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Stock returns volatility of select NSE – listed FMCG Stocks: An empirical study

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Abstract

Stock market volatility plays a crucial role in investment decision-making, risk management, and portfolio diversification. Global financial meltdowns have massive shock on different sectors as well as on scripts returns. The study aims to measure and analyze the stock return volatility of select Fast-Moving Consumer Goods (FMCG) companies listed on the National Stock Exchange (NSE) of India based on time series dataset taking into consideration of daily closing adjusted stock price from 2001-02 to 2015-16. The objective of this paper is to study volatility design of daily stock returns. The application of GARCH, and T-GARCH models provides the evidence of the persistence of time varying asymmetric volatility. Main findings suggest that time varying volatility behavior of Indian stock market may be due to recent global financial meltdown which is originated from US sub-prime crisis. The study provides valuable insights for investors, policymakers, and financial analysts by offering a deeper understanding of risk-return dynamics within the FMCG sector.

Keywords: Asymmetric volatility, conditional volatility, financial meltdown

Introduction

The Background of the Study

Stock market volatility is a critical factor influencing investment decisions, risk management, and financial stability. Investors and financial analysts closely monitor volatility to assess market risk and make informed investment choices. The Fast-Moving Consumer Goods (FMCG) sector, a key component of the Indian economy, comprises companies engaged in the production and distribution of essential consumer goods such as food, beverages, personal care products, and household items. Given its essential nature, the FMCG sector is often considered a defensive investment choice, relatively insulated from economic downturns compared to cyclical industries. However, market fluctuations, macroeconomic conditions, and sector-specific events can still impact stock return volatility. Despite their perceived stability, the stock prices of these companies exhibit varying levels of volatility due to factors such as inflation, changes in consumer demand, raw material costs, regulatory policies, and global economic trends. Understanding the volatility of FMCG stocks is crucial for investors, portfolio managers, and policymakers in assessing risk exposure and making strategic investment decisions. Considering the daily log returns of stock, the daily volatility is not directly observable from the return data because there is only one observation in a trading day. It can be defined as a statistical measure of the dispersion of stock price returns for a given security or market index and it can either be measured using the standard deviation or variance between returns from that same security or market index (John, et. al., 2016) [10]. Understanding stock return volatility is crucial for financial market participants, as it influences investment strategies, asset allocation, and risk assessment. A highly volatile stock may present opportunities for short-term traders but poses risks for long-term investors. Conversely, less volatile stocks may provide stability but offer lower returns. Volatility is useful for superior returns. Higher volatility causes higher risk (Kumar, 2016) [13, 15]. By analyzing the volatility of NSE-listed stocks, this study contributes to the academic literature on financial risk management and provides practical insights for investors, regulators, and financial institutions.

Past Studies and Research Gap

Fama (1970) explored that stock prices fully reflect all available information. According to Efficient Market Hypothesis (EMH), stock price movements follow a random walk, implying that predicting future price movements based on past trends is not possible. However, real-world stock markets exhibit fluctuations due to investor sentiment, macroeconomic events, and market inefficiencies, leading to deviations from the EMH. Engle (1982) introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model, which was later extended by Bollerslev (1986) into the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. These models capture time-varying volatility and help in forecasting stock market fluctuations. The GARCH model is widely applied in stock return volatility studies due to its ability to model persistence and clustering of volatility. Bekaert and Harvey (1997) analyzed stock return volatility in emerging markets, finding that developing economies exhibit higher and more unpredictable volatility compared to developed markets. Kumar and Mukhopadhyay (2002) examined Indian stock market volatility and concluded that macroeconomic variables, such as inflation and interest rates, significantly impact stock return fluctuations. Sehgal and Tripathi (2007) studied the volatility behavior of Indian stock indices and found that Indian markets exhibit asymmetric volatility, meaning negative market shocks lead to higher volatility than positive shocks. Goyal and Aggarwal (2020) analyzed sectoral volatility patterns on the NSE and reported that sectors such as IT and banking experience higher volatility compared to defensive sectors like FMCG. Singh and Yadav (2021) studied sectoral beta coefficients and concluded that FMCG and pharmaceutical stocks generally have low beta values, indicating defensive characteristics. Padhi (2006) [24, 25] investigated that market volatility at the individual script level and at the indices level to know how volatility changes in the same trend or it varies across the sectors and conducted that LM test is using to confirm the presence of ARCH effect. Different ARCH coefficients are found for different indices at different lag values and argued that many sectors showing the same trend for volatility characteristics.

