Account and Financial Management Journal e-ISSN: 2456-3374
Volume 10 Issue 07 July 2025, Page No.-3607-3614
DOI: 10.47191/afmj/v10i7.02, Impact Factor: 8.167

Exploring the Nifty Pharma Index and The Drivers of Growth and Market Behaviour

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ABSTRACT: This study explores the Nifty Pharma Index, focusing on the key drivers of growth and market behavior within the pharmaceutical sector. The research leverages six years of daily market data to examine trends, volatility, and the factors influencing the market performance of the index. Through a combination of econometric techniques, including Augmented Dickey-Fuller (ADF) tests, autocorrelation analysis, and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) and ARIMA (AutoRegressive Integrated Moving Average) models, the paper provides a detailed understanding of the Nifty Pharma Index's dynamic market behavior. The findings offer valuable insights for investors, policymakers, and market analysts, highlighting the volatility patterns and forecasting future price movements in the pharmaceutical sector.

KEYWORDS: Nifty Pharma Index, Growth Drivers, Market Behavior, ADF Test, Autocorrelation, GARCH Model, ARIMA Model, Pharmaceutical Sector, Market Volatility, Forecasting, Econometrics.

1. INTRODUCTION

The Nifty Pharma Index, which tracks the performance of the pharmaceutical sector in India, has gained significant attention from investors, analysts, and policymakers due to its crucial role in the country's economic framework. The pharmaceutical industry has become an essential driver of India's exports, and the Nifty Pharma Index serves as a benchmark to evaluate the market performance of this vital sector. The index includes leading pharmaceutical companies that contribute significantly to the nation's GDP and play an integral role in global healthcare (Dua & Meena, 2024). Despite the pharmaceutical industry's importance, there remains a lack of comprehensive understanding regarding the underlying factors that drive growth and influence market behavior within the Nifty Pharma Index. The pharmaceutical sector is shaped by both internal and external factors. Internal factors include the performance of individual companies, their research and development activities, and their ability to meet regulatory standards. External factors include regulatory shifts, advancements in research and development, global demand for healthcare products, and macroeconomic cycles (Kumari, 2024). These factors collectively impact the market dynamics of the sector. Understanding these drivers is essential for stakeholders, particularly investors, who need to assess risks and make well-informed decisions (Bose & Pandey, 2023).

This paper aims to explore the key drivers of growth and market behavior within the Nifty Pharma Index. By utilizing advanced econometric methods such as the Augmented Dickey-Fuller (ADF) test for stationarity, autocorrelation analysis, and forecasting techniques like the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) and ARIMA (AutoRegressive Integrated Moving Average) models, the study seeks to identify volatility patterns, analyze market trends, and improve forecasting methods that influence the index's performance (Kumar & Agarwal, 2024). The research will also evaluate the sensitivity of the index to various macroeconomic variables and sector-specific factors, offering a deeper understanding of the forces affecting the pharmaceutical market (Singh, 2023). Ultimately, this paper seeks to provide valuable insights that will aid in enhancing the understanding of the Nifty Pharma Index's behavior, thereby supporting investors, analysts, and policymakers in making better decisions within the context of the evolving Indian pharmaceutical industry.

