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A Data Driven Hybrid Approach for Stock Market Forecasting Using Arima and Asymmetric Garch Models

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ABSTRACT: Due to the highly unpredictable character of financial markets, precise forecasting of stock markets is crucial for traders, analysts, and policymakers. The NASDAQ Composite Indicator is challenging to predict due to its numerous geopolitical and economic factors. The GJR-GARCH model addresses asymmetric volatility effects, particularly the pronounced impact of negative market fluctuations on instability, whereas the ARIMA model identifies linear patterns within the time series. This study forecasts the NASDAQ Composite Index by analyzing historical price trends and fluctuations in the market through the ARIMA and GJR-GARCH methods. The model demonstrates strong predicted accuracy when this strategy is utilized on daily closing prices from 2010 to 2024. The outcomes aim to assist financial professionals and investors in enhancing decision-making and effectively managing risks.

Keywords: Stock price forecasting, Time Series Analysis, ARIMA Model, SGARCH Model, GJR-GARCH Model, volatility modelling, conditional heteroskedasticity, market volatility.

Contents

1. Introduction

Forecasting stock prices is a crucial endeavor for shareholders and financial experts, who are perpetually pursuing an optimized investing plan. In time series investigation, stationarity is a fundamental notion, as it guarantees model integrity and forecast precision. Stationarity is defined as the stability of statistical properties, including mean, variance, and covariance, throughout time within the data. The stationarity of time series data is frequently evaluated by several procedures. It is essential to reiterate that tests for stationarity are a vital component of time series data analysis, critical for developing robust models and providing accurate forecasts. If a time series contravenes stationarity assumptions, varying or logarithmic transformations may be employed to achieve stationarity; these techniques eliminate trends, fluctuation, and other nonstationary elements in the data. Autocorrelation in time series datasets, such as stock price data, can be studied using a variety of statistical methods, one of which is the Ljung-Box test. It is mainly utilized in determining whether there is a consistent relationship between consecutive observations.

This test evaluates the null hypothesis, which is no autocorrelation; the alternative hypothesis shows that there is autocorrelation. Computation of the Lung-Box statistic is an integral part of this test as it

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measures the sum of squared autocorrelations for a series up to a particular lag.Volatility mainly refers to investment markets and can be defined as the variation in the price of a stock or significant index over a period of time. It denotes the level of ups and downs in price which a security has experienced. Higher volatility signifies large variations in prices that can happen quickly and in any direction. Schwert[1] has identified that immediately after the stock prices fall, particularly during recession and financial crisis, volatility tends to increase, and thereby creates uncertainty for efficient investments. According to Black [2], with negative rumours, the market prices tend to fall while with positive rumors prices move upwards and it depends on the index. The smart investors use volatility to identify the undervalued securities to buy and overvalued securities to sell. Gencay and Selcuk[3] and Llaudes et al.[4] have highlighted that the emerging stock market economies are very prone to regime switches in a brief span of time, and hence it becomes comparatively easy for strategic investors to invest in such markets.

Researchers frequently rely on market-based volatility estimates to assess stock market vulnerability. Recent studies by Baker et al. [5], Beer et al. [6], and Li et al. [7] highlight that investor sentiment is significantly impacted by stock market trends.Thus,volatility has become an important factor in analyzing the stock market for portfolio management, pricing options, and making regulatory decisions. Persistent volatility trends determine investor attitude, which may be a problem for Bangladeshi investors. Research outcomes indicate that, within a period, stock returns show little volatility, while on other occasions, volatility is high. To capture volatility in financial time series data, Engle [8] proposed the ARCH model, which is now central in univariate time series analysis. It is still computationally burdensome to forecast financial market trends. To increase the efficiency in estimation, Bollerslev [9] proposed the Generalized ARCH (GARCH) model, which resulted in better conditional variance forecasts with quite dramatic success. The GARCH model can be applied in a wide range of areas, and it links the mean and variance equations.It effectively captures time- dependent volatility in conditional variances, making it conditionally heteroskedastic while being unconditionally homoscedastic. Studies by Nor et al. [10], Ezzat [11], and Ehlert et al. [12] have demonstrated significant improvements in forecasting conditional variance using GARCH models. Researchers and practitioners can react to changing market conditions, improve risk management, optimization of portfolios, and derivative pricing techniques, and achieve higher predicted accuracy by combining these methodologies [24,25].