While existing studies provide insights into general market trends, there is a need for sector-specific analysis of different NSE-listed FMCG stocks to better understand volatility patterns in major stock exchanges in India and to explore how volatility of individual script changes with respect to different time period in respect to different economic policies, incident, etc. and underlying different factors and shocks which can affect individual securities. Keeping in mind of this research gap, specific objectives of the current study are set. This study aims to fill these gaps by applying different GARCH models to selected NSE-listed stocks, providing empirical insights into their risk-return dynamics.

Objectives of the Study

The objectives of the current study are as follows:

1. To examine the presence of volatility in FMCG companies daily return series using ARCH (1) model;
2. To analyse volatility in select NSE listed FMCG companies using GARCH and TGARCH Model.

Data and Methodology

The current study is based on secondary data. Daily adjusted closing share price of select NSE-listed fast-moving consumer goods (FMCG) sector companies collected from Capitaline corporate database and NSE official website as well, are considered here for calculation of daily stock price return series of each company and yearly stock returns volatility (Beta value) of them. The sample design follows the judgment sample technique based on market capitalization of sample top companies. It tries to measure volatility of diversified sector's top market capitalisation companies, which were listed and actively traded in NSE from 2000-01 to 2015- 2016. The study has been made considering the Global financial recession period, which includes the study period from 7th August, 2007 to 2nd April, 2009.

Different statistical tools are used in this study, such as Autoregressive Conditional Heteroskedasticity (ARCH) Test, Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model, Threshold Generalized Autoregressive Conditional Heteroskedasticity (T-GARCH) Model.

Statistical Tools used	Analysis to address stated objectives of the study
ARCH Test	To examine the presence of ARCH effect in sample companies daily return series using ARCH (1) model (Decision Rule: If p- value <0.05, then H_0 is rejected and vice versa).
GARCH Model	To explain the stock market volatility (conditional variance) at the individual script level from the select sample companies (Decision Rule: If the sum of the two estimated ARCH & GARCH coefficient is equal to one, it indicates volatility shocks are quite persistent).
T-GARCH Model	To explain the stock market volatility (asymmetry or leverage effect) at the individual script level from the select sample companies (Decision Rule: If leverage term (γ) is significant and positive, negative shocks have a larger effect on conditional volatility than the positive shocks).

Results and Analysis

1. **Examining the presence of volatility in select NSE listed FMCG Sector companies daily return series using ARCH (1) model**

ARCH effect has become important tools in the analysis of financial time series data, particularly in financial time series application. ARCH effect means heteroskedasticity, which is modelled as conditional variance of squared residuals obtained from mean equation as from AR (1) model. The results are as follows:

Table 1: Heteroskedasticity Test Results – ARCH (1) for Global Recession Period

Companies	F-statistic	Prob. F	Obs* R- squared	Prob. Chi-Square	Decision on Ho	ARCH effects are present or not
Britania	1.38	0.239	1.39	0.239	Accepted	No ARCH effects
Colgate Palmolive	6.27	0.05	6.21	0.05	Accepted	No ARCH effects
Nestle India	16.99	0.37	16.56	0.37	Accepted	No ARCH effects
Hind. Unilever	59.20	0.000	51.89	0.000	Rejected	ARCH effects are present
ITC	13.02	0.000	12.70	0.000	Rejected	ARCH effects are present
P&G Hyge	0.084	0.77	0.084	0.77	Accepted	No ARCH effects
Godrej Ind	12.88	0.000	12.55	0.000	Rejected	ARCH effects are present
Dabour	15.79	0.000	15.27	0.000	Rejected	ARCH effects are present
MARICO	41.04	0.000	37.44	0.000	Rejected	ARCH effects are present

