valuable insights into themodel's effectiveness in predicting stock prices within the Nifty 50 index.

Data Analysis:

The line diagram of daily closing share price for each company is shown below in Figure 1.

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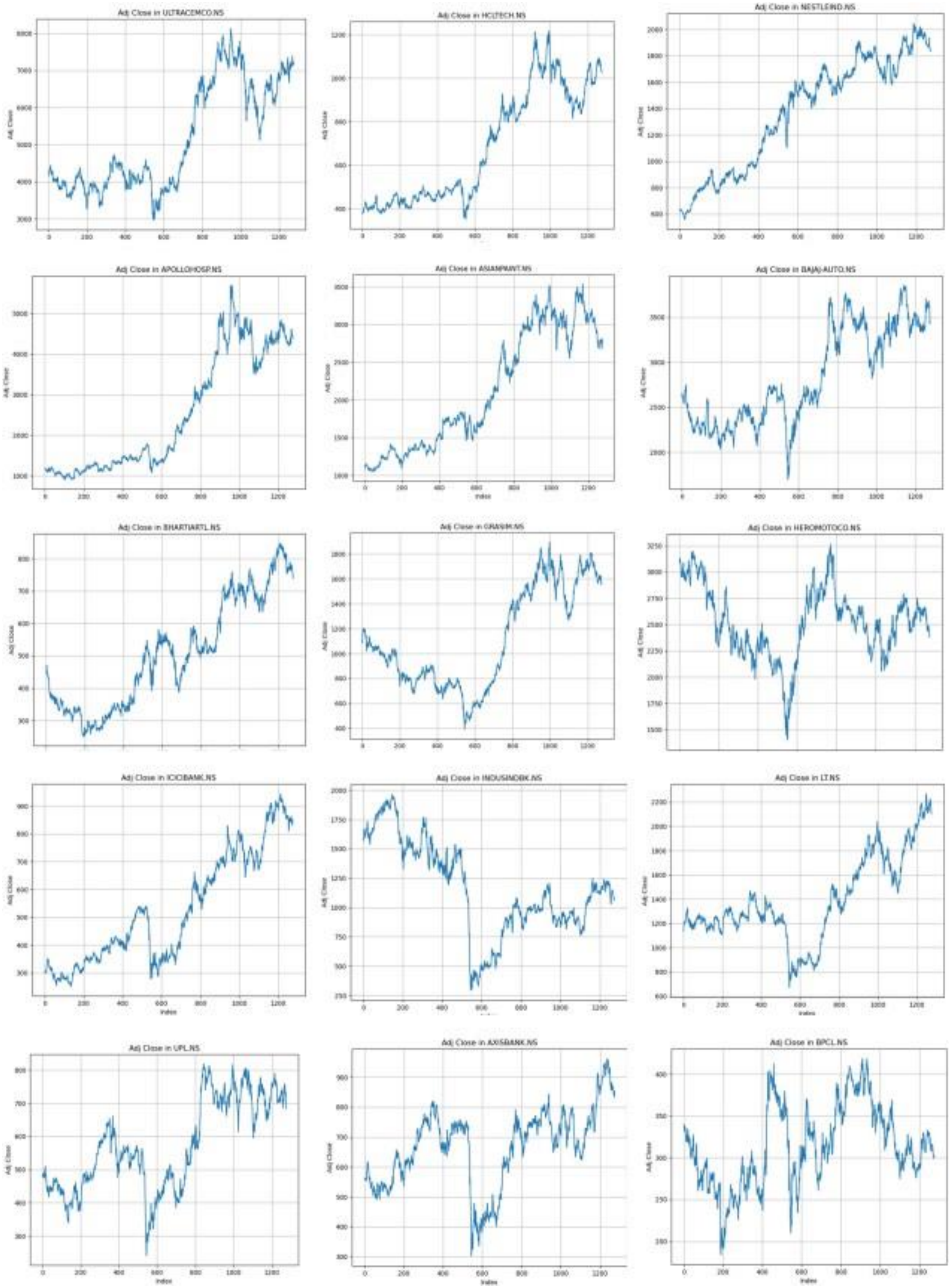