The presence of autocorrelation in the residuals suggests that there may be opportunities to enhance the forecasting model. Improving the model by adding more lagged values or changing the model parameters to better capture the data's underlying patterns is one way to deal with autocorrelation. Volatility forecasting is challenging for researchers due to the lack of a generally acknowledged model or approach. Diverse methodologies, including error statistics, are developed and employed by various scholars to evaluate volatility forecasting models. The GJR-GARCH model is deemed the most suitable for forecasting volatility in the Australian daily stock market, as per Brailsford and Faff [13].

Furthermore, it has been demonstrated that GARCH-type models are appropriate for modeling stock return volatility in both developed and emerging markets. Abdalla and Winker have demonstrated the effectiveness of GARCH-type models in emerging economies [14]. Poon and Granger [15] claim that the EGARCH and GJR-GARCH models outperform the conventional GARCH model. Value-at-Risk (VaR) has been successfully estimated by Allen et al. [16] using GARCH models. According to Wei and Hai-nan [17], GJR models are highly effective at predicting high-frequency data. Awartani and Corradi [18] showed that the GARCH (1, 1) model was more accurate or effective than the other modls examined. Ederington and Guan found that when it comes to predicting volatility in developing stock markets, the GARCH (1, 1) model outperforms other models [19]. For their most effective asymmetric GARCH model, Alberg et al. [20] used the EGARCH approach with a skewed student's t distribution for predicting. According to Dutta [21], asymmetric GARCH models outperform non- asymmetric models when it comes to estimates. Research by Liu et al. [22] indicates that when it comes to predicting the volatility of the stock market, the EGARCH model outperforms competing models. Measurements of model accuracy and error statistics indicate that the GJR-GARCH model outperforms competing models, as stated by Onwukwe et al. [23].Because financial markets are so volatile, accurate forecasting is essential for analysts, investors, and policymakers. Global, political, and economic factors all have an impact on the NASDAQ Composite Index, a significant stock market benchmark. Financial time series data often exhibit volatility clustering, which classic models such as the Autoregressive Integrated Moving Average

(ARIMA) have difficulty addressing.

Stock price forecasts using asymmetric GARCH models have grown in popularity throughout the last 20 years. One statistical model that can be used to simulate the time-varying fluctuation of financial assets, like stocks, is the asymmetric GARCH model. According to these models, the effect of negative returns on volatility is greater than that of positive returns. Therefore, data on finances with asymmetry and volatility clusters are better modeled using asymmetrical GARCH models. Calculating the parameter values from historical data and then utilizing them to predict future stock price and volatility is what the asymmetric GARCH model is all about when it comes to stock price prediction. Stock price projections using these algorithms have been incredibly accurate, especially during times of financial instability and market shocks. This work attempts to improve the forecasting accuracy by using GJR-GARCH technique. This model is better than the ARIMA model in capturing asymmetric volatility, in which a negative market move has greater impact than its positive counterpart, because ARIMA models are usually concerned with trend and seasonality. As shown in this paper, better forecast results concerning short-term price movements and volatility estimation can be obtained by applying the GJR-GARCH methodology on historical NASDAQ data. This study will help stock holders to make informed investment decisions and manage financial risks more effectively.