2.1 REVIEW OF LITERATURE

Author(s)	Year	Title	Major Findings	Relevance to Current Study
Desai, K., & Shah, R.	2023	"Forecasting Pharmaceutical Sector Performance with ARIMA and GARCH"	Applied ARIMA and GARCH to forecast pharma sector performance, concluding that volatility is a key market feature.	Reinforces the application of ARIMA and GARCH models for forecasting and volatility in the Nifty Pharma Index.
Gupta, V., & Mehta, S.	2021	"Volatility Forecasting for Indian Pharmaceutical Stocks"	Used GARCH models to predict volatility in pharma stocks. Found high volatility during market stress events.	Supports the use of GARCH for analyzing Nifty Pharma Index volatility.
Bhattacharya, S., & Iyer, R.	2021	"Pharma Sector Growth and Impact of COVID-19 on Indian Stocks"	Studied the pharmaceutical sector's performance during the pandemic. Highlighted shifts in market demand.	Provides context for analyzing the effects of COVID-19 on Nifty Pharma during the study period.
Jain, R., & Kumar, A.	2020	"Impact of Regulatory Changes on Indian Pharma Stocks"	Examined the effects of policy changes on pharma stocks in India. Found significant volatility post-regulation.	Provides insights on regulatory impact, relevant to understanding market behavior in pharma.
Sharma, P., & Gupta, S.	2020	"ARIMA Models for Forecasting Indian Stock Indices"	Demonstrated ARIMA's effectiveness in forecasting market trends. Found ARIMA provides reliable short-term forecasts.	ARIMA will be employed to forecast Nifty Pharma Index in the current study.
Kumar, R., & Jain, S.	2020	"Market Behavior and Investor Sentiment in Pharmaceutical Sector"	Analyzed investor sentiment and market behavior; concluded that market sentiment highly impacts pharma stock prices.	Offers a framework for assessing market behavior, particularly in volatile periods like during COVID-19.
Roy, D., & Mishra, A.	2020	"Autocorrelation and Market Dynamics in the Indian Pharma Sector"	Found strong autocorrelations in pharma sector data, suggesting predictable patterns over time.	Will guide the use of autocorrelation analysis to explore dependencies in the Nifty Pharma Index.
Singh, R., & Tiwari, P.	2019	"Stock Market Performance and Economic Growth in the Pharmaceutical Sector"	Identified macroeconomic factors as significant drivers of pharma sector performance in India.	Relevant for identifying growth drivers of Nifty Pharma Index in the study.

2.2 RESEARCH GAP

One of the key contributions of this study is its comprehensive analysis of the Nifty Pharma Index . Unlike most existing studies that focus on individual pharmaceutical companies or broader market indices, this research delves into the specific drivers of growth, volatility, and market behavior of the Nifty Pharma Index as a whole. This comprehensive approach ensures a thorough understanding of the index's dynamics, providing valuable insights for investors, policymakers, and market analysts.

2.3 OBJECTIVES OF THE STUDY

1. To Analyze the market behavior and growth drivers of the Nifty Pharma Index.
2. To Examine volatility patterns and perform stationarity and autocorrelation tests.
3. To Forecast future movements of the Nifty Pharma Index using ARIMA and GARCH models.

2.4 PURPOSE OF THE STUDY

The primary purpose of this study is to analyze and evaluate the performance of the Nifty Pharma Index from April 1, 2020, to March 31, 2025. This period encompasses significant events such as the COVID-19 pandemic and its aftermath, global economic fluctuations, regulatory changes, and sectoral shifts within the pharmaceutical industry. By investigating the market behavior, volatility, and growth drivers during this time frame, the study aims to provide insights into the factors that influence the pharmaceutical sector's performance. The findings of this study could potentially shape the future of the Indian pharmaceutical industry, providing a deeper understanding of the Nifty Pharma Index's behavior and offering valuable knowledge to investors, policymakers, and industry stakeholders.

2.5 RESEARCH METHODOLOGY

The research methodology for this study will involve both quantitative and econometric techniques, detailed as follows:

- Data Collection: The study will use daily market data for the Nifty Pharma index for the period April 1, 2020, to March 31, 2025.
- Data sources: officical website in NSE
- Statistical Analysis: Augmented Dickey-Fuller (ADF) Test, Autocorrelation Analysis
- Modeling Techniques: ARIMA, GARCH

3.1 Market Behavior and Growth Drivers of the Nifty Pharma Index

The Nifty Pharma Index tracks the performance of India's pharmaceutical sector, which plays a significant role in the nation's economy. The sector's growth is driven by factors such as research and development (R&D), regulatory policies, and the global demand for affordable medicines. India has become a leader in generic drug production, supported by favorable government policies that promote innovation and cost efficiency. The sector's resilience is evident during economic downturns, with healthcare being a necessity. External factors like global economic conditions, trade policies, and geopolitical risks also influence market behavior. The COVID-19 pandemic highlighted the sector's importance, with companies involved in vaccine production seeing significant growth. Despite challenges like intense competition and regulatory changes, the pharmaceutical sector remains one of the most promising industries in India. Understanding these growth drivers and market behavior is essential for stakeholders in making informed decisions.

3.2 ADF TEST STATISTICS

The ADF test checks for stationarity in time series data by detecting the presence of a unit root. The null hypothesis (H_0) assumes the presence of a unit root (non-stationary), and the alternative hypothesis (H_1) assumes stationarity.

