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Forecasting Stock Prices and Volatility: A Time Series Modelling Using ARIMA and GARCH

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ABSTRACT

The analysis examines stock price data of HDFC BANK, WIPRO, and ONGC from 2020 to 2023, using ARIMA and GARCH models for forecasting low and high prices. The ARIMA models, selected based on AIC and BIC values, provided accurate and consistent forecasts with low errors. For example, the ARIMA (3,1,4) modelled HDFC BANK's low prices with high accuracy, as evidenced by a MAPE of 1.14%. Similarly, ARIMA (0,1,2) achieved precise forecasts for HDFC BANK's high prices, with an MAPE of 1.09%. GARCH models effectively captured volatility dynamics across all stocks. Key parameters, such as alpha1 and beta1, demonstrated significant contributions of past shocks and variances to current volatility, with high persistence observed in all cases. For instance, HDFC BANK's GARCH (1,1) model indicated strong volatility clustering, with α_1 at 0.075 and β_1 at 0.879. The results highlight that ARIMA models are robust for trend forecasting, while GARCH models are superior for understanding volatility dynamics. The study concludes that these models, applied with appropriate parameters, provide reliable predictions and insights into stock price behaviours, enabling better financial decision-making. Volatility trends suggest increasing risk over time across all analysed stocks.

1. Introduction

Investing in the stock market is challenging due to the volatile nature of stock prices. Analysis is crucial for simplifying the investment process, and it can be approached in two ways: Technical and fundamental analysis. Technical analysis examines stock price variations, while Fundamental analysis evaluates stocks

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based on factors like company news and analyst opinions. However, Fundamental analysis can be seen as less reliable since it may lack scientific grounding. (Ponnam *et al.*, 2016). Forecasting stock prices is a significant and widely studied topic in both finance and academia due to the numerous factors influencing the behaviour of these prices over time (Xu & Berkely, 2012). For data with less volatility, studies typically use the ARIMA approach, which was introduced by Box and Jenkins. This method involves a systematic class of models known as autoregressive integrated moving average (ARIMA) models, designed for time-correlated modelling and forecasting (Shumway & Stoffer, 2011). ARCH and GARCH models, introduced by Engle (1982) and Bollerslev (1986), effectively capture volatility (Dana, 2016). Forecasting stock market returns is an effective method for evaluating and diversifying a portfolio (Satrio *et al.*, 2021). The ARIMA model uses only prior data for forecasting. The ARIMA model enhances prediction accuracy while minimising parameters (Junior *et al.*, 2019). Stock market prices are primarily concerned with several key factors such as the opening prices, closing prices, lowest price, highest prices, adjusted closing prices, and trading volume. In technical analysis, the highest and lowest prices reflect the ongoing competition among various market forces. Trading volume indicates the level of market activity, while the closing price represents the equilibrium reached after this competition. It can also be viewed as the opening price for the next trading day. Additionally, the closing price of a trading day is not only influenced by that day's closing price but also has a connection to the closing price of the previous trading day (Mohamed *et al.*, 2017). Volatility fluctuation is common in stock markets, where high volatility is often followed by low volatility and vice versa. Forecasting stock volatility is crucial for effective financial decision-making. This review examines the performance of various models—ARIMA, XGBOOST, GARCH, and LSTM—in predicting stock volatility. Evaluating these models can enhance practical applications in modern stock markets, potentially improving investor profitability. The ARIMA model, a classic time series forecasting tool, consists of autoregressive (AR), moving average (MA), and differencing (I) components, and is effective at capturing linear relationships between variables (Ariyo *et al.*, 2014).

2. Review of Literature

Srihari *et al.* (2024) conducted a study that utilises ARIMA and GARCH models to forecast stock prices and analyse return volatility. The ARIMA models are specifically employed for price forecasting, while the GARCH models assess volatility. Adhikari (2024) proposed a hybrid ARIMA-GARCH model that captures linear trends and temporal dependencies through ARIMA, while GARCH addresses volatility clustering in financial time series. This combination enhances the accuracy of stock index predictions, specifically for the NEPSE index, between stock price movements and their corresponding volatility. Feng (2023) introduced the GARCH (Generalised Autoregressive Conditional Heteroskedasticity) model, which complements the ARIMA (Autoregressive Integrated Moving Average) model by effectively modelling volatility in financial time series. The ARIMA-GARCH model captures both the dynamic behaviour and volatility characteristics of stock prices, thereby enhancing predictive accuracy. Fadhilah *et al.* (2024) introduced the ARIMA-GARCH model, which combines the Autoregressive Integrated Moving Average (ARIMA) for forecasting stock returns with Generalized Autoregressive Conditional Heteroskedasticity (GARCH) to address volatility and heteroskedasticity in financial time series data. Hillmer and Tiao (1982) applied the ARIMA technique for seasonal adjustment and to decompose time series data into its components, such as trend, seasonality, and noise. This analysis assumes that the time series follows the Gaussian ARIMA model. Floros (2008) employed the GARCH model and its variants to analyse volatility and financial market risk using daily data from Egypt's CMA General Index and Israel's TASE-100 Index. The analysis revealed that the Egyptian CMA index was the most volatile due to economic and price uncertainties during the period studied.

While several studies analyse closing prices of the stock market data, there is limited research on the predictive significance of low and high prices. An attempt has been made to examine how high and low prices data across diverse sectors like IT, finance and energy can help to improve forecasting models and provide deeper insights into market behaviour and sectoral risk assessment.