2. Methodology

This study employs a structured approach to forecasting the NASDAQ Composite Index using ARIMA, SGARCH, and GJR-GARCH models. The methodology consists of the following key steps:

2.1 Data Collection and Pre-processing

Historical daily closing prices of the NASDAQ Composite Index were obtained from a reliable financial database. Missing values were handled, and the data were transformed into logarithmic returns to achieve stationarity. ADF and PP tests were conducted to confirm stationarity.

Historical daily closing prices of the NASDAQ Composite Index were obtained from a reliable financial database. Missing values were handled, and the data were transformed into logarithmic returns to achieve stationarity. ADF and PP tests were conducted to confirm stationarity.

Historical daily closing prices of the NASDAQ Composite Index were obtained from Yahoo Finance. The analysis utilized data from **2010-01-03** to **2023-01-15**. When working with stock price data, the closing price column is often considered crucial. Typically, these closing prices are transformed into daily returns. However, after this transformation, the first row in the returns column contains a missing value and must be removed.

The calculation of returns involves finding the difference between the current day's closing price and the previous day's closing price, then dividing this difference by the previous day's closing price. Mathematically, the daily return is computed as

$$\text{Returns}(t) = \frac{y(t) - y(t-1)}{y(t-1)},$$

where $y(t)$ represents the closing price at time t, and $y(t-1)$ is the closing price at the previous time period.

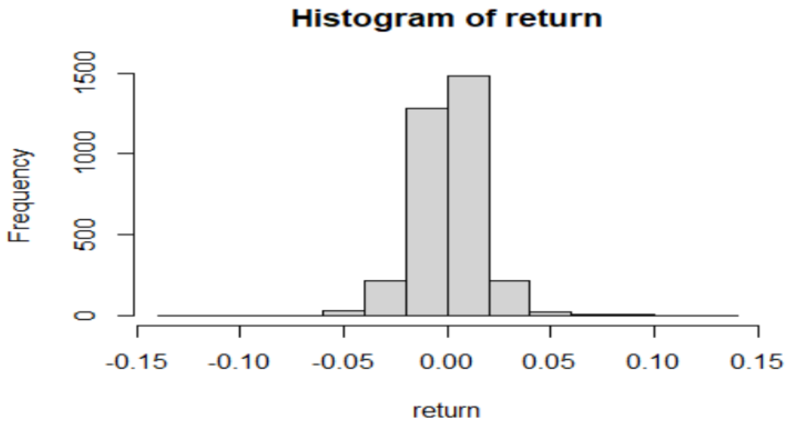

Figure 1: Histogram for Stock Price Returns

Figure 1 of stock price data follows a symmetric distribution, it suggests that the returns are distributed around the mean in a balanced manner. In such cases, the positive and negative returns are roughly equally likely to occur, resulting in a symmetric histogram.

2.2 ADF Test

The P-value in the ADF test is less than 0.05; therefore, there is evidence to reject the null hypothesis, and the data is stationary.