(**Source:** Compilation of Stock price returns data using EViews 8.0)

Heteroskedasticity has been tested using ARCH (1) model in order to know whether there is ARCH effect in the residuals in select return series during the study period. ARCH results comprise of F value, Probability of F value, obs. R squared value and probability of χ^2 value. If p value of T. R^2 statistics is less than 0.01 or 1%, null hypothesis (H_0) is rejected. Hence, it can be stated that there is in existence of ARCH effect. However, during the global recession period, four stocks out of nine FMCG stocks do not have ARCH effect in their return series

2. Analyzing Volatility in select NSE listed FMCG Sector Companies using GARCH Model

The general process for a GARCH model involves overcoming some of the drawbacks of the ARCH model**.** GARCH model represents generalized ARCH processes in the sense that the squared volatility (σ_t^2) of the concerned period is allowed to depend on previous squared volatilities, as well as previous squared values of the process. The present study has employed GARCH (1, 1) technique to capture the conditional volatility in the return series. The results are as follows:

Table 2: GARCH Model (Global Recession Period)

Company Name/ Sectors	Estimated Model with values				AIC	SIC	Log Likelihood	Decision
First Period - Coefficients - GARCH (1, 1)								(Decision Rule: Volatility of shocks is highly persistence when $\alpha_j+\beta_i$=1)
FMCG	α_0	α_1	β_1	$\alpha_j+\beta_i$				
Hind. Unilever	6.07	0.256	0.634	0.596	-5.06	-5.04	3811.2	Comparatively low persistence value
ITC	0.0001	0.205	0.607	0.812	-5.18	-5.16	3899.3	Comparatively low persistence value
Godrej Ind	0.0001	0.132	0.821	0.953	-3.95	-3.93	2676.5	Comparatively low persistence value
Dabour	0.0001	0.195	0.681	0.876	-4.95	-4.71	3560.7	Very high persistence value
MARICO	0.0001	0.135	0.640	0.775	-4.95	-4.93	3698.3	Comparatively low persistence value

(**Source:** Compilation of Stock price returns data using EViews 8.0)

The present study has employed GARCH (1, 1) technique to capture the conditional volatility in the return series. There is different lag order model in GARCH and finally GARCH (1, 1) model is found. Log likelihood ratio becomes maximum where we find minimum value of AIC, SIC, HQ value of selected empirical estimation. Our GARCH test results found to be significant. It implies that coefficient of constant (α_0), ARCH term (α_1) and GARCH term (β_1) are highly significant at 1% level of significant. In the conditional variance equation, the estimation β_1 coefficient is considered to be greater than α_1 coefficient which resembles that the market has a memory longer than one period and volatility is highly dependable on its assumed lag values. GARCH model depicts effects of new surprise in the market values due to price sensitive information. It depicts the nature of persistence in the volatility. If the results of α_1 & β_1 are close to unity (i.e. one), then the possibility of more persistent is the stock to conditional variance in return. This clearly proves the high volatility among these companies. The coefficient results of ARCH effect show mixed results during the study period.

3. Analyzing Volatility in select NSE listed FMCG Sector Companies using T-GARCH Model

The Threshold GARCH (T-GATRCH) model has been proposed by Zakoian (1991). In this section, T-GATCH model has been adopted in stock price of return series data in select stocks. The main target of this is to capture asymmetry in terms of negative and positive stocks and multiplicative dummy variable to check whether there are statistically significant differences when shocks are positive and negative. The results are as follows:

Table 3: T-GARCH Model (Global Recession Period)