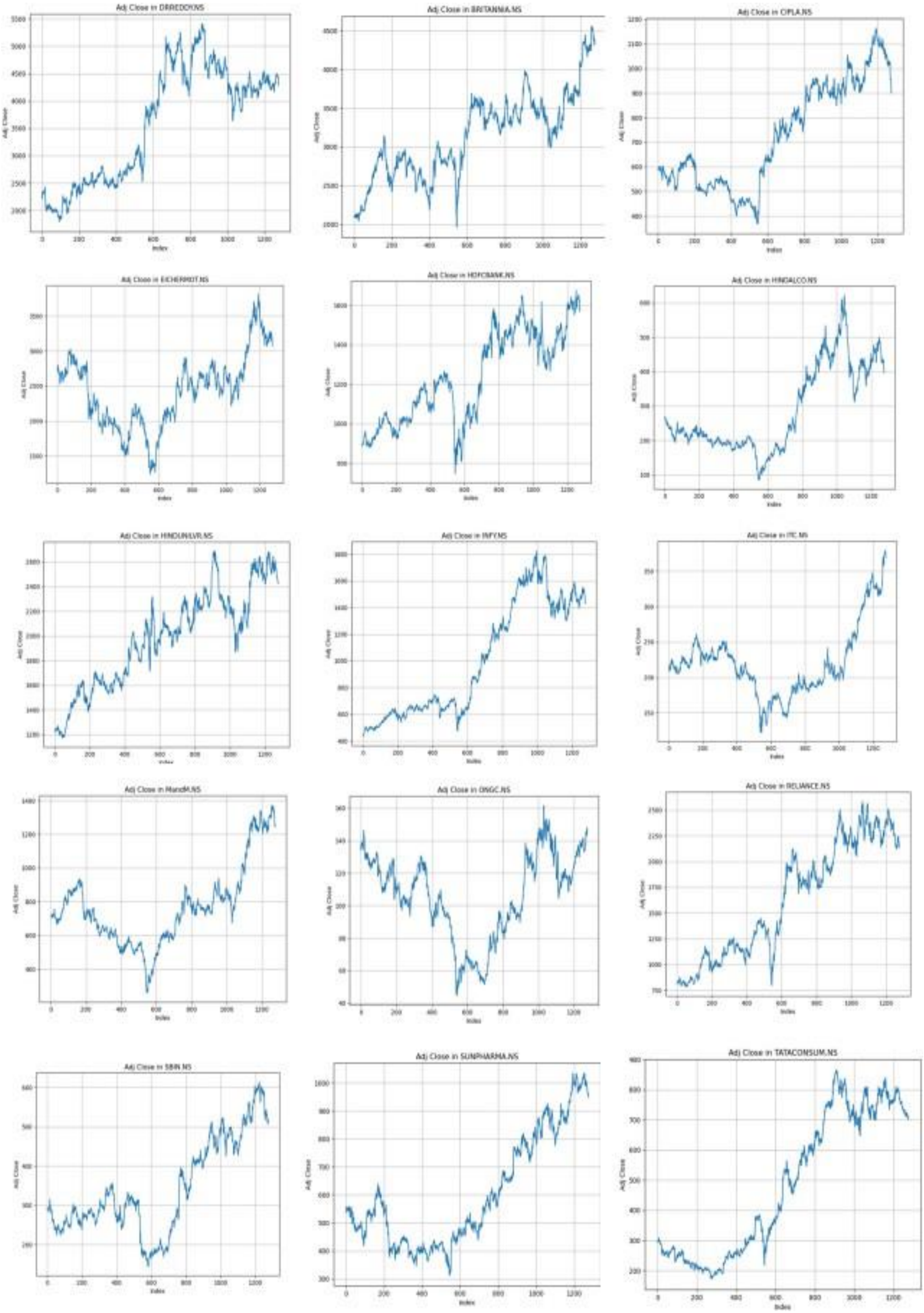
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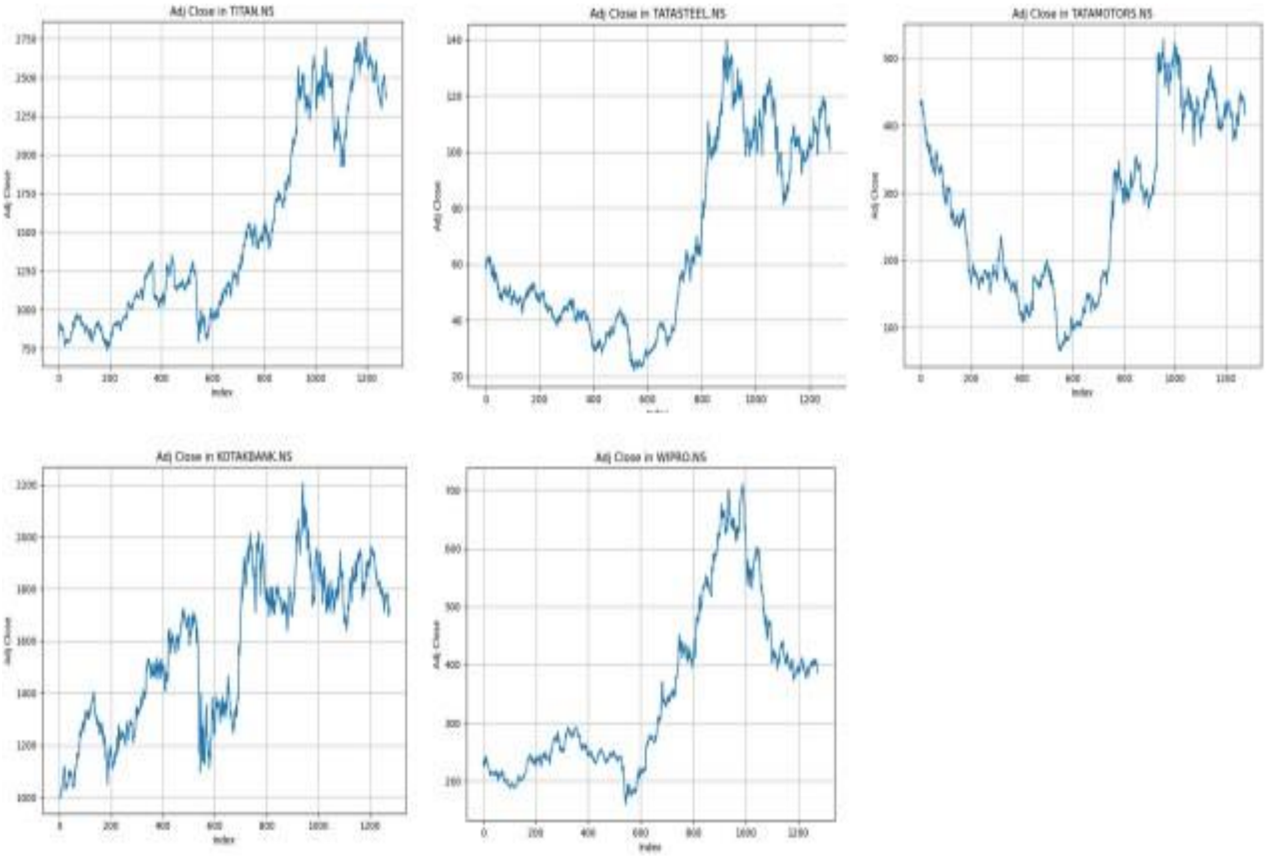


Figure 1: Line diagram of closing price

Based on the analysis of the provided data, it is evident that there is no discernible trend in theclosing prices of the stocks under consideration. Consequently, the Augmented Dickey-Fuller(ADF) test conducted on the closing prices of all the aforementioned companies yielded p- values exceeding 0.05, indicating a lack of significance. To address this, percentage changes inclosing prices were calculated, and subsequent ADF tests were performed. The test statistics Z (t) for Augmented Dickey-Fuller Test varies from -37.398 to -6.620 (with p-value 0.00E+00 to 6.04E-9). These tests yielded p-values below 0.05, indicating statistical significance. Consequently, the ADF tests were conducted on the percentage changes in closing prices for all the companies in the Nifty50 index. Thus, we accept Alternate Hypothesis 2 while rejectingNull Hypothesis 2, leading to the conclusion that the share price data exhibit non-stationarity,whereas the percentage changes are stationary. Therefore, the Augmented Dickey-Fuller test was carried out, and the pertinent data and results are presented in Table 1 for reference.

Table 1: Augmented Dickey-Fuller Test and Model selection result

Companies	ADF Statistic	p-value	Model Selection
SBI Life Insurance Company Ltd.	-17.141	7.05E-30	ARIMA(2, 0, 2)
LTIMindtree Ltd.	-7.525	3.71E-11	ARIMA(0, 0, 0)
HDFC Life Insurance Company Ltd.	-12.541	2.31E-23	ARIMA(0, 0, 0)
Coal India Ltd.	-10.975	7.73E-20	ARIMA(0, 0, 0)
Adani Ports and Special Economic Zone Ltd.	-15.038	9.67E-28	ARIMA(0, 0, 0)
Power Grid Corporation of India Ltd.	-16.258	3.59E-29	ARIMA(2, 0, 2)
Tech Mahindra Ltd.	-12.371	5.29E-23	ARIMA(1, 0, 2)

