Section of the conference: Management

Sekcja konferencji: Kierownictwo

How to cite: Dhany, K. A. (2025). Dissecting volatility: Do sectoral dynamics drive the Nifty 50 index? A GARCH family approach. *World Conference on Emerging Science, Innovation and Policy 2025*. Futurity Research Publishing. https://doi.org/10.5281/zenodo.16559331

Dissecting Volatility: Do Sectoral Dynamics Drive the Nifty 50 Index? A GARCH Family Approach

K A Dhanya [1]

[1]M Com, MBA, M Phil , PhD, Assistant Professor, School of Business & Management
Christ University, Bangalore, India

Accepted: July 5, 2025 | **Published**: July 20, 2025 | **Language:** English

Abstract: Volatility in financial markets is crucial factor impacting portfolio management and investment decisions. This study investigates the impact of sectoral dynamics on Nifty 50 volatility using GARCH family models. Daily log returns of Nifty50, Bank nifty, Fin nifty and Nifty midcap is taken over a one-year sample period. Result shows the existence of ARCH effect, with volatility responding to past shocks. GARCH results shows that sectoral log returns do not significantly impact the nifty50 volatility. EGARCH effects shows significant leverage effect indicating negative shocks have more impact on volatility than positive shocks.

Keywords: Volatility clustering, GARCH, EGARCH, Sectoral dynamics, ARCH effect, Positive shocks, Negative shocks, leverage effect.

Introduction

Volatility modelling has become an integral part of financial scrutiny especially in the context of risk management, investment analysis, portfolio management. Nifty50 is a benchmark of market performance and investor confidence for emerging economies like India. Over the years, researchers have been trying to fathom the reasons behind volatility dynamics in Nifty50 index. Due to its high trading volume and liquidity, it's always a topic of interest for investors too. Therefor studies related to volatility is always relevant and welcoming. Vivek et.al (2022) in their study pointed out that volatility clustering exists in nifty50, using GARCH (1.1) model. They also found that shock is persistent and strong over the period. They concluded that negative shocks are more effective than positive shocks. R, S. (2021) in their study analyzed the volatility of blue chip companies listed in Nifty 50. Results shows that all the selected stocks have time varying conditional volatility as both ARCH and GARCH models were statistically significant. Shock volatility is also persistent over the period. Mukherjee, T., & Mandal, S. (2024) examines the impact of market volatility on Nifty 50 , with relationship between India VIX and Nifty 50. Granger causality test was adopted to know the cause and effect between the variables. A paper on Stock returns and volatility, investigates the volatility of Nifty 50 returns, through comparison of various conditional heteroscedasticity models. Results shows that there is significant evidence of asymmetry in stock returns captured by EGARCH and persistence of shocks into volatility (Palanisamy, K., & Parthasarathy, K. 2016). Another study on volatility of Nifty 50 indicated high volatility existence in Nifty 50, leading to excellent investment opportunity in the long run. Few studies are also conducted with regard to analyzing the impact of sectoral indices on nifty 50. Relationship between futures trading and volatility of stocks in bank nifty index were examined using GARCH models and result shows that only 2 banks out of six banks showed statistically significant impact on volatility (Paientko, T., & Pundir, R. R. K, 2024). In another study on analyzing dynamic relationship between Nifty 50 and sectoral indices, shows that nifty pharma and bank nifty has lesser correlation with nifty 50 returns. (Gupta,2024). Another study noticed strong positive correlation between Nifty 50 returns and sectoral indices like Bank nifty, financial services nifty but weak relationship between Nifty IT and Nifty Auto index. Grander causality test also establishes a causal relationship between these variables. (Sujyoti & Suresh, 2024)

Research Question and Gap identified

At this juncture, it is worth noting that the study on volatility and its factors is highly relevant. Present study tries to develop a research question, do sectoral indices impact the volatility behavior of Nifty 50 returns or not? Even though many studies have been conducted related to nifty 50 volatility, very few studies have taken into consideration the impact of sectoral indices on volatility, with special focus on GARCH model. This study is unique as it tries to come out with research output in relation to two specific objectives under one frame.

Hypothesis

$H_0 1$: Sectoral indices do not significantly impact the volatility of Nifty 50 returns
$H_0 2$: Nifty 50 returns do not exhibit time varying conditional volatility
$H_0 3$: There is no presence of asymmetry in nifty 50 returns.

Research Methodology

This study specifically examines the relationship between sectoral indices and their impact on nifty50 returns with special focus on volatility. EViews software has been used for the analysis of data. Dependent variables selected for the study is nifty 50 returns and independent variables selected are Bank nifty returns, financial services nifty returns and midcap nifty. Daily closing price for a period of 1 year starting from 1st June 2024 to 31st may 2025 is taken for the study (219 observations) and its log returns are calculated. Log values of the all the variables are checked for stationarity, using

ADF test. ARCH- GARCH (1,1) model is applied to see the volatility behavior of Nifty 50. Asymmetric effects are tested using EGARCH.

Research Results

Log values of all variables are taken into consideration and the result of ADF test shows that, all data sets are stationary at I (0). Since the p values are less than .05, stationarity test result is statistically significant to proceed further [Table 1]. To check whether independent variables explain nifty50 returns, a multiple regression model is being applied.

$$Nifty50_t = \beta_