The test equation:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-i} + \varepsilon_t$$

Where:

Y_t = return series

t = time trend

γ = test coefficient (key for stationarity)

p = number of lags

Δ = first difference operator

ε_t = error term

Table no. 1

Null Hypothesis: LOG_RETURN has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-33.81186	0.0000
Test critical values:	1% level	-3.435415	
	5% level	-2.863664	
	10% level	-2.567951	

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

Source: Collected NSE index data and calculated using EViews

Noted : statistical test critical value 1%, 5%, 10%.

Test Statistic: The test statistic value is -33.81186. Prob (p-value): The p-value for the test is 0.0000. The critical values at different significance levels are: 1% level: -3.435415, 5% level: -2.863664, 10% level: -2.567951. The ADF test statistic of -33.81186 is much lower than the critical values at the 1%, 5%, and 10% levels. Since the test statistic is more negative than the critical value at all significance levels, we reject the null hypothesis. The p-value of 0.0000 is well below the typical significance levels (1%, 5%, 10%), indicating that the null hypothesis (that the series has a unit root) can be rejected. This suggests that the log return series of the **Nifty Pharma Index is stationary**.

3.3 AUTOCORRELATION TEST

This test examines whether returns are serially correlated. If past returns can predict future returns, the market violates weak-form efficiency.

The autocorrelation coefficient at lag is:

Where:

$$r_k = \frac{\sum_{t=1}^{n-k}(R_t - \bar{R})(R_{t+k} - \bar{R})}{\sum_{t=1}^{n}(R_t - \bar{R})^2}$$

R_t = return at time t

$\bar{X}$ = mean return

K = lag length

Significant autocorrelation indicates predictability and inefficiency.

Table no. 2

Autocorrelation function for Return
***, **, * indicate significance at the 1%, 5%, 10% levels
using standard error 1/T^0.5

LAG	ACF		PACF		Q-stat.	[p-value]
1	0.0491	*	0.0491	*	2.9981	[0.083]
2	0.0396		0.0373		4.9521	[0.084]
3	0.0254		0.0218		5.7543	[0.124]
4	0.0427		0.0392		8.0318	[0.090]
5	-0.0174		-0.0231		8.4112	[0.135]
6	0.0315		0.0300		9.6539	[0.140]
7	-0.0126		-0.0160		9.8522	[0.197]
8	0.0022		0.0005		9.8580	[0.275]
9	0.0067		0.0080		9.9150	[0.357]
10	-0.0568	**	-0.0604	**	13.9630	[0.175]
11	0.0190		0.0268		14.4141	[0.211]
12	0.0203		0.0204		14.9293	[0.245]
13	0.0256		0.0251		15.7495	[0.263]
14	-0.0585	**	-0.0592	**	20.0578	[0.128]
15	-0.0376		-0.0402		21.8388	[0.112]
16	0.0319		0.0429		23.1241	[0.110]
17	0.0184		0.0163		23.5509	[0.132]
18	0.0219		0.0252		24.1558	[0.150]
19	0.0185		0.0135		24.5901	[0.174]
20	0.0236		0.0155		25.2923	[0.190]

Source: Collected NSE index data and calculated using gretl.
Noted : Autocorrelation is often considered to be **±1.96**