NTPC Ltd.	-14.189	1.87E-26	ARIMA(0, 0, 0)
Maruti Suzuki India Ltd.	-11.801	9.32E-22	ARIMA(0, 0, 0)
JSW Steel Ltd.	-8.736	3.10E-14	ARIMA(1, 0, 2)
Divi's Laboratories Ltd.	-35.674	0.00E+00	ARIMA(2, 0, 2)
Adani Enterprises Ltd.	-6.621	6.04E-09	ARIMA(2, 0, 2)
Bajaj Finserv Ltd.	-8.213	6.75E-13	ARIMA(0, 0, 0)
Bajaj Finance Ltd.	-8.001	2.34E-12	ARIMA(0, 0, 0)
Tata Consultancy Services Ltd.	-14.956	1.26E-27	ARIMA(0, 0, 1)
UltraTech Cement Ltd.	-9.763	7.48E-17	ARIMA(2, 0, 1)
HCL Technologies Ltd.	-12.306	7.27E-23	ARIMA(1, 0, 2)
Nestle India Ltd.	-11.570	3.12E-21	ARIMA(3, 0, 0)
Apollo Hospitals Enterprise Ltd.	-10.092	1.12E-17	ARIMA(0, 0, 0)
Asian Paints Ltd.	-37.225	0.00E+00	ARIMA(1, 0, 0)
Bajaj Auto Ltd.	-37.398	0.00E+00	ARIMA(1, 0, 0)
Bharti Airtel Ltd.	-27.142	0.00E+00	ARIMA(0, 0, 2)
Grasim Industries Ltd.	-12.629	1.52E-23	ARIMA(0, 0, 3)
Hero MotoCorp Ltd.	-26.958	0.00E+00	ARIMA(0, 0, 0)
ICICI Bank Ltd.	-14.551	4.96E-27	ARIMA(0, 0, 1)
IndusInd Bank Ltd.	-10.967	8.04E-20	ARIMA(2, 0, 2)
Larsen & Toubro Ltd.	-11.122	3.44E-20	ARIMA(0, 0, 1)
UPL Ltd.	-23.019	0.00E+00	ARIMA(0, 0, 2)
Axis Bank Ltd.	-36.198	0.00E+00	ARIMA(0, 0, 0)
Bharat Petroleum Corporation Ltd.	-13.155	1.34E-24	ARIMA(2, 0, 1)
Dr. Reddy's Laboratories Ltd.	-34.883	0.00E+00	ARIMA(0, 0, 0)
Britannia Industries Ltd.	-9.465	4.25E-16	ARIMA(0, 0, 0)
Cipla Ltd.	-19.368	0.00E+00	ARIMA(3, 0, 0)
Eicher Motors Ltd.	-36.365	0.00E+00	ARIMA(0, 0, 0)
HDFC Bank Ltd.	-12.735	9.21E-24	ARIMA(5, 0, 3)
Hindalco Industries Ltd.	-12.699	1.09E-23	ARIMA(1, 0, 0)
Hindustan Unilever Ltd.	-12.430	3.95E-23	ARIMA(0, 0, 1)
Infosys Ltd.	-13.479	3.27E-25	ARIMA(0, 0, 0)
ITC Ltd.	-10.492	1.14E-18	ARIMA(2, 0, 2)
Mahindra & Mahindra Ltd.	-13.461	3.53E-25	ARIMA(0, 0, 0)
Oil & Natural Gas Corporation Ltd.	-12.170	1.43E-22	ARIMA(2, 0, 3)
Reliance Industries Ltd.	-10.704	3.47E-19	ARIMA(0, 0, 0)

State Bank of India	-12.552	2.19E-23	ARIMA(0, 0, 0)
Sun Pharmaceutical Industries Ltd.	-15.400	3.23E-28	ARIMA(0, 0, 0)
Tata Consumer Products Ltd.	-13.612	1.87E-25	ARIMA(0, 0, 0)
Titan Company Ltd.	-23.898	0.00E+00	ARIMA(0, 0, 0)
Tata Steel Ltd.	-8.154	9.50E-13	ARIMA(0, 0, 0)
Tata Motors Ltd.	-23.874	0.00E+00	ARIMA(1, 0, 1)
Kotak Mahindra Bank Ltd.	-15.907	8.20E-29	ARIMA(0, 0, 3)
Wipro Ltd.	-35.751	0.00E+00	ARIMA(0, 0, 0)

Delving into the realm of financial forecasting using time series analysis necessitates meticulous attention to a fundamental concept: stationarity. In essence, stationarity implies thatthe statistical properties of the data, such as mean and variance, remain relatively constant overtime, absent of any trends or seasonal fluctuations. These fluctuations can significantly distortthe results of time series models, leading to inaccurate or misleading forecasts.

In the context of our investigation into the Nifty 50 index, we initially examined the closing prices of the 50 constituent companies over a five-year period spanning January 2018 to February 2023. Upon closer inspection, it became readily apparent that the closing price data exhibited a discernible trend, either upward or downward, over the course of the analysis window. This inherent trend violates the core assumption of stationarity that underpins the efficacy of time series models like ARIMA. To illustrate, imagine a stock price consistently increasing over time; a model built on such data would likely predict continued upward movement even if the underlying market conditions had shifted, leading to a potentially significant forecast error.

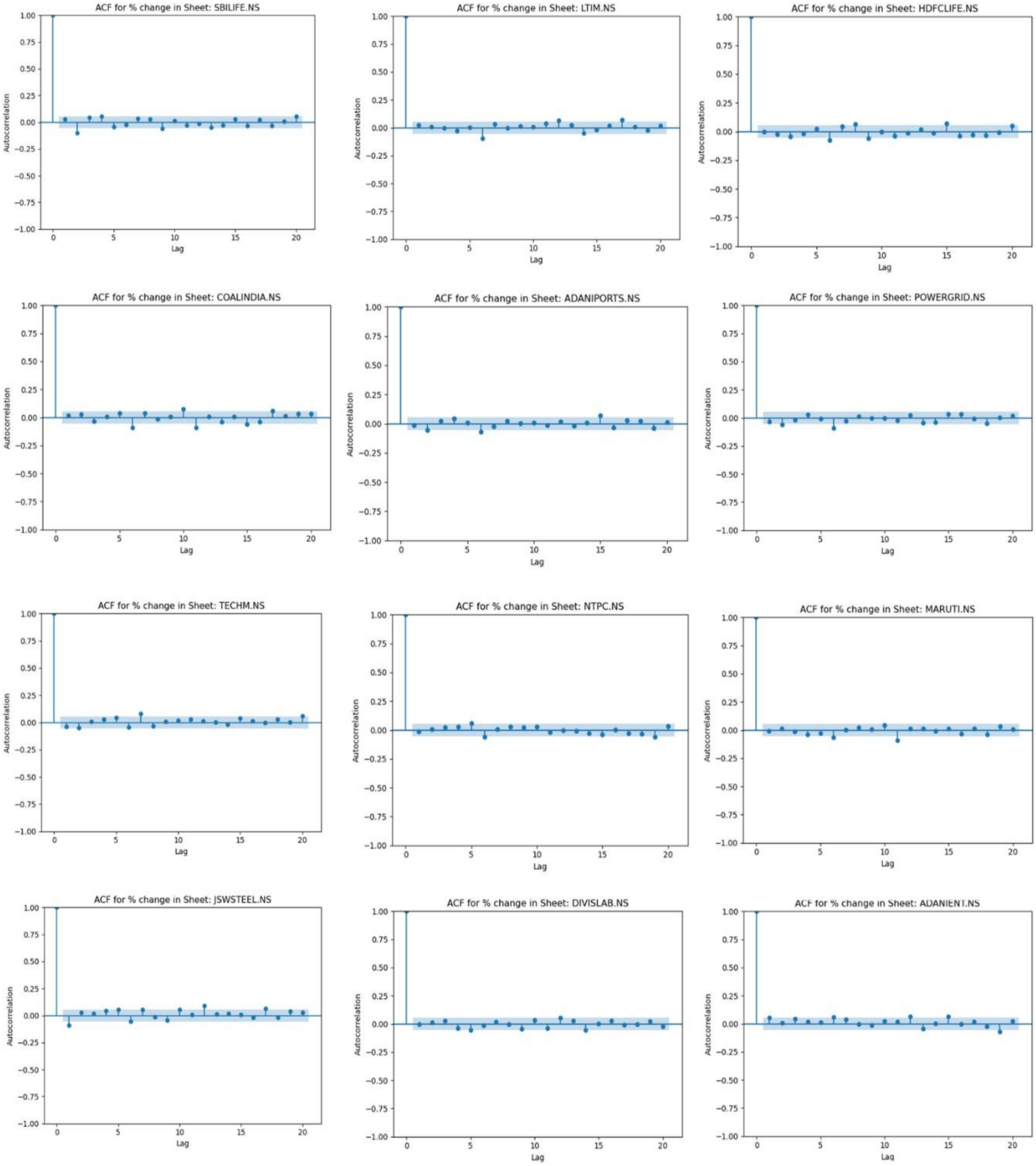
Recognizing this limitation, we employed a robust statistical test known as the Augmented Dickey-Fuller (ADF) test to formally assess the stationarity of the closing price data for each company. The ADF test specifically targets the presence of a "unit root," a statistical characteristic indicative of non-stationarity. As anticipated, the results of the ADF test on the closing prices yielded p-values exceeding 0.05, which statistically signifies a lack of significance. In simpler terms, the test results confirmed our visual observation - the closing prices exhibited a trend and were not inherently suitable for direct application within our chosen time series model.