3. Methodology

ARIMA: The ARIMA model makes use of time series to forecast future data trends by providing insight into past data. The general equation of an ARIMA model is given below

$$\hat{y}_t = c + \emptyset_1 y_{t-1} + \cdots + \emptyset_p y_{t-p} - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q} + e_t$$

ARIMA uses autoregressive (AR) and moving average (MA) components, modelled as (p,d,q)(p, d, q). Here, pp is the AR component, dd represents differencing for stationarity, and qq is the MA component. ARIMA is applied to analyse stock trends, helping to visualise and evaluate stock performance. Before modelling, the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots are used to check for stationarity. The ACF and PACF plots are key in determining the ARIMA model. If the nature of the data is not stationary, differencing is applied. ACF and PACF plots of the differenced data help check for stationarity, indicating when to proceed with ARIMA modelling.

GARCH MODEL: Heteroscedastic conditional autoregressive (ARCH) models, introduced by Engle (1982), are widely used for forecasting high volatility. These models capture time-varying variance (heteroscedasticity) through a deterministic mapping of past errors. An ARCH model of order p≥0 is defined as:

$$y_t = \sqrt{h_t \epsilon_t}, \quad h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i {y^2}_{t-i}$$

Where $\in_t$~i.i.d. (0,1) and α_0>0,α_i ≥0. The generalised autoregressive conditional heteroskedasticity (GARCH) model extends ARCH by incorporating lagged conditional variances:

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i {y^2}_{t-i} + \sum_{j=1}^{q} \beta_j {h^2}_{t-j}$$

This process is denoted as GARCH (p,q). The conditional variance, h_t, varies over time, reflecting the time-varying volatility of the series.

Linear GARCH models may struggle with asymmetries in time series data. An alternative is the Exponential GARCH (EGARCH) model, which introduces nonlinearity. Model selection was based on Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), while parameters were estimated using maximum likelihood estimation (MLE). Forecasting utilises one-step-ahead predictions over a fixed horizon.

4. Sources of Data

The data required for the present study is secondary and has been compiled from an online source, viz., Kaggle. The daily adj. closing price of Wipro on the NSE is obtained from the website. The selection of Wipro, HDFC, and ONGC represents a strategic choice to analyse stock performance and volatility across three diverse and influential sectors of the Indian economy: information technology (Wipro), banking and finance (HDFC), and energy (ONGC). These companies are industry leaders with strong market presence, global reach, and varying risk-return profiles. Studying them allows for a comprehensive understanding of sector-specific dynamics and how different economic factors influence stock behaviour.

WIPRO*:* Wipro is a leading provider of IT, consulting, and business process outsourcing services worldwide. It uses cloud, analytics, robots, hyper-automation, cognitive computing, and emerging technologies to help clients succeed in the digital age. M.H. Hasham Premji founded Western India Vegetable Products (WIPRO) in 1945, and his son, Azim Premji, took over the company in 1966. Initially a food products manufacturer, Azim Premji diversified the company into personal computers and software from 1984 onwards (Ramamurti, 2001). Wipro's price-earnings ratio on the New York Stock Exchange is 70 or higher. It serves many Fortune 500 companies, offering software maintenance, research, and innovation services. Wipro was the first to receive the CMM-Level 5 accreditation from Carnegie Mellon University’s Software Engineering Institute. In India, it is also known for its ethical and competent business practices.

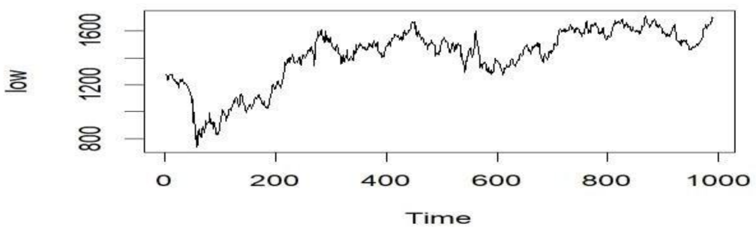
HDFC: HDFC Bank Limited, incorporated in 1994, is a Mumbai-based commercial bank with over 4,805 branches and 12,860 networked ATMs. The Reserve Bank of India gave its approval for the establishment of a private sector bank. Retail and wholesale banking, treasury, personal and vehicle loans, and digital goods are just a few of the goods and services that HDFC provides.

ONGC: ONGC, a major Asian oil company, is involved in oil exploration and production in India, producing 30% of the country's crude oil requirement. The company operates over 11,000 pipelines and diversified into the downstream sector in 2002-03. It also entered the retailing business and made significant investments in Vietnam, Sakhalin, and Sudan, earning its first hydrocarbon revenue from Vietnam.

5. Results and Analysis

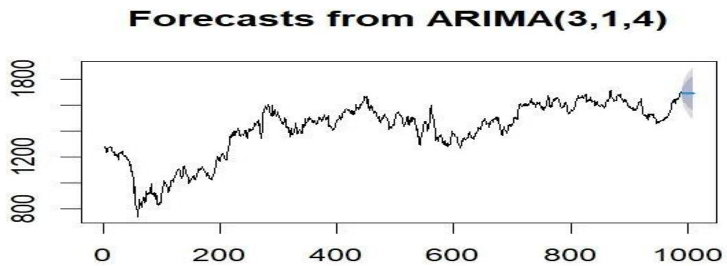
The analysis is conducted using low and high price data for HDFC BANK, WIPRO, and ONGC stocks from 2020 to 2023. The data for each stock is divided into 96% training set and 4 % testing set. The ARIMA and GARCH models were then applied to each stock's low and high prices.

Figure 1.1 Timeseries plot of daily low prices of HDFCBANK stock for the period from 2020 to 2023



In order to forecast low prices, we compared the AIC and BIC values with various values of parameter p and q. The optimum model for low price forecasting was determined to be ARIMA (3,1,4).