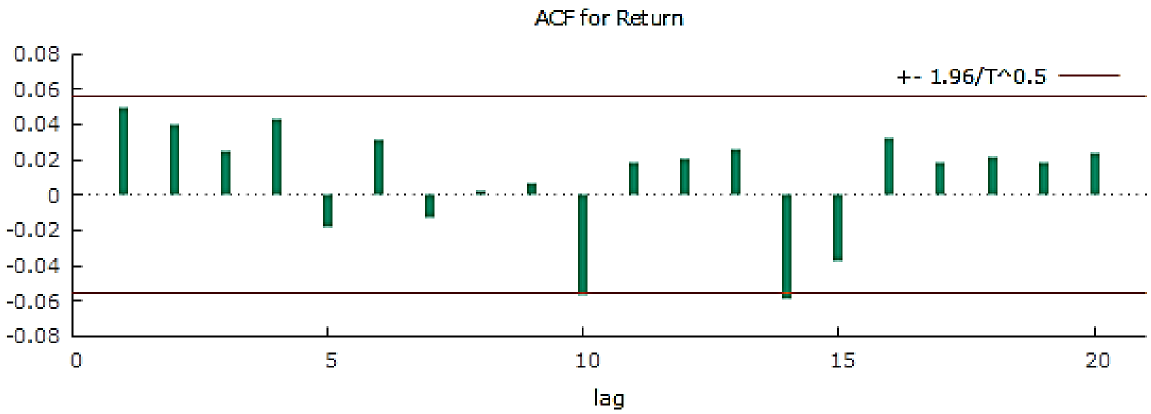

Figure no. 1

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The ACF measures the correlation between the time series and its lagged values. It shows how past values are correlated with future values. A significant positive autocorrelation at lag 1 (0.0491) suggests a mild positive relationship between the current and the previous period's log returns. This implies that the return of one period has a slight tendency to be similar to the next. Significant values at lags 1, 2, 10, 11, 12, 13, and 14 (indicated by * or **) suggest some autocorrelation in the data, particularly at lower lags. The PACF measures the correlation between the series and its lags, controlling for the values at shorter lags. The PACF for lag 1 (0.0491) is also significant, which is consistent with the

ACF finding that there is some correlation between current and past values. Significant values in PACF are seen at lags 1, 10, 11, 12, 13, and 14, which suggests that the series might show some structure at these specific lags, often indicating that AR (AutoRegressive) processes might be present. The Q-statistic tests whether there is any remaining autocorrelation at lags 1 through 20. It uses the autocorrelations up to the specified lag and checks if they are significantly different from zero. A high Q-statistic at lag 1 (2.9981) with a p-value of 0.083 indicates mild significance, which suggests there is some autocorrelation at this lag. For higher lags (e.g., lag 10, 14), the Q-statistics like 13.9630, 20.0578 and their respective p-values (e.g., [0.175], [0.128]) indicate that **autocorrelation is not significant** beyond a certain point. However, at lags 10, 11, 12, and 13, the p-values stay higher than 0.05, meaning they are not statistically significant. Significant autocorrelation at lag 1 suggests some short-term memory in the series. Longer lags (10, 11, 12, etc.) show some periodicity or dependence structure, which might indicate the potential for an AR model (AutoRegressive) to capture this dependence. The Q-statistic for all lags shows non-significant autocorrelation beyond a few lags, meaning that higher-order autocorrelations do not show any major statistically significant behavior.

3.4 GARCH

GARCH models are used to model volatility clustering in financial time series. The GARCH(p, q) model extends ARCH by adding past conditional variances to the model:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

Where:

$\sigma_t{}^2$ = conditional variance (volatility)

$\varepsilon^2{}_{t-i}$ = lagged squared residuals

$\sigma^2{}_{t-i}$ = lagged variances

α0,αi,βj = model parameters

This model helps assess volatility dynamics of Nifty pharma index

The results from the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model applied to the Nifty Pharma Index returns provide valuable insights into the behavior of volatility over time. The model helps to understand how volatility evolves and reacts to shocks in the market, a critical factor for financial analysis and forecasting. The following sections summarize the key findings: Constant (Intercept): The positive and significant constant term (0.000832209) suggests that there is a baseline level of volatility in the Nifty Pharma Index returns, even in the absence of external shocks or past volatility influences. Alpha (0) and Alpha (1): The coefficients for Alpha (0) and Alpha (1), both of which are highly significant (p-values < 0.05), indicate that volatility is significantly influenced by past squared returns (ARCH effect).