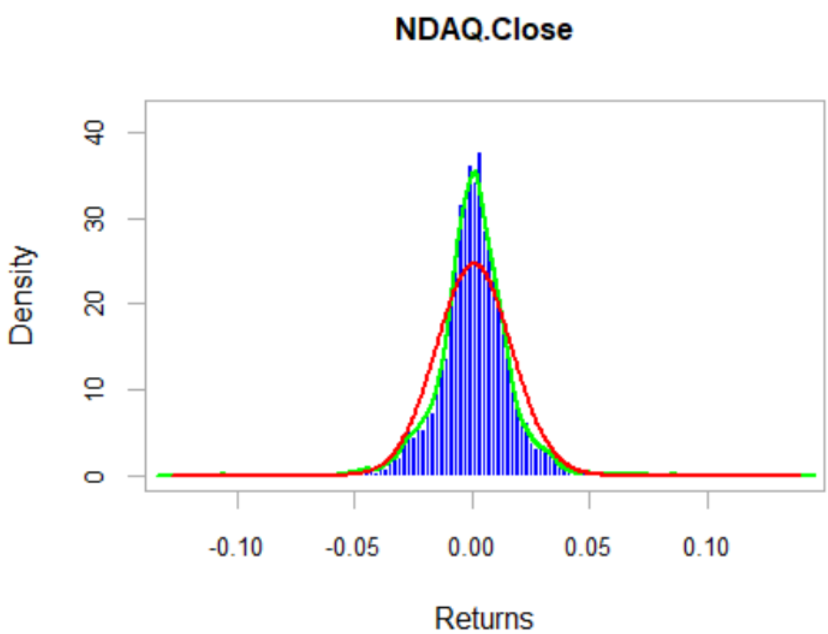

Figure 2: Density Plot of Returns

Figure 2 represents for the identification of days with unusually high or low returns compared to the normal distribution. Upon observation, it may become apparent that the t-distribution is a better fit for modelling returns compared to the standard normal distribution. The inclusion of a normal distribution curve and density curve in the histogram can provide insights into the distributional characteristics of the data. By comparing the observed distribution with the normal distribution, any deviations or discrepancies can be identified. In case of returns, if there are significantly more days with extreme values-very large or very small-compared to what would be expected under a normal distribution, then it suggests that this data has heavier tails or outliers. Additionally, the mention of the -distribution shows it could offer a better fit for modeling returns than does the standard normal distribution. The distribution is known for allowing for heavier tails and accounting for the possibility of outliers or extreme values in the data.

2.3 ARIMA Model Implementation

Linear patterns of the time series have been identified with the ARIMA model. The BIC and AIC were used to find the best ARIMA. Once the model had been fitted, residuals were examined to look for patterns or persistence in volatility.

2.4 GJR-GARCH Model Implementation

The residuals from the ARIMA model are subjected to a GJR-GARCH (1,1) model, since financial time series usually demonstrate volatility clustering. This model was chosen because it can account for asymmetric volatility-that is, market volatility is often increased more by negative shocks than by positive ones. Estimation of the model parameters was performed by the method of maximum likelihood estimation.

2.5 Forecasting and Performance Evaluation

The ARIMA-GJR-GARCH model was estimated and then used for out-of-sample forecasting of future prices and volatility in the near future. Forecast confidence intervals were computed to measure uncertainty in predictions. This will ensure that the approach for the NASDAQ forecast is comprehensive and robust, as both a linear time series analysis and volatility modeling are considered in developing a better predictor.