Figure 1.2 Forecast from ARIMA (3,1,4) model for Low prices of HDFC BANK stock



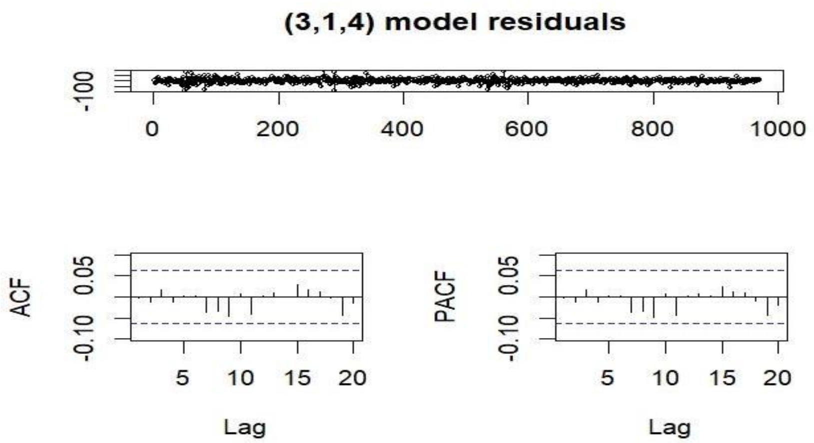
The plot of Figure 1.2, shows the forecast of a timeseries using an ARIMA (3,1,4) model. The data exhibits an upward trend with fluctuations, and the model includes three autoregressive terms, one differencing step. For stationarity, and four moving average terms. The forecast is marked by a blue point, with a shaded confidence interval that widens, indicating increasing uncertainty.

Table 1.1 Accuracy measures of the fitted ARIMA (3,1,4) model

RMSE	MAPE
20.78383	1.136721

The Mean Absolute Percentage Error (MAPE) of 1.136721 indicates that the model demonstrates high accuracy. The Root Mean Square Error (RMSE) of 20.78383 reflects the standard deviation of prediction errors, emphasising larger errors more due to its squared nature. Together, these metrics confirm that the ARIMA model provides both accurate and consistent forecasts.

Figure 1.3 Residual plot of ARIMA (3,1,4) model



The residuals plot reveals no discernible patterns or trends, implying that the residuals behave like white noise. This indicates that the model correctly captured the data's underlying structure. The ACF and PACF plots of the residual show that most of the spikes lie within the significance bounds, indicating that the residuals are uncorrelated. Therefore, the ARIMA (3,1,4) model appears to provide an adequate fit to the Low prices of HDFC BANK data.

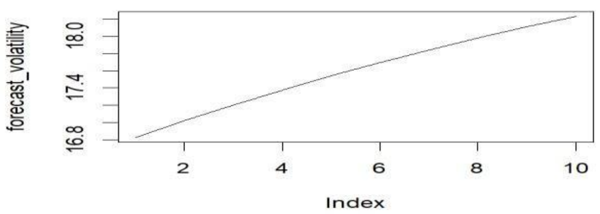
In order to fit the GARCH model, we varied the alpha and beta parameters. Then, by comparing the AIC and BIC values for each model, we succeeded in identifying GARCH (1,1) as the best model.

Table 1.2 Estimated Parameters of the GARCH (1,1) Model.

	Estimate	Std. Error	t value	Pr(>|t|)
Mu	1.2713e+03	18.930620	67.1576	0.000000
ar1	9.9696e-01	0.002724	366.0514	0.000000
ma1	1.6196e-01	0.035479	4.5651	0.000005
omega	1.9415e+01	6.761524	2.8713	0.004088
alpha1	7.5842e-02	0.016403	4.6237	0.000004
beta1	8.7868e-01	0.026947	32.6078	0.000000

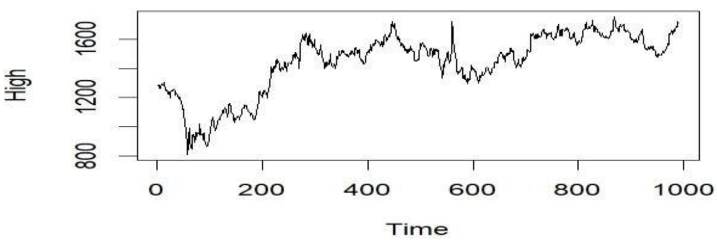
The GARCH model's optimal parameter values reveal critical insights into the volatility dynamics of the time series. The ARCH parameter α_1= 0.075842, indicates that recent shocks have a measurable but transient impact on volatility, ensuring that their influence dissipates over time. Meanwhile, the GARCH parameter β_1= 0.87868, demonstrates strong persistence in volatility, with past conditional variances contributing significantly to current volatility levels. The combination of a relatively small $\alpha_1$and a high value highlights a process characterised by volatility clustering, where shocks have a lasting but controlled influence, making the model effective for capturing and forecasting time-varying volatility.

Figure1.4 Forecasted volatility of Low prices of HDFC BANK stock



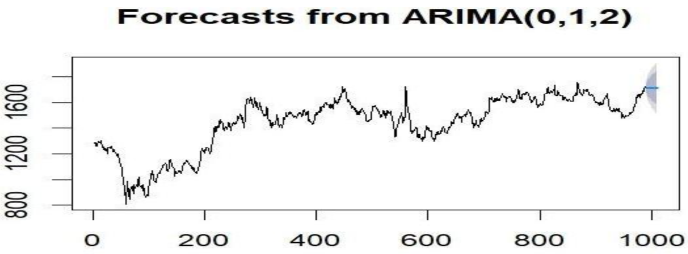
The trend in Figure 1.4 shows a steady increase in volatility over time, suggesting that the model predicts higher uncertainty or risk in the later periods.