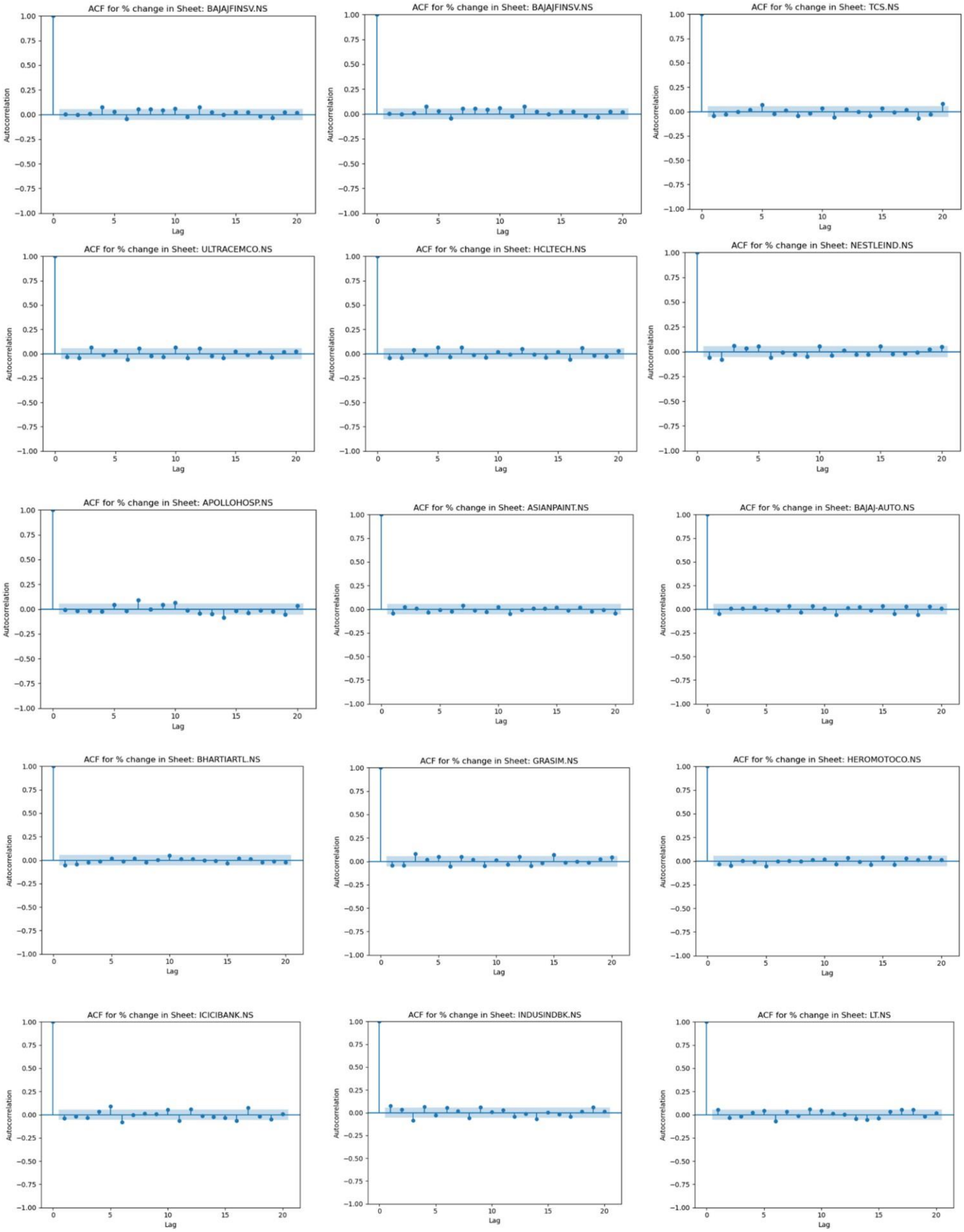
However, this initial setback did not deter us from our pursuit of leveraging time series analysisfor stock price prediction within the Nifty 50. Financial data, by its very nature, can often be strategically transformed to make it more amenable to time series modelling techniques. In ourcase, we hypothesized that by calculating the percentage change in closing prices for each company, we might be able to effectively remove the long-term trend and achieve the desiredlevel of stationarity. This data transformation essentially focuses on the relative price movements of the stocks rather than their absolute values. By analyzing the percentage changes, we can potentially strip away any underlying trends and isolate the more nuanced fluctuations in price movements, potentially yielding data that aligns better with the assumptions of the ARIMA model.

To validate this hypothesis and formally assess the stationarity of the transformed data, we conducted subsequent ADF tests on the percentage changes in closing prices for all companieswithin the Nifty 50 index. This time, the results were far more encouraging. The test statisticsZ (t) for the Augmented Dickey-Fuller Test exhibited a wider range, varying from a low of -
37.398 to -6.620. Correspondingly, the associated p-values fell within a much narrower range,spanning from 0.00E+00 to 6.04E-9. These p-values, all falling well below the commonly accepted threshold of 0.05, indicate a very strong level of statistical significance. In simpler terms, the test results provided compelling evidence that the percentage changes in closing prices exhibited the desired level of stationarity. The data, having shed its long-term trend, wasnow perfectly suited for our ARIMA forecasting model.

Therefore, based on the findings of the ADF tests, we were able to confidently reject the nullhypothesis (which states that the data has a unit root and is non-stationary) for the percentage changes in closing prices. Conversely, we accepted the alternative hypothesis (which states thatthe data is stationary). The relevant data and results from the ADF tests for both closing pricesand percentage changes are summarized in Table 1 for your reference. This critical transformation process effectively paved the way for us to construct robust ARIMA models foreach company within the Nifty 50 index, bringing us a significant step closer to our goal of exploring the potential of time series analysis for stock price prediction within this key Indianstock market benchmark.

In our study of the Auto Regression Integrated Moving Average (ARIMA) model, a key toolfor time series research, we did a thorough examination using Python programming. Specifically, we used Python modules to compute the Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF), which are critical components in defining the orderof the ARIMA model. Figures 2 (ACF) and 3 (PACF) show the visual findings of our analysis,which provide insights into the autocorrelation and partial autocorrelation structures of the timeseries data under consideration.