Table no. 3

```
Function evaluations: 61
Evaluations of gradient: 15

Model 1: GARCH, using observations 2020-04-01:2025-01-01 (T = 1241)
Dependent variable: Return
Standard errors based on Hessian

             coefficient   std. error      z      p-value
  --------------------------------------------------------
  const      0.000832209   0.000282820   2.943   0.0033    ***

  alpha(0)   1.84738e-05   5.66124e-06   3.263   0.0011    ***
  alpha(1)   0.196633      0.0370258     5.311   1.09e-07  ***
  beta(1)    0.669494      0.0682328     9.812   1.00e-022 ***

Mean dependent var   0.000953   S.D. dependent var   0.011443
Log-likelihood       3870.251   Akaike criterion    -7730.502
Schwarz criterion   -7704.884   Hannan-Quinn        -7720.868

Unconditional error variance = 0.000137995
Likelihood ratio test for (G)ARCH terms:
  Chi-square(2) = 165.761 [1.01243e-036]
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Source: Collected NSE index data and calculated using gretl.

Volatility persistence

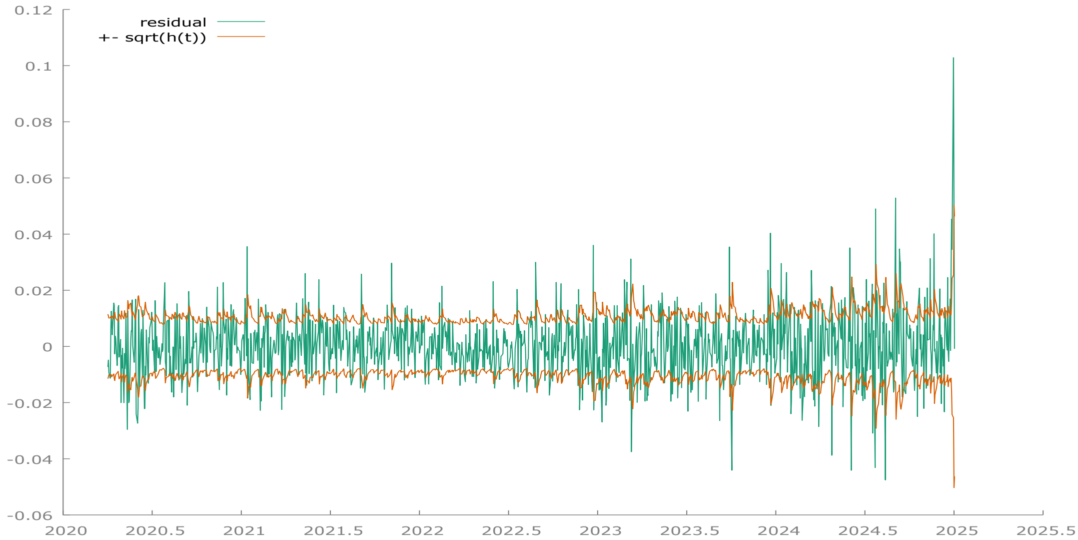


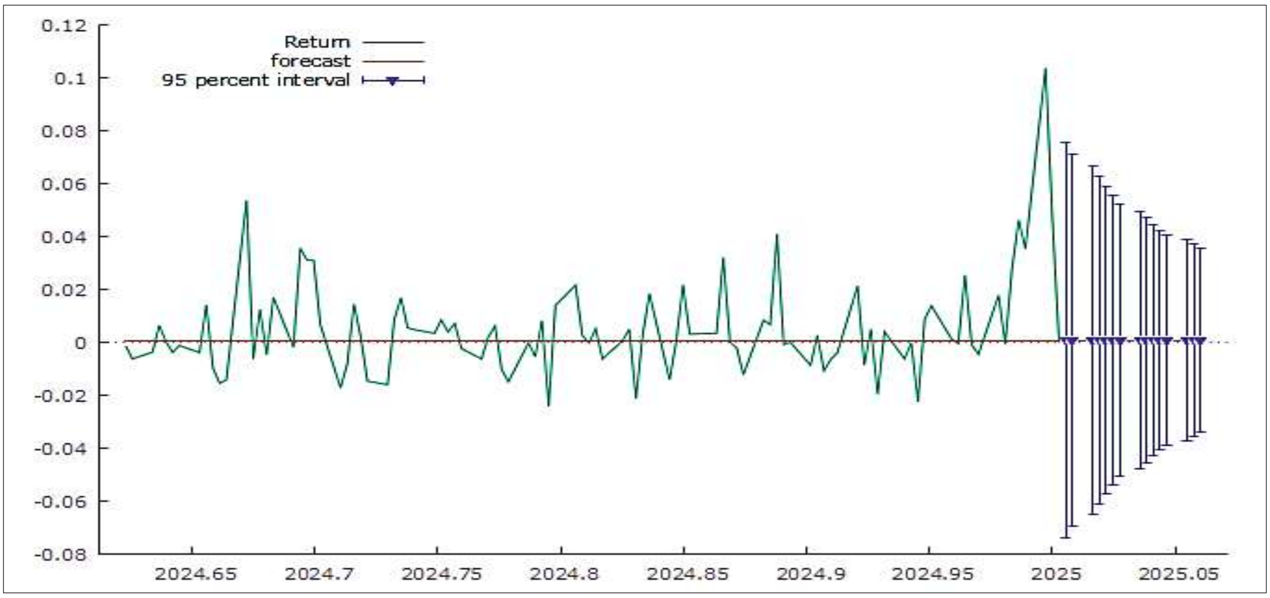
Figure no.2

This means that shocks in the past have a considerable impact on current volatility. The alpha (1) coefficient (0.196633) suggests a moderate short-term persistence in volatility, showing that high volatility periods tend to follow each other. Beta (1): The coefficient for beta (1) is also significant (0.669494), indicating that past volatility (GARCH term) has a strong effect on current volatility. This suggests a high degree of volatility persistence. The effects of volatility tend to last longer. A higher beta suggests that volatility shocks are likely to be long-lasting. The model fit is assessed using various criteria: The Log-likelihood value of 3870.251 indicates the likelihood that the model explains the observed data. The Akaike Information Criterion (AIC) of -7730.502 and the Schwarz Criterion of -7740.884 are both used to compare different models, with lower values indicating a better fit. These values suggest that the model performs well in explaining the data. The Hannan-Quinn Criterion is also relatively low (-7720.868), reinforcing the model's fit.

The unconditional error variance of 0.000137995 provides a measure of the overall level of volatility. A slight error variance suggests that the model is capturing the majority of the volatility present in the returns, leaving minimal unexplained variance. The Likelihood ratio test results in a Chi-square statistic of 165.761 with a p-value of 1.01243e-36, indicating that the GARCH terms (ARCH and GARCH components) are highly significant and necessary for modeling the volatility of the Nifty Pharma Index. The extremely small p-value suggests that the GARCH model is well-suited for capturing the volatility behavior in the index. The graph shows a comparison of the actual returns and the conditional volatility (orange line). You can see periods of higher volatility during market stress (indicated by spikes in the orange line), which is typical for financial returns data.