Figure 1.5 Timeseries plot of daily high prices of HDFC BANK stock for the period from 2020 to 2023



In order to forecast high prices, we compared the AIC and BIC values with various values of parameter p and q. The optimum model for low price forecasting was determined to be ARIMA (0,1,2).

Figure 1.6 Forecast from ARIMA (0,1,2) model for High prices of HDFC BANK stock.



The plot of Figure 1.6, shows the forecast of a timeseries using an ARIMA (0,1,2) model. The data exhibits an upward trend with fluctuations, and the model includes one differencing step for stationarity, and two moving average terms. The forecast is marked by a blue point, with a shaded confidence interval that widens, indicating increasing uncertainty.

Table 1.3 Accuracy measures of the fitted ARIMA (0,1,2) model.

RMSE	MAPE
21.53048	1.090936

The Root Mean Square Error (RMSE) of 21.53048 indicates the average magnitude of prediction errors, with slightly higher sensitivity to large deviations. The Mean Absolute Percentage Error (MAPE) of 1.090936 highlights the model's high accuracy, as the average percentage error relative to the actual values is very low. These results suggest that the ARIMA model effectively captures the underlying patterns in the data and provides accurate forecasts with minimal error.

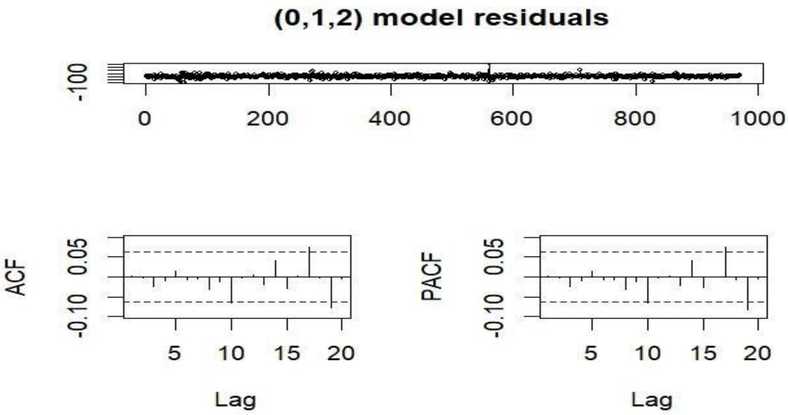
In order to fit the GARCH model, we varied the alpha and beta parameters. Then, by comparing the AIC and BIC values for each model, we succeeded in identifying GARCH (1,1) as the best model.

Table 1.4 Estimated Parameters of the GARCH (1,1) Model

	Estimate	Std.Error	t-value	Pr(>|t|)
mu	1280.86868	19.417910	65.9633	0.000000
ar1	0.99739	0.002662	374.6670	0.000000
ma1	0.11521	0.037648	3.0603	0.002211
omega	27.20662	10.186761	2.6708	0.007567
alpha1	0.08127	0.020826	3.9024	0.000095
beta1	0.86372	0.035105	24.6041	0.000000

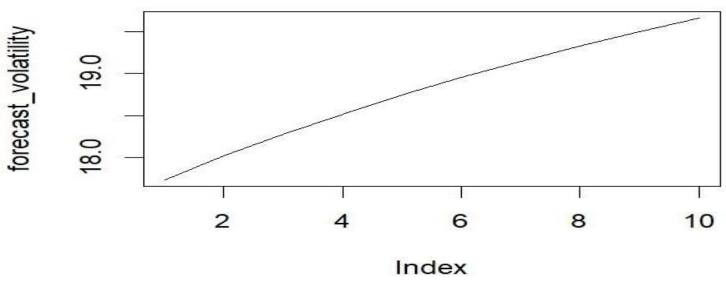
In the estimated GARCH model, the parameter α_1, with a value of 0.08127, measures the magnitude of the immediate impact of lagged squared residuals on conditional volatility. The statistically significant t-value and p-value indicates that this effect is highly significant, confirming that past innovations influence current volatility. The parameter β_1, with an estimate of 0.86372, represents the persistence of volatility over time, reflecting the contribution of the lagged conditional variance to the current conditional variance. The large and statistically significant t-value and p-value suggested strong persistence in volatility.

Figure 1.7 Residual plot of ARIMA (0,1,2) model



The residuals plot in Figure 1.7, shows no discernible patterns or trends, suggesting that the residuals behave like white noise. The ACF and PACF plots reveal that most of the residual autocorrelations fall within the significance bounds, indicating minimal autocorrelation. This suggests that the model has successfully captured the underlying nature of the data, and the remaining noise is random and uncorrelated.

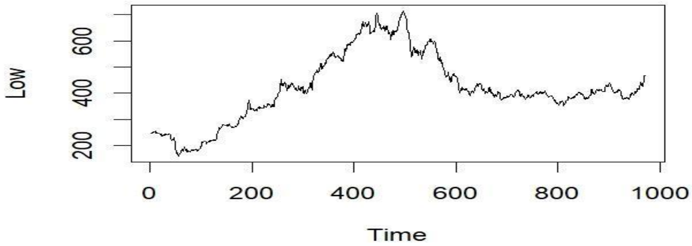
Figure 1.8 Forecasted volatility of High prices of HDFC BANK stock



The Figure1.8, shows a steady increase in volatility over time, suggesting that the model predicts higher uncertainty or risk in the later periods.