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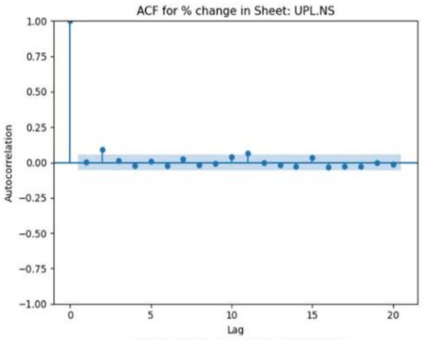

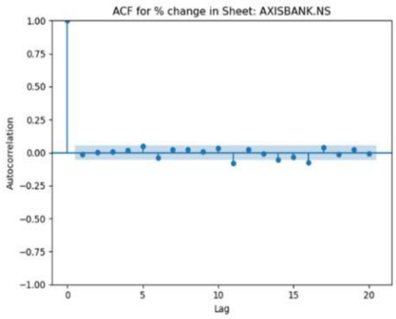

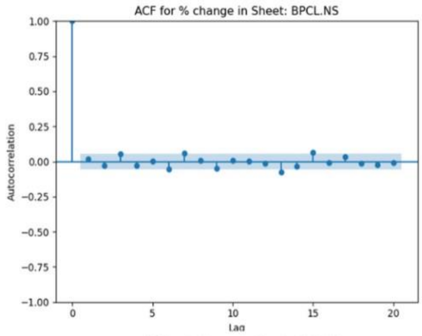

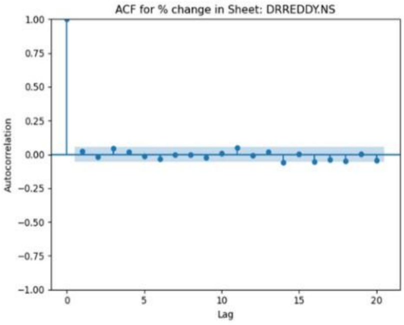

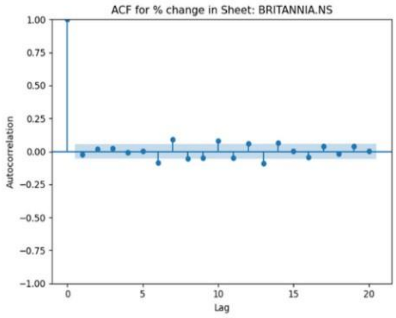

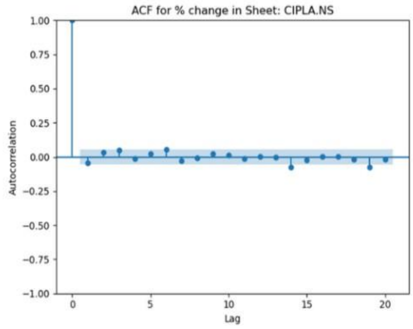

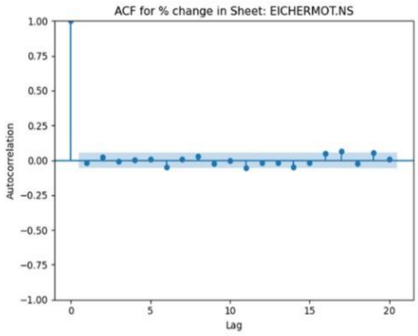

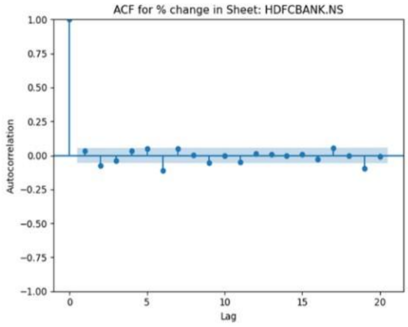