Company Name	Estimated Model with values				AIC	SIC	Log Likelihood	Decision
First Period - Coefficients - GARCH (1, 1) with Threshold order 1								
FMCG	α_0	α_1	γ	β_1				
Hind. Unilever	6.02	0.115	0.299	0.638	-5.06	-5.04	3815.45	Positive γ which implies negative shocks is larger effect on volatility
ITC	0.0001	0.072	0.187	0.669	-5.18	-5.16	3900.27	Positive γ which implies negative shocks is larger effect on volatility
Godrej Ind	9.86	0.046	0.135	0.848	-3.95	-0.93	2679.76	Positive γ which implies negative shocks is larger effect on volatility
Dabour	6.76	0.061	0.119	0.788	-4.73	-4.71	3563.15	Positive γ which implies negative shocks is larger effect on volatility
MARICO	0.0001	0.124	0.013	0.648	-4.94	-4.92	3698	Positive γ which implies negative shocks is larger effect on volatility
Dabour								
MARICO								

(**Source:** Compilation of Stock price returns data using EViews 8.0)

T-GARCH model has been used to know that positive and negative shocks of equal magnitude have a different impact on stock market volatility, which may be attributed to 'leverage effect'. In ARCH model, return series represent hetroskedasticity for different period. GARCH model generally used the conditional variance as a linear function of lagged conditional variances and squared past returns. The T-GARCH table results clearly prove that good news has an impact of ARCH term (α_1), while bad news has impact on ARCH as well as leverage. But the GARCH effect is significant for all FMCG stocks during the time period. No ARCH effect is found for P&G Hyge for pre-global financial meltdown period. During the recession time period, maximum scripts do not have any ARCH effect like Britania, Colgate Palmolive, Nestle India and P&G Hyge.

The coefficient of leverage (δ) is positive in maximum cases and significant at 1% level representing negative shocks or bad news.

Conclusion

In GARCH model, it appears that the combined value or sum of coefficient of ARCH and GARCH value is around one, it indicates volatility clustering and persistency. However, T-GARCH model indicates that negative shocks or bad news has a greater effect on the conditional variance than the positive shocks or good news. The analysis reveals that stock return volatility varies significantly across different sectors and companies, with some stocks exhibiting high fluctuations due to macroeconomic conditions, investor sentiment, and market dynamics. Furthermore, the GARCH model confirmed the presence of volatility clustering, indicating that stock markets experience periods of high and low volatility in cycles rather than remaining constant over time. This finding aligns with previous research suggesting that market shocks, economic policy changes, and external factors such as global financial events significantly impact stock return volatility.