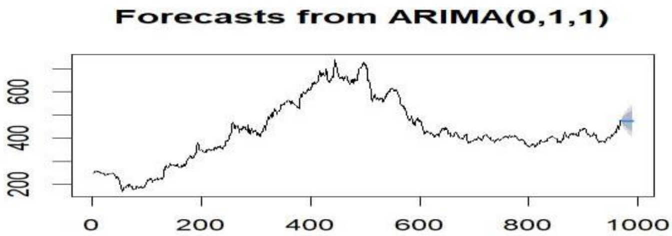
A similar process has been used with WIPRO stock price data.

Figure 2.1 Timeseries plot of daily low prices of WIPRO stock for the period from 2020 to 2023



In order to forecast low prices of WIPRO stock, we compared the AIC and BIC values with various values of parameters p and q. The optimum model for low price forecasting was determined to be ARIMA (0,1,1).

Figure 2.2 Forecast from ARIMA (0,1,1) model for Low prices of WIPRO stock.



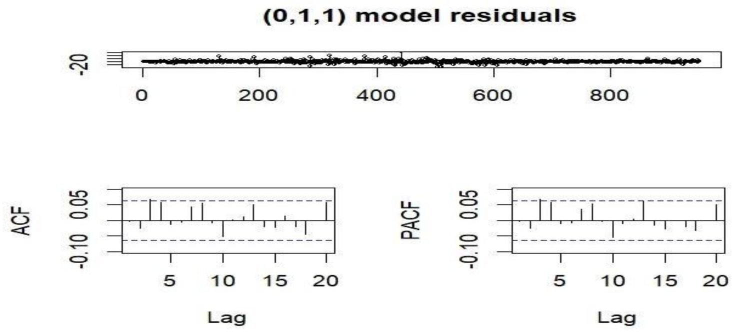
The ARIMA (0,1,1) model's forecast of a timeseries is displayed in the plot of Figure 3.2. One differencing step for stationarity and one moving average term are included in the model, and the data shows an increasing trend with variations. A shaded confidence interval that widens to represent growing uncertainty surrounds the forecast, which is represented by a blue point.

Table 2.1 Accuracy measures of the fitted ARIMA (0,1,1) model

RMSE	MAPE
6.93471	1.207802

The model's performance is evaluated using Root Mean Square Error (RMSE) of 6.93471 and a Mean Absolute Percentage Error (MAPE) of 1.207802. The RMSE indicates the model's average prediction error magnitude, with smaller values representing better accuracy. The low MAPE signifies that the model's forecasts deviate by only about 1.21% on average from the actual values, highlighting its strong predictive capability. These metrics collectively suggest that the ARIMA model achieves a good statistical fit and provides reliable forecasts.

Figure 2.3 Residual plot of ARIMA (0,1,1) model



It appears that the residuals behave like white noise since the residuals plot lacks any obvious patterns or trends. There is no autocorrelation indicated by the ACF and PACF plots, showing that the model has effectively represented the data's underlying structure.

Table 2.2 Estimated Parameters of the GARCH (1,1) Model

	Estimate	Std. Error	t value	Pr(>|t|)
mu	245.95705	4.922453	49.9664	0.000000
ar1	1.00000	0.001358	736.2780	0.000000
ma1	0.13359	0.036796	3.6307	0.000283
omega	2.07699	0.871473	2.3833	0.017158
alpha1	0.11951	0.042029	2.8434	0.004463
beta1	0.84792	0.049490	17.1331	0.000000

The model parameters are statistically significant, indicating an effective capture of volatility dynamics. The constant omega is estimated at 2.07699 with a t-value of 2.3833, reflecting its significance. The ARCH parameter α_1 is 0.11951 with a t-value of 2.8434, highlighting the impact of past shocks on current volatility. The GARCH parameter β_1 is 0.84792 with a high t-value of 17.1331, demonstrating strong persistence in volatility over time. These results confirm that the model appropriately captures the conditional variance structure.

Figure 2.4 Forecasted volatility Low prices of WIPRO stock

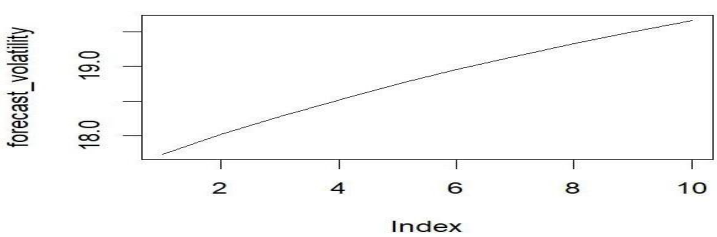
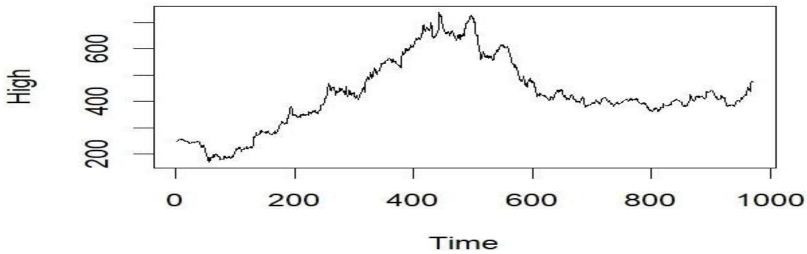


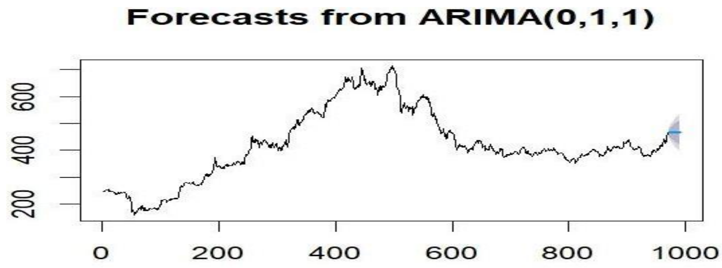
Figure 2.4 indicates a consistent rise in volatility over time, indicating that the model anticipates greater risk or uncertainty in subsequent periods.