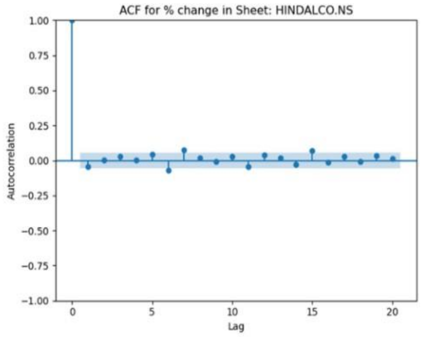

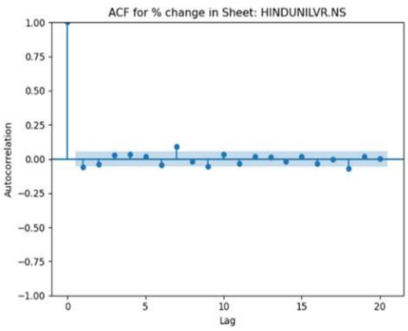

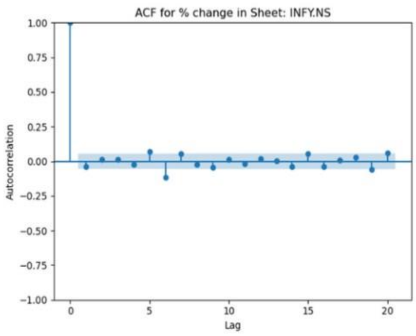

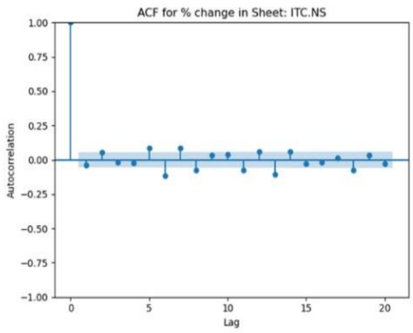

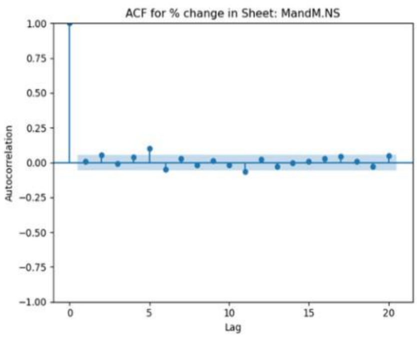

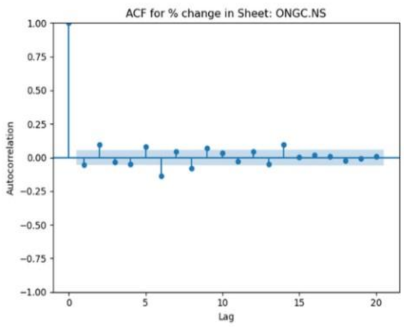

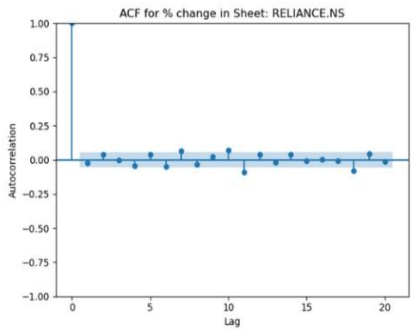

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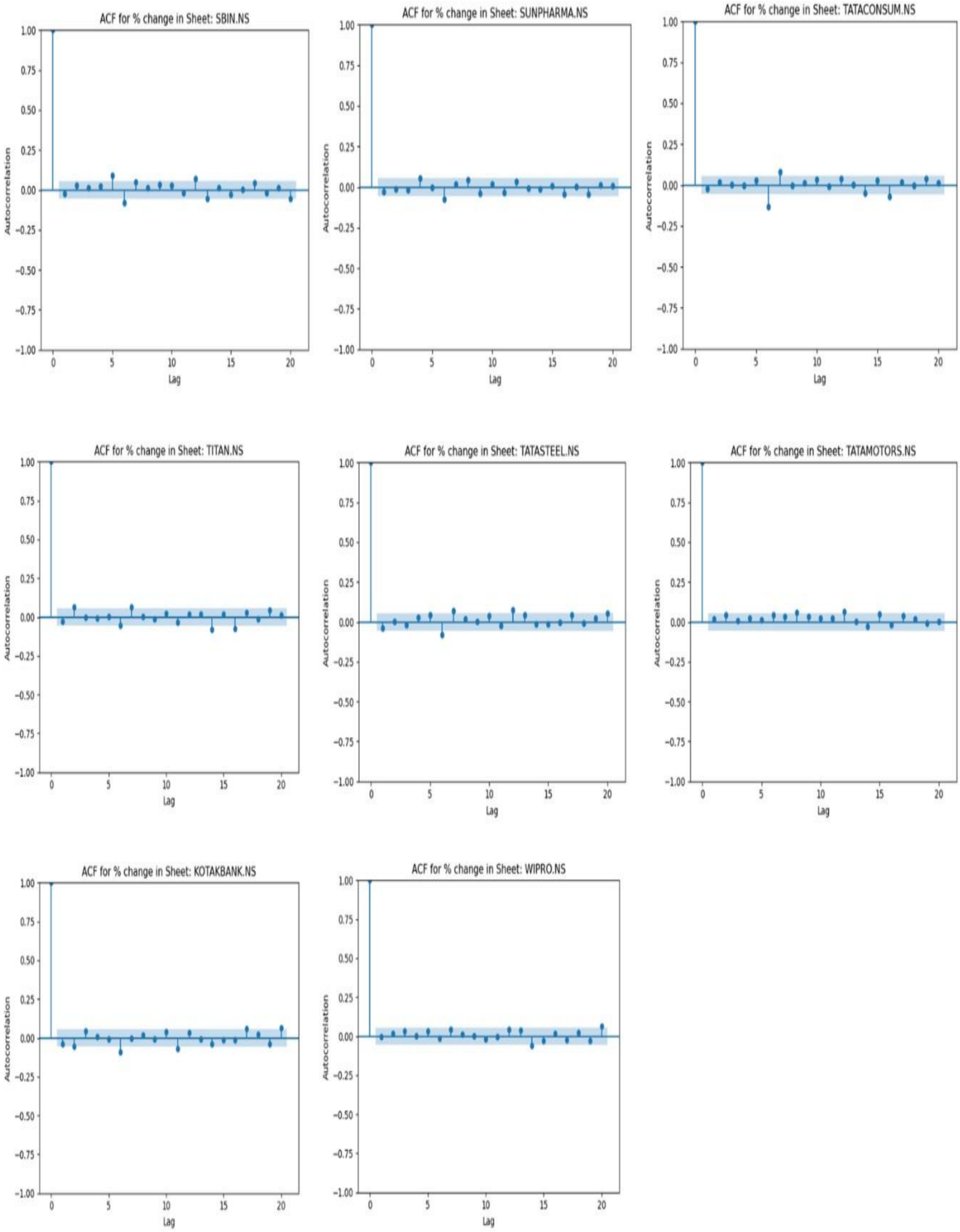
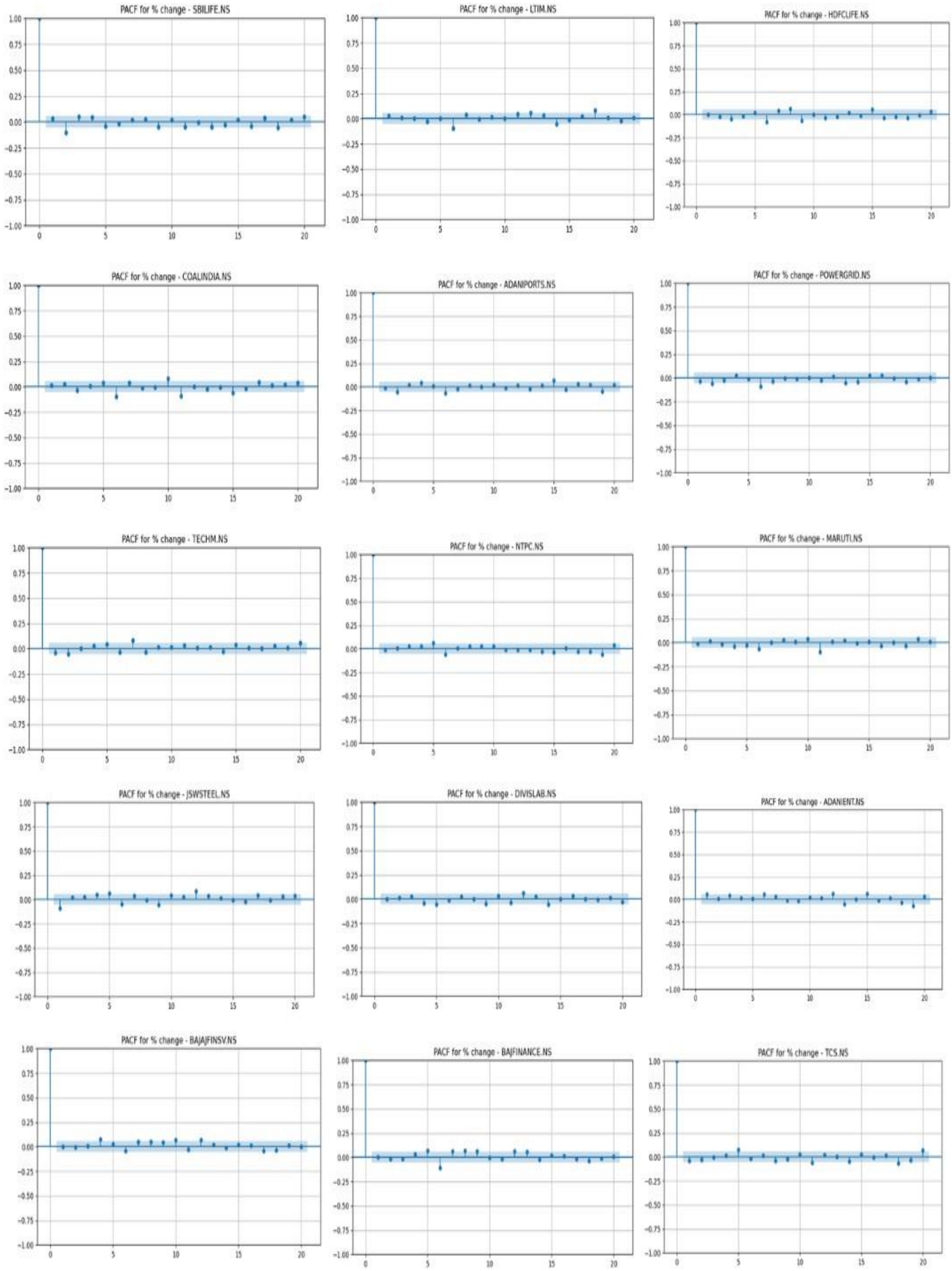