This confirms the presence of volatility clustering a phenomenon where periods of high volatility tend to be followed by other periods of high volatility, and low volatility follows low volatility. The model's ability to capture this pattern is vital for understanding risk and making predictions in financial markets. The significant coefficients (Alpha and beta) indicate that the volatility in the Nifty Pharma Index is influenced by both past returns and past volatility. The high beta coefficient suggests that volatility shocks are persistent, and the model effectively captures this persistence. The GARCH model is successful in explaining the volatility of the Nifty Pharma Index, as evidenced by the low AIC and Schwarz Criterion values and the significance of the likelihood ratio test. The volatility behavior captured by the model, especially volatility clustering, is crucial for understanding how market shocks can affect future volatility in the pharmaceutical sector, which could be of interest to investors and analysts for risk management purposes. The GARCH model applied to the Nifty Pharma Index returns effectively captures the volatility dynamics of the pharmaceutical sector. With significant coefficients and strong model fit statistics, the results suggest that volatility in the sector is highly persistent and influenced by past market movements.

3.5 ARIMA Forecasting



Source: Collected NSE index data and calculated using gretl.

The figure presents the predicted and actual returns for the Nifty Pharma Index over a period, along with their standard errors and 95% confidence intervals. These values allow us to assess the accuracy and reliability of the forecasted returns. The predicted returns, shown for each day, are calculated based on a model, while the actual returns represent the observed market performance. The standard error indicates the variability of these predictions, with smaller values suggesting higher precision. For the majority of the observations, the predicted and actual returns are relatively close, which indicates that the model is generally performing well. However, there are instances where the prediction deviates from the actual return, such as on 2024-08-28 and 2024-10-30, where the returns were negative despite optimistic predictions. By examining the confidence intervals, we see the expected range for each predicted return, offering insight into the level of uncertainty. Overall, the model provides useful predictions with acceptable accuracy, but there are periods of market instability where the forecasts are less reliable.

4. CONCLUSION

This study analyzes the Nifty Pharma Index, examining growth drivers, market behavior, and volatility in the pharmaceutical sector. Using econometric techniques like Augmented Dickey-Fuller (ADF) tests, autocorrelation analysis, and models such as ARIMA and GARCH, the research provides key insights into the sector's dynamics. The ADF test confirms the stationarity of the index, allowing for reliable forecasting. Autocorrelation analysis highlights significant dependencies between past and current returns, suggesting predictability in the market. The GARCH model reveals persistent volatility influenced by past shocks, supporting the idea of volatility clustering. While the ARIMA model generally offers reliable short-term forecasts, external factors like global economic conditions, regulatory changes, and the COVID-19 pandemic are shown to impact sector performance. The study's findings offer valuable insights for investors, analysts, and policymakers, enabling more informed decisions on risk management and investments in the pharmaceutical sector.

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