3. Review of Results

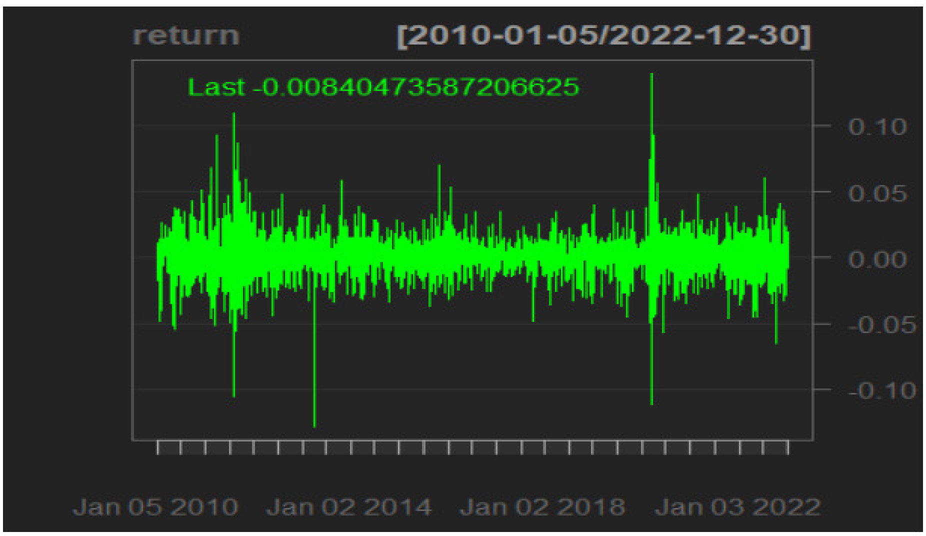

Figure 3: Time Series Plot of Stock Returns

Figure 3 gives the impression that the series data is stationary. It does not show any trend or s easonality in the data. Stationary data usually has a constant mean and variance for all time in tervals; this would imply that the behavior of the data is similar at any point in time. Even in t he presence of stationary data, it contains fluctuations or periods of high volatility. These are moments when markets become highly volatile and prices either surge upwards with big swin gs or fall below with huge plunges. The opposite is also true: at other times, the market will e xperience relatively lower or low volatility, where prices display smaller and more stable mo vements. Volatility patterns can be influenced by factors such as market conditions, economic events, news announcements, investor sentiment, and other external factors. Characterizing th ese types of volatility and studying their attributes are very important to the proper and correct interpretation of the market. This can be effectively analyzed by incorporating an array of statistical methods or models that can better capture the changes in volatility. For example, volatility can be quantified and modelled by techniques like GARCH models or volatility clustering analysis.

3.1 ARIMA MODEL

The order of the ARIMA model fitted to the data is $(4, 0, 0)$. With parameter coefficients, the model equation is given by

$$Y_t = 0.0001 + 0.0879\,Y_{t-1} - 0.0305\,Y_{t-2} + 0.0443\,Y_{t-3} + 0.0512\,Y_{t-4}.$$

The AIC value of the model is -17738.73.

In order to verify the appropriateness of the ARIMA model for data analysis, it is important to check whether the residuals exhibit autocorrelation or heteroskedasticity. If the residuals have no significant autocorrelation and exhibit no heteroskedasticity, then the fit of the ARIMA model is good and thus valid for analysis.However, if there is indication of autocorrelation or heteroskedasticity in the residuals. In such cases, further adjustments or alternative models might be necessary.

3.2 ARCH LM-test

Based on the result of the ARCH LM test, the p-value is 2.2×10^{-16}. Here the p-value is small, so there is a presence of heteroscedasticity in the model.

Box-Ljung Test

Based on the result of this test, the p-value is 0.9965. In the Ljung–Box test, a p-value higher than 0.05 indicates that the data does not contain autocorrelation.

Shapiro–Wilk Normality Test

Based on the result of this test, the p-value is 2.2×10^{-16}. Here, the low p-value indicates that the residuals are not normally distributed.

If a fitted model's residuals exhibit heteroskedasticity or serial correlation, it indicates that the model may not be appropriate for forecasting. In such cases, ARCH and GARCH models are commonly employed to address the issues of autocorrelation and heteroskedasticity, enabling more accurate predictions.

3.3 GARCH MODELS:-

SGARCH(1,1) MODEL

Table 1: Optimal Parameter Values of SGARCH(1,1) ARMA(0,0)Model

Parameter	Estimate	Std. error	t-value	pr(> $\|t\|$)
μ	0.001017	0.000367	2.7743	0.005533
Ω	0.000024	0.000007	3.4744	0.000512
α_1	0.185766	0.038143	4.8702	0.000001
β_1	0.712963	0.058023	12.2877	0.00000

The GARCH model equation is

$$R_t = 0.001017 + \varepsilon_t \quad \text{(constant mean equation)}$$

$$\sigma_t^2 = 0.000024 + 0.185766\,\varepsilon_{t-1}^2 + 0.712963\,\sigma_{t-1}^2$$

Table 2: Weighted Ljung-Box Test on Standardized Residuals

Lag	**Statistic**	p–**value**
Lag[1]	0.3244	0.5690
Lag$\left[2(p+q)+(p+q)-1\right]$[2]	0.5636	0.6645
Lag$\left[2(p+q)+(p+q)-1\right]$[5]	0.9157	0.8785