Figure 2: ACF Diagram on Percentage change of Adjusted Closing price of each stock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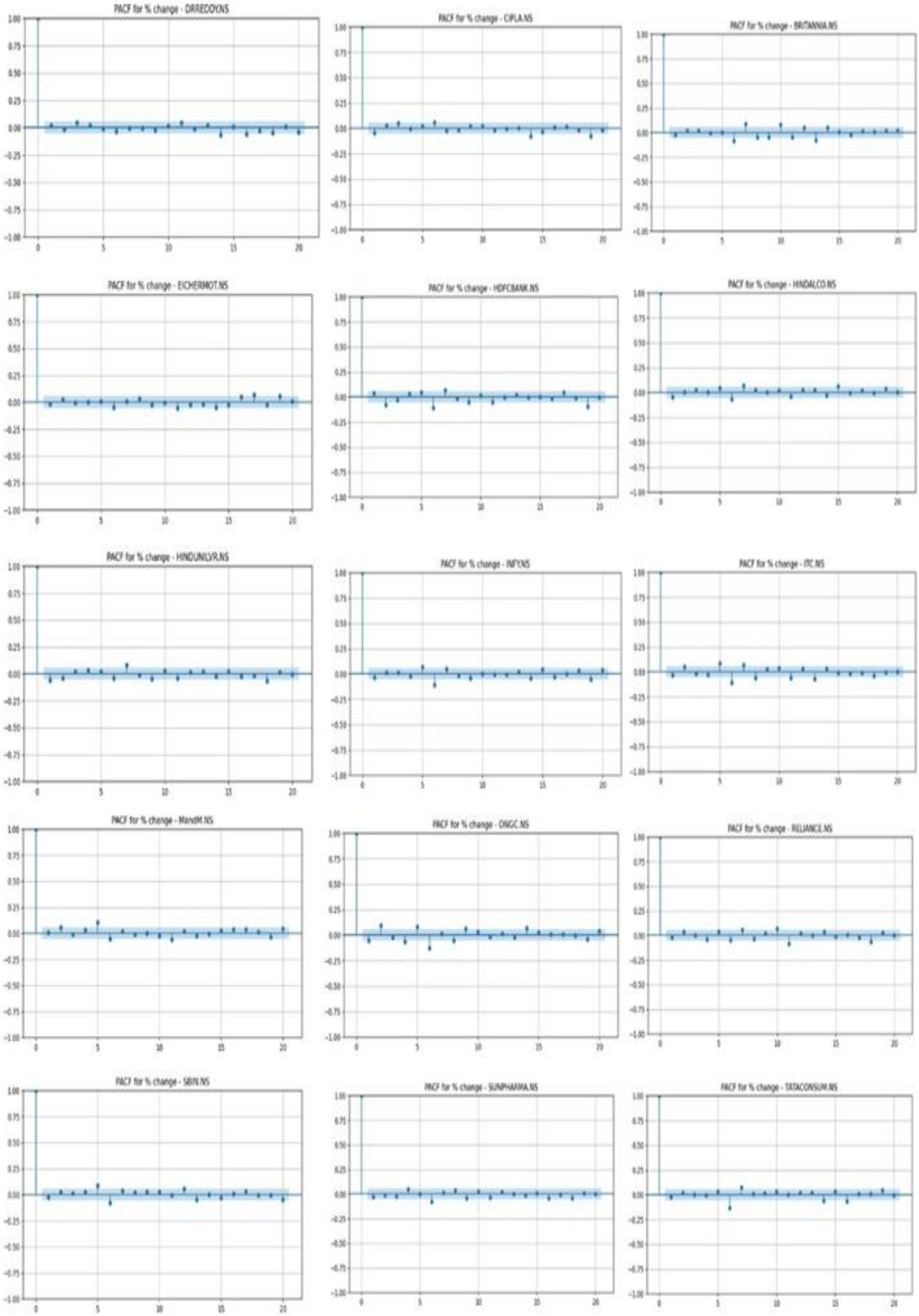

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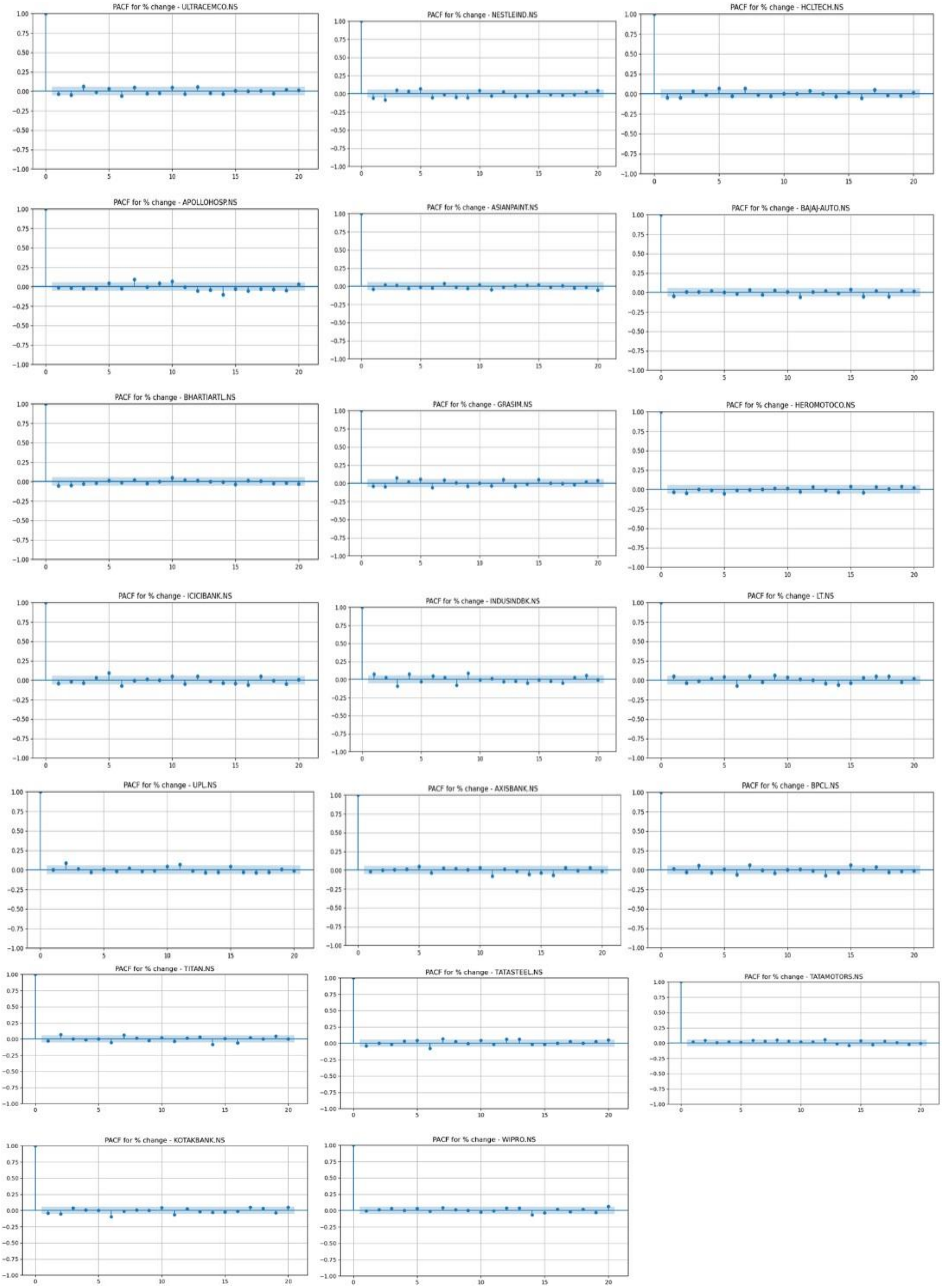