Figure 2.5 Time series plot of daily high prices of WIPRO stock for the period from 2020 to 2023.



We compared the AIC and BIC values with different values of parameters p and q in order to predict High prices of WIPRO stock. ARIMA (0,1,1) is found to be the best model for forecasting.

Figure 2.6 Forecast from ARIMA (0,1,1) model for High prices of WIPRO stock.



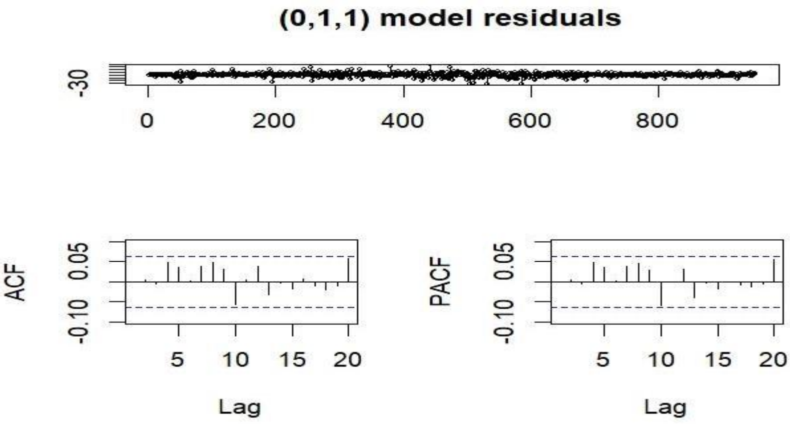
The plot shows time series data with forecasts from an ARIMA (0,1,1) model. The series trends upward, peaks, declines, and stabilises. Forecasts suggest a continuation of the recent trend with widening confidence intervals, reflecting increasing uncertainty over time.

Table 2.3 Accuracy measures of the fitted ARIMA (0,1,1) model.

RMSE	MAPE
7.41979	1.175146

The model's accuracy is assessed using Root Mean Square Error (RMSE) of 7.41979 and a Mean Absolute Percentage Error (MAPE) of 1.175146. The RMSE represents the average magnitude of prediction errors, where smaller values indicate better model fit. The MAPE, at approximately 1.18, signifies that the model's forecasts deviate from actual values by a very small percentage on average.

Figure 2.7 Residual plot of ARIMA (0,1,1) model



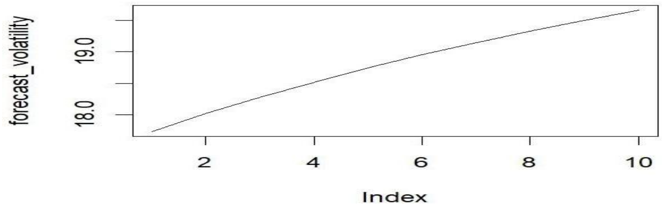
The residual plot for the ARIMA (0,1,1) model shows residuals fluctuating around zero, indicating no apparent trend or systematic pattern. The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots display most lags within the 95% confidence bounds, suggesting that the residuals are uncorrelated and resemble white noise. This indicates the ARIMA (0,1,1) model accurately reflects the underlying structure of the given data.

Table 2.4 Estimated Parameters of the GARCH (1,1) Model.

	Estimate	Std.Error	t-value	Pr(>|t|)
mu	248.437247	5.483923	45.3028	0.000000
ar1	1.000000	0.001324	755.5642	0.000000
ma1	0.103539	0.035167	2.9442	0.003238
omega	0.296589	0.140756	2.1071	0.035108
alpha1	0.033053	0.006436	5.1354	0.000000
beta1	0.964049	0.006499	148.3322	0.000000

The GARCH model parameters are statistically significant, indicating a robust representation of volatility dynamics. The constant omega is estimated at 0.296589 with a t-value of 2.1071, showing its relevance in the model. The ARCH parameter α_1, representing the impact of past shocks, is 0.033053 with a t-value of 5.1354, highlighting its significance. The GARCH parameter, β_1 which measures volatility persistence, is 0.964049 with an exceptionally high t-value of 148.3322, confirming the strong influence of past variances on current volatility.

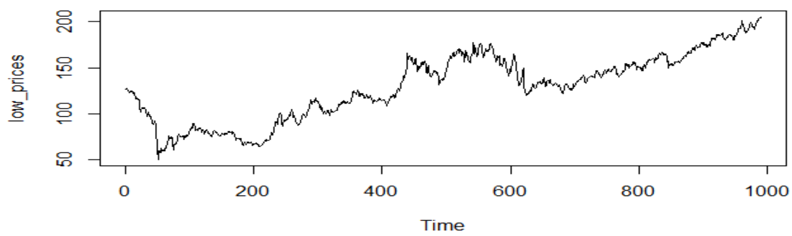
Figure 2.8 Forecasted Volatility High prices of WIPRO stock



The forecasted volatility exhibits a gradual upward trend, indicating an expected increase in market uncertainty or risk over time. The smooth curve suggests that the volatility estimates are stable and consistent, reflecting the model's ability to capture the persistence of volatility in the data.

A similar process has been used with ONGC stock prices data.

Figure 3.1 Time series plot of daily low prices of ONGC stock for the period from 2020 to 2023.