Table 3: Weighted Ljung-Box Test on Standardized Squared Residuals

Lag	**Statistic**	p – *value*
Lag[1]	**0.1956**	0.6583
Lag $[2(p+q)+(p+q)-1]$ [5]	**1.1227**	0.8313
Lag $[4(p+q)+(p+q)-1]$ [9]	**1.9238**	0.9139

Tables 2 and 3 show that the standard residuals and standardised squared residuals exhibit no serial correlation. The Ljung–Box test p-values exceed 0.05, indicating acceptance of H_0. Since both residuals and squared residuals show no autocorrelation, this confirms that the GARCH model is appropriate and accurately specified.

Table 4: Adjusted Pearson Goodness-of-Fit Test

	Group	**Shape**	$\boldsymbol{p}$ – value$\boldsymbol{(g-1)}$
1	20	55.37	$2.040\,e^{-0.5}$
2	30	65.32	$1.288\,e^{-0.4}$
3	40	85.69	$2.361\,e^{-0.5}$
4	50	99.29	$2.867\,e^{-0.5}$

Table 4 shows that null hypothesis asserts the residuals have a normal distribution throughout the goodness of fit test, but the alternative hypothesis argues that they do not. Since the calculated p-values in this case are less than 0.05, there is sufficient evidence to reject the null hypothesis.

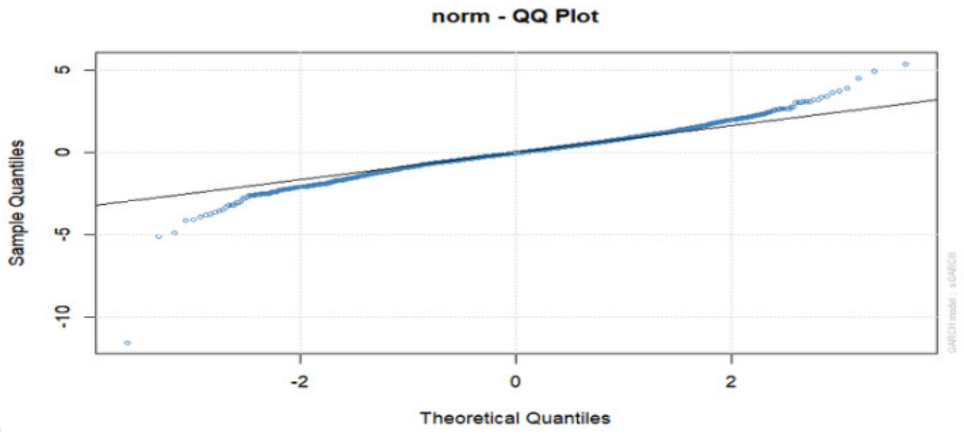

Figure 4: QQ Plot for residuals

Figure 4 evident that the tails of the distribution exhibit significant deviation from a normal distribution, both in the lower and higher value ranges. This deviation suggests that the residuals do not adhere to the characteristics of a normal distribution.

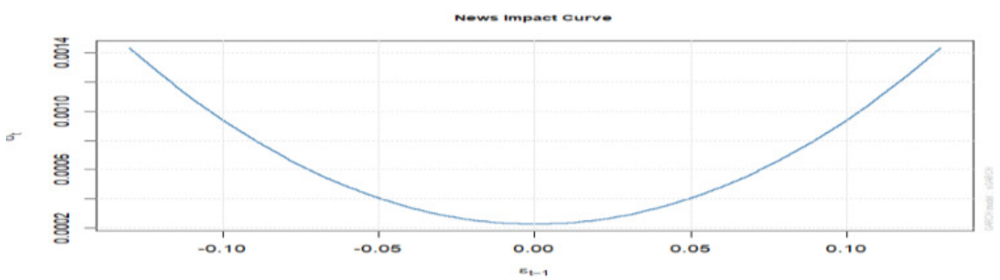

Figure 5: News Impact Curve

Figure 5 implies that positive and negative news have an equal impact on stock returns. However, empirical analysis of the stock price data reveals that negative news has a more effect on prices compared to positive news. As a result, this model is deemed unsuitable for accurately forecasting stock price data. Therefore, the model with *SGARCH(1,1)* and *ARMA(0,0)* using a normal distribution is not an appropriate choice for forecasting the stock price data.