Figure 3: PACF Diagram on Percentage change of Adjusted Closing price of each stock

To effectively build the ARIMA models for each stock, we began by computing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). These functionsare crucial for identifying the order of the ARIMA model, which refers to the number of past lags of the time series data and the error terms incorporated into the model. The ACF helps visualize the correlation between a time series and its lagged versions, while the PACF isolatesthe impact of a specific lag from the influence of intervening lags. By analyzing these functions,we can determine the most appropriate number of autoregressive (AR) terms and moving average (MA) terms to include in the ARIMA model, capturing the essential patterns influencing the stock price movements.

Once the ARIMA models were built for each Nifty 50 stock, we utilized them to generate forecasts for three distinct timeframes: 30 days, 60 days, and 180 days. This allowed us to assess the model's effectiveness in predicting stock prices across different horizons. To evaluatethe accuracy of these forecasts, we employed three well-established error metrics: Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). Each metric provides valuable insights into the magnitude and distribution of forecast errors. MAPE expresses the error as a percentage of the actual value, offering a relativemeasure of prediction accuracy. MAE reflects the average absolute difference between the predicted and actual values, providing a straightforward measure of error in the same units as the data. RMSE squares the forecast errors before averaging them, giving greater weight to larger errors.

By comparing the MAPE, MAE, and RMSE values across the three timeframes, we were ableto identify the timeframe that yielded the most accurate forecasts. As presented in Table 2, the 30-day forecast window consistently exhibited the lowest error values across all three metrics.The significantly lower RMSE of 90.38 for the 30-day forecasts compared to 121.86 for 60 days and 216.96 for 180 days underscores the superior accuracy of the short-term predictions.Similarly, the MAPE and MAE values followed the same trend, with the 30-day forecasts demonstrating the least deviation from the actual stock prices. These findings suggest that theARIMA models were most effective in capturing short-term trends and predicting near-futurestock movements within the Nifty 50 index.

Table 2: Average of RMSE, MAE and MAPE for all nifty 50 stocks for different time frame

Time frame	**RMSE**	**MAPE**	**MAE**
30 days	90.3893	3.793976	76.6037
60 days	121.8675	5.169607	102.7885
180 days	216.9662	8.816693	188.2541

These findings emphasize the importance of timing in the ARIMA model's forecasting accuracy. As a result, the null hypothesis 1 that there is no change in accuracy across timeframesis rejected. The alternative hypothesis 1, which proposes changing accuracy over times, is upheld. Thus, our analysis offers compelling evidence that period selection influences the efficacy of ARIMA model predictions, underlining the significance of careful attention when setting forecasting timeframes.

Table 3: Average of RMSE, MAE and MAPE for Financial Services and Remaining Industries

Industry	**RMSE**	**MAE**	**MAPE**
Financial Services	79.15314606	70.25526816	3.243538085
Remaining industries	75.54417845	64.07772184	3.870088821

In our study, we addressed the unique composition of the Nifty50 index, which includes approximately 10 companies from the financial services sector. To evaluate the performance ofthe ARIMA model across different sectors, we opted to exclude these financial services companies and instead focused on the average performance of the remaining 40 companies spanning various industries. By doing so, we aimed to provide a more balanced comparison between the financial services sector and the broader spectrum of industries represented in the index. Our analysis, detailed in Table 3, juxtaposes key metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) for both the financial services sector and the remaining industries.

Upon examination, we noted that the RMSE for the financial services sector stands at 79.15, marginally higher than the corresponding value of 75.54 for the remaining industries. Similarly,the MAE for financial services registers at 70.25, slightly surpassing the value of 64.07 observed for the remaining industries. Interestingly, while the MAPE for the financial servicessector is lower at 3.24 compared to 3.87 for the remaining industries, it is imperative to considerthe overall error metrics.

Despite the lower MAPE for the financial services sector, the cumulative RMSE and MAE values for this sector exceed those of the remaining industries. Although the disparity in errormetrics is not substantial, it warrants a careful evaluation of sector-specific performance withinthe ARIMA modelling framework.

Considering our findings, we conclude that the accuracy of the ARIMA model for the financialservices sector does not exhibit a significant advantage over that of the remaining industries. Thus, our analysis lends support to the acceptance of the null hypothesis, signifying the absenceof a notable discrepancy in accuracy across sectors, while rejecting the alternative hypothesis.These insights emphasize the importance of considering sector-specific dynamics when assessing the efficacy of forecasting models in financial analysis.

Table 4: Sector wise average of all the companies

Sector	**RMSE**	**MAE**	**MAPE**
Metals & Mining	126.8946	122.7903	7.8640
Services	65.8107	60.4887	9.1039
Healthcare	132.2762	100.6361	3.1117
Consumer Durables	83.3918	70.6961	2.6999
Automobile and Auto Components	141.0475	115.9751	4.3959
Telecommunication	13.3328	11.1644	1.4658
Oil Gas & Consumable Fuels	26.3444	22.5810	3.2820
Fast Moving Consumer Goods	66.4501	59.5124	2.4503
Construction	114.5423	93.0128	2.6380
Information Technology	109.0388	88.4355	4.6535
Power	3.8739	3.2165	1.9133
Chemicals	23.5272	20.4237	2.8627
Financial Services	79.1531	70.2553	3.2435

Conclusion

In our investigation, we noted a significant outcome from the Augmented Dickey-Fuller test,indicating that the data attains stationarity when analysing percentage changes in adjusted closing prices. This suggests the presence of a seasonal trend within the data. Subsequently, when utilizing the ARIMA model to forecast future values, a discernible trend emerged - theaccuracy of the model diminishes as the forecasting horizon extends. Specifically, our analysis revealed that the ARIMA model yields the most accurate predictions for the shortest timeframe, namely the 30-day forecast, followed by the 60-day forecast, and then the 180-dayforecast.

Furthermore, we assessed the accuracy of the ARIMA model across different industries by examining the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Ranking these metrics from lowest to highest allowed usto identify sectors where the ARIMA model performs well for short-term forecasts. Notably, the sectors of Power, Telecommunication, Chemicals, Oil, Services, IT, Construction,

Healthcare, and Automobiles demonstrated relatively high accuracy for short-term forecasts.This suggests that the ARIMA model can be effectively applied within these sectors when analysing a substantial dataset.

Moreover, our analysis revealed an intriguing observation regarding the financial services sector. Despite its prominence in terms of the number of companies represented, our findingsindicate that the sector does not significantly influence the overall accuracy of the ARIMA model. This suggests that the presence of the financial services sector may skew the average error metrics, thereby affecting the perceived accuracy of the model.

In conclusion, our study suggests that the ARIMA model may be reliably applied to forecastfuture values of Nifty 50 stocks within the identified sectors, particularly for short-term forecasts.

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