The daily low prices of ONGC stock from 2020 to 2023 show an initial decline, likely due to the COVID-19 pandemic, followed by recovery and an overall upward trend. This indicates resilience and growth in the stock over the period. The Augmented Dickey-Fuller (ADF) test results show a test statistic of -10.127, with a p-value of 0.01. Since the p-value is below the common significance level of 0.05, we reject the null hypothesis, indicating that the time series is stationary.

Figure 3.2 Forecast from ARIMA (2,1,0) model for Low prices of ONGC stock

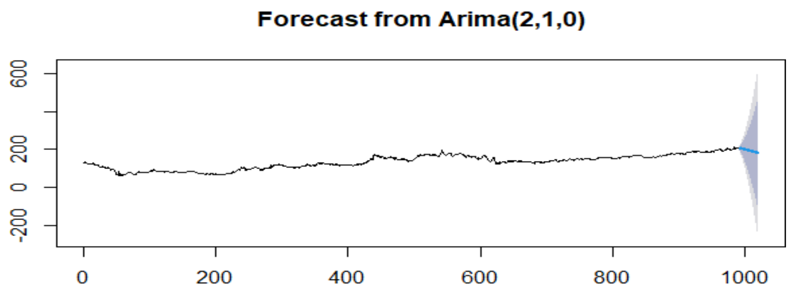
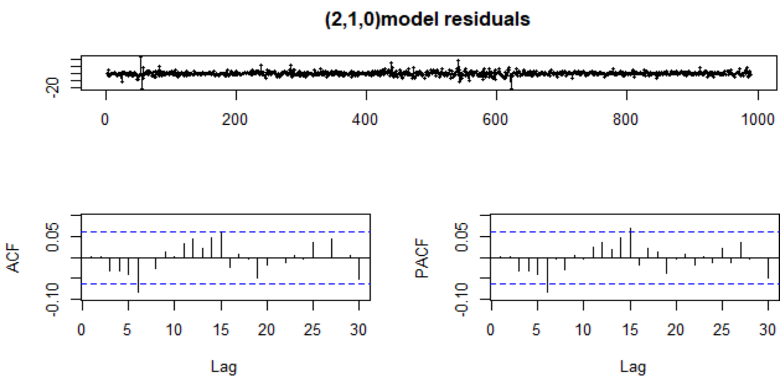


Table 3.1 Accuracy measures of the fitted ARIMA (2,1,0) model.

RMSE	MAPE
1.346593	1.123958

The low RMSE (1.34) and MAPE (1.12%) indicate that the forecasting model provides accurate predictions of ONGC stock's low prices, with minimal errors in both absolute terms and percentage deviation.

Figure 3.3 Residual plot of ARIMA (2,1,0) model.



The ARIMA (2,1,0) model shows well-behaved residuals that are randomly distributed around zero, with no significant autocorrelations in the ACF and PACF plots. This confirms the model is appropriate for capturing the underlying data structure.

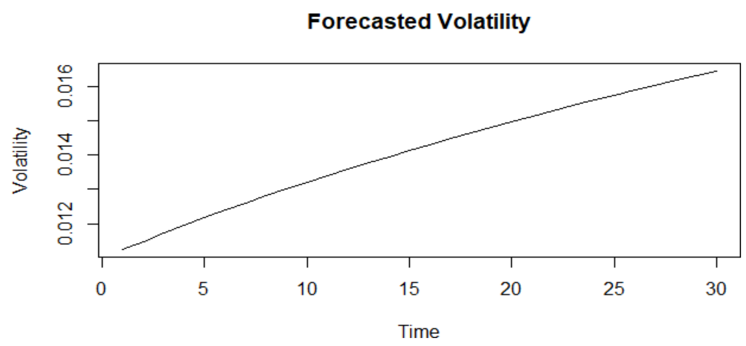
Table 3.2 Estimated Parameters of the GARCH (1,1) Model.

	Estimate	Std. Error	t value	Pr(>|t|)
mu	0.000871	0.000543	1.6042	0.10868
omega	0.000006	0.000004	1.4260	0.15388
alpha1	0.097192	0.017048	5.7011	0.00000
beta1	0.895783	0.018027	49.6898	0.00000

The GARCH model's parameter estimates suggest mixed results. The mean return (μ) and the constant term (ω) are not statistically significant, indicating that they may not contribute meaningfully to the model. However, the parameters α_1 (0.097) and β_1 (0.896) are highly significant, showing that past shocks and past

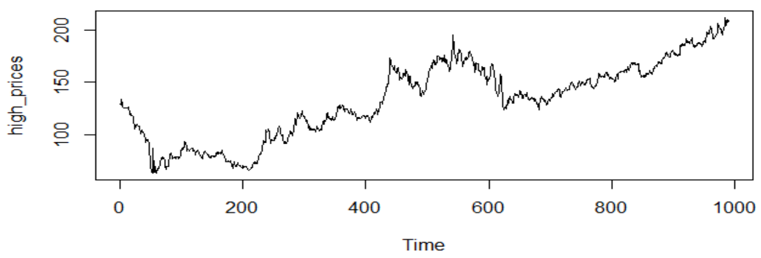
volatility strongly influence current volatility. The sum of $\alpha_1 + \beta_1$= 0.993 is close to 1, suggesting persistent volatility, a common feature in financial time series. Overall, the model captures volatility clustering effectively despite insignificant intercept terms.

Figure 3.4 Forecasted volatility of low prices of ONGC stock.



The forecasted volatility of ONGC stock's low prices shows a gradual increase over time, indicating a steady rise in uncertainty or risk in the future.