References

1. Ali I. Stock market volatility and returns: A study of NSE & BSE in India. International Journal of Humanities & Social Science Studies,2016:2(4):202–211.
2. Anbukarasi M, Nithya B. Return and volatility analysis of the Indian sectoral indices – with special reference to NSE. EPRA International Journal of Economic and Business Review,2014:2(8):90–97.
3. Banumathy K, Azhagaiah R. Modelling stock market volatility: Evidence from India. Managing Global Transitions,2015:13(1):27–42.
4. Bhaumik SK. Principles of Econometrics: A Modern Approach Using E-views (1st Ed.). Oxford University Press, New Delhi, 2015.
5. Binny AB. Analysis of stock market volatility: A comparative study of India and China. Apeejay Journal of Management and Technology,2014:9(2):8–17.
6. Dash M, Duuta A, Sabharwal M. Seasonality and market crashes in Indian stock markets. Asian Journal of Finance & Accounting,2011:3(1):174–183.
7. Ekta R. GARCH based volatility modeling in bank's stock. Researchers World,2013:4(4):95–102.
8. Eryilmaz F. Modelling stock market volatility: The case of BIST–100. ABP,2015:1(5):37–47.
9. Ezzat H. The application of GARCH and EGARCH in modeling the volatility of daily stock returns during massive shocks: The empirical case of Egypt. IRJFE,2012:1(96):153–164.
10. John A, Oduro FT, Prah JA. Modelling volatility and the risk–return relationship of some stocks on the Ghana stock exchange. American Journal of Economics,2016:6(6):281–299.
11. Kothari CR. Research Methodology: Methods and Techniques (2nd Ed.). New Age International Publishers, New Delhi, 2010.
12. Kumar R, Debroy B, Ghosh J, Mahajan V, Seeta Prabhu K. Global financial crisis impact on India's poor – some initial perspectives. United Nations Development Programme (UNDP) India,2009:8–25.
13. Kumar B, Singh P. The dynamic relationship between stock return, trading volume and volatility: Evidence from Indian stock market. Research Gate,2016:1–49.
14. Kumar B, Singh P. Volatility modeling, seasonality and risk return relationship in GARCH-in-mean framework: The case of Indian stock and commodity markets. Indian Institute of Management, Ahmedabad, Working Paper,2008:1–31.
15. Kumar NS. Study on volatility of stock market data of selected companies engaging in retail finance in India. PIJMIS,2016:5(1):1–13.
16. Kumar R, Gupta H. Volatility in the Indian stock market: A case of individual securities. JARE,2009:1(1):43–53.
17. Lakshmi PS. Volatility patterns in various sectoral indices in Indian stock market. Global Journal of Management and Business Studies,2013:3(8):879–886.
18. Mall M, Mishra S, Mishra PK, Pradhan BB. A study on relation between India VIX and NIFTY returns. IJBIF,2014:1(3):1–7.
19. Mail M, Pradhan BB, Mishra PK. Volatility of India's stock index futures market: An empirical analysis. Researchers World,2011:2(3):119–126.
20. Maqsood A, Safdar S, Shafi R, Lelit NJ. Modeling stock market volatility using GARCH models: A case study of Nairobi Securities Exchange (NSE). Open Journal of Statistics,2017:1(7):369–381.
21. Malhotra NK. Marketing Research: An Applied Orientation (3rd Ed.). Pearson Education Asia, New Delhi, 2003.
22. Najjar DA. Modelling and estimation of volatility using ARCH/GARCH models in Jordan's stock market. Asian Journal of Finance & Accounting,2016:8(1):152–167.
23. Naveen S, Mallikarjunappa T. A study on comparative analysis of risk and return with reference to stocks of CNX BANK NIFTY. International Journal of Scientific Research and Modern Education,2016:1(1):737–743.
24. Padhi P. Stock returns volatility: A case study of pharmaceuticals and computer software in India. Journal of Academic Research in Economics,2006:1(1):1–13.
25. Padhi P. Stock market volatility in India: A case of select scripts. Journal of Academic Research in Economics,2006:1(1):1–54.
26. Palit A. South Asia - Beyond the Global Financial Crisis. World Scientific Publishing Co. Pvt. Ltd., 2011.
27. Pandey A. Capital Market & Financial System in India (1st Ed.). New Century Publications, 2010.
28. Rakesh HM. A study on volatility of FMCG and auto indices of National Stock Exchange. IJCBM,2014:3(4):618–622.
29. Sainy R. A study of factors affecting stock price volatility: Perception of stock brokers. Intercontinental Journal of Finance Research Review,2016:4(2):1–10.
30. Shankar C, Ramulu K. Volatility and correlation of stock indices on Indian stock market. IJRBM,2014:2(4):17–26.
31. Shannmugasundran G, Benedict J. Volatility of the Indian sectoral indices – a study with reference to National Stock Exchange. IJMFSMR,2013:2(8):1–11.
32. Tripathy T, Alana LAG. Suitability of volatility models for forecasting stock markets returns: A study on the

Indian National Stock Exchange. AJAS,2010:7(11):1487–1494.
33. Tripathy TK. Modelling volatility of daily stock returns: Evidence from NSE listed computer software & multimedia scripts. IJACMSS,2020:3(3):141–148.
34. Tripathy TK. Modelling volatility of daily stock returns: Evidence from select banking and finance companies in India. Business Studies,2021:42(1&2):1–25.
35. Tsay RS. Analysis of Financial Time Series (2nd Ed.). Wiley–Blackwell, USA, 2016.
36. Yadav S. Impact of derivatives trading on the volatility of stock market in India: A review. Asian Journal of Management Research,2016:6(3):567–579.
37. Retrieved from https://www.crestmontresearch.com/docs/stock-volatility-perspective.pdf.
38. Retrieved from https://www.nseindia.com/education/content/prs_publications.htm.