Considering the above-mentioned volatility patterns observed in this stock price data set, standard forecasting models are not suitable to predict the future trend in stock prices. The market dynamics might change due to major events such as a financial crisis and pandemic, which can lead to changes in volatility that a standard forecasting model cannot capture. Therefore, there is a need to search for some other forecasting technique or model that considers volatility clustering and structural breaks in data. This model must be able to reflect the unique characteristics and dynamics of the stock market with respect to the effects brought about by major events on the level of volatility.

GJR-GARCH Model With ARMA(0,0)

The GJR-GARCH model equation is

Table 5: Optimal parameter values of GJR-GARCH Model With ARMA(0,0)

	Estimate	**Std. Error**	t**–value**	**pr**$(>|\mathbf{t}|)$
μ	0.000746	0.000364	2.0477	0.040588
Ω	0.000010	0.000001	9.6918	0.000000
α_1	0.040268	0.014958	2.6921	0.00710
β_1	0.850314	0.018793	45.2456	0.000000
γ_1	0.142270	0.035386	4.0205	0.000058
skew	0.908337	0.036313	25.0140	0.000000
shape	6.517559	1.157446	5.6310	0.000000

$$R_t = 0.000746 + \varepsilon_t$$

$$\sigma_t^2 = 0.000010 + (0.040268 + 0.142270)\varepsilon_{t-1}^2 + 0.850314\,\sigma_{t-1}^2$$

Table 6: Adjusted Pearson Goodness-of-Fit Test

	Group	**Statistic**	$\mathbf{p-value(g-1)}$
1	20	27.46	0.09439
2	30	32.55	0.29638
3	40	43.33	0.29181
4	50	49.58	0.48992

Table 6 it is observed that all the p-values obtained are greater than 0.05. This implies that the model using sstd for the residuals is considered a suitable choice.

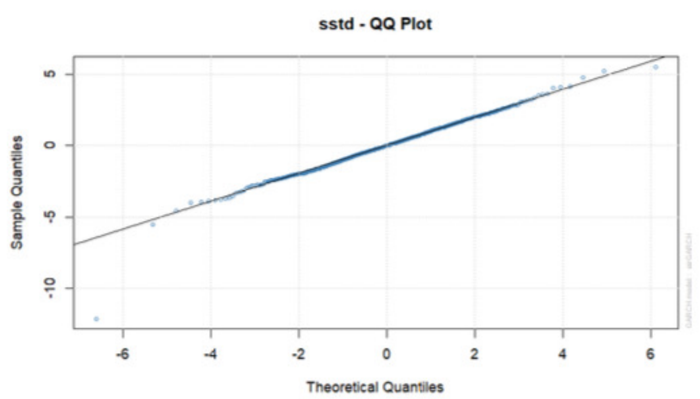

Figure 6: SSTD QQ Plot

Figure 6 observed that the lower tails and upper tails of the data approximately form a straight line. This suggests that the skewed student t distribution for errors is a suitable choice.