Figure 3.5 Timeseries plot of daily high prices of ONGC stock for the period from 2020 to 2023



The time series plot of ONGC's daily high prices from 2020 to 2023 shows fluctuations with a general upward trend over the period. This suggests that despite periodic volatility, the stock's high prices have increased overall during the observed time frame. The Augmented Dickey-Fuller (ADF) test result indicates that the p-value is 0.01, which is less than the common significance level (0.05). This means we reject the null hypothesis of non-stationarity. Therefore, the series is stationary.

Figure 3.6 Forecast from ARIMA (5,2,0) model for High prices of ONGC stock

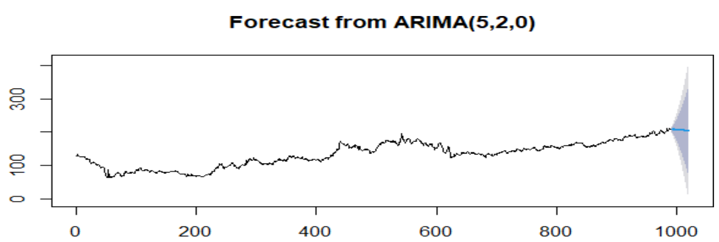
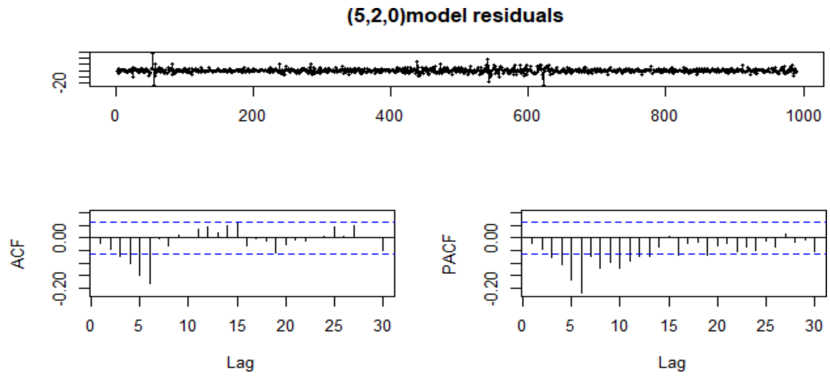


Table 3.3 Accuracy measures of the fitted ARIMA (5,2,0) model.

RMSE	MAPE
2.182076	3.466125

The RMSE (2.182) and MAPE (3.47%) indicate that the model has a low prediction error and high accuracy. A MAPE below 10% suggests that the model provides highly accurate forecasts.

Figure 3.7 Residual plot of ARIMA (5,2,0) model.



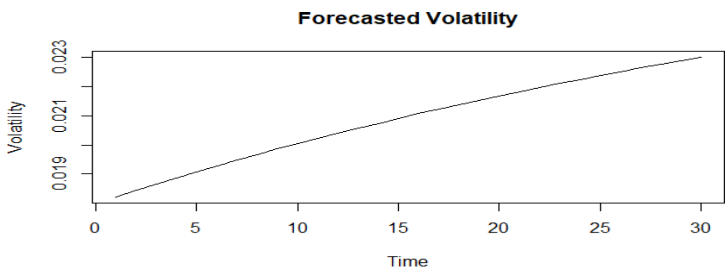
The residual diagnostics for the ARIMA (5,2,0) model reveal that the residuals are randomly distributed about zero, with no visible patterns in the residual plot, indicating that the model effectively reflects the data's trend and seasonality. The ACF and PACF plots show that the majority of the autocorrelations are inside the confidence intervals, indicating that there is no significant autocorrelation in the residuals. This implies that the residuals approximate white noise, satisfying the requirement of independence needed for a good ARIMA model fit. Overall, the ARIMA (5,2,0) model appears appropriate and well-specified for the given data, with no significant model inadequacies or misfit issues observed.

Table 3.4 Estimated Parameters of GARCH (1,1) Model.

	Estimate	Std. Error	t value	Pr(>|t|)
mu	0.001348	0.000566	2.3809	0.017270
omega	0.000013	0.000004	3.5899	0.000331
alpha1	0.108433	0.012815	8.4617	0.000001
beta1	0.877865	0.007574	115.9101	0.0000025

The GARCH model's parameter estimates suggest that it is well-specified. The intercept μ is statistically significant, indicating a meaningful mean return. The low value of ω (0.000013) signifies low constant volatility. Both α_1(0.108) and β_1(0.878) are significant, highlighting that past shocks and past volatility contribute to current volatility. The sum of $\alpha_1 + \beta_1$=0.9860, which is close to 1, indicating persistent volatility, which is typical in financial timeseries. Overall, the GARCH model effectively captures volatility clustering and persistence in the data.

Figure 3.8 Forecasted volatility of High prices of ONGC stock



The forecasted volatility plot shows a gradual increase over time, indicating rising uncertainty or risk in future periods. This suggests that the modelled series expects higher volatility in the near future.

6. Conclusion

The analysis concludes that ARIMA and GARCH models are effective tools for forecasting stock prices and volatility, respectively, providing valuable insights into market dynamics. ARIMA models, selected based on AIC and BIC values, demonstrated high accuracy in capturing trends, with minimal errors across HDFC BANK, WIPRO, and ONGC stock prices. For example, MAPE values were consistently low, confirming reliable trend forecasts.

GARCH models effectively captured volatility clustering and persistence, with significant α_1 and β_1 values indicating the influence of past shocks and variances on current volatility. High persistence in volatility underscores the model's suitability for financial time series.

The findings highlight increasing volatility and risk across stocks, suggesting market uncertainty in the future. This underscores the importance of these models for informed decision-making in financial markets. The combined use of ARIMA and GARCH models enhances forecasting reliability and provides a comprehensive understanding of stock price behaviours.

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