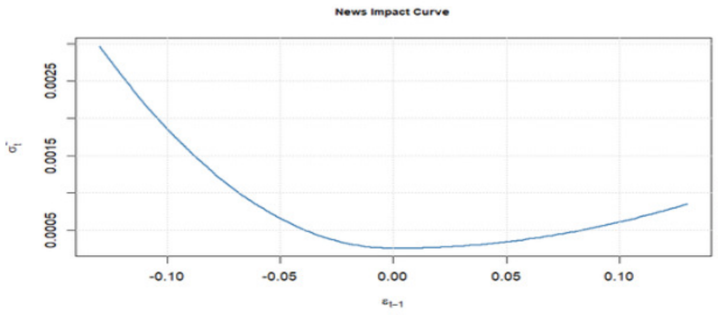

Figure 7: News Impact Curve

Figure 7 becomes evident that when positive news affects stock prices, the prices gradually increase without any sudden large movements. However, in the case of negative news, the impact is considerably higher, resulting in significant changes in stock prices. This indicates that the news impact in this model is asymmetric, with a much greater influence from negative news compared to positive news. Therefore, the GJR-GARCH (1,1) , ARMA (0,0) model with sstd is considered a suitable choice for forecasting stock price data.

GJR-GARCH Model With ARMA(1,0)

Table 7: Optimal Parameter Values of GJR-GARCH(1,1), ARMA(1,0) Model with sstd

	Estimate	**Std. Error**	t**–value**	$pr(>\|t\|)$
μ	0.000719	0.000210	3.4161	0.000635
ar1	-0.026195	0.017539	-1.4935	0.135297
Ω	0.000006	0.000002	3.4196	0.0006277
α_1	0.040256	0.014936	2.69524	0.007034
β_1	0.850452	0.08759	45.33609	0.000000
γ_1	0.141869	0.035374	4.01058	0.000061
skew	0.908130	0.036358	24.97725	0.000000
shape	6.514529	1.158097	5.6252	0.000000

Table 7 shows that this particular model, the parameter ar1 is determined to be statistically insignificant as the associated p values are greater than 0.05. Consequently, this indicates that the ar1 parameter does not hold statistical significance in the model. As a result, this model is deemed invalid for forecasting the stock price data.

GJR-GARCH with ARCH-M model

Table 8: Optimal Parameter Values of GJR-GARCH(1,1)ARCH-M Model with sstd

	Estimate	**Std. Error**	t − **value**	$pr(>\|t\|)$
μ	0.000365	0.000465	0.65556	0.512104
archm	2.638637	1.991289	1.32509	0.185141
Ω	0.000011	0.000001	19.46594	0.000000
α_1	0.041502	0.015430	2.68968	0.007152
β_1	0.839658	0.018239	46.03626	0.000000
γ_1	0.141217	0.036047	3.91761	0.000089
skew	0.908033	0.036166	25.10724	0.000000
shape	0.604170	1.226970	5.38250	0.000000

Table 8 In the GJR-GARCH (1,1), ARCH-M model, the error distribution is assumed to be sstd. Nevertheless, the statistical significance of the ARCH-M parameter is assessed by examining its associated p-value. In this particular case, the computed p-value is greater than 0.05, suggesting that the ARCH-M parameter lacks statistical significance. As a result, this model is deemed invalid for forecasting stock price data. After analyzing the results, GJR-GARCH(1,1), ARMA(0,0) has been found as the best fit model for the forecasting of stock price data as compared to other models.

4. Conclusions

As a result of its ability to accurately reflect the NASDAQ Composite Index's returns' linear pattern and asymmetric volatility, the ARIMA-GJR-GARCH model provides a solid foundation for short-term forecasting. There are just too many unknowns in the financial markets for any model to provide a reliable prediction. This study focuses on building time series models like ARIMA, SGARCH, and GJR-GARCH to improve stock market sentiment predictions. Data for the historical dataset comes from a variety of sources, including Yahoo! Finance. The results showed that the GJR-GARCH model performed better in forecasting, as supported by the strong assessment measures, such as RMSE, MAPE, and MAE. This study demonstrates remarkable accuracy in result generation, supported by assessment metrics, including MAE: 0.0098 and RMSE: 0.011. This suggests that GJR-GARCH offers potential for assisting traders and investors in making informed judgments in the tumultuous realm of stock market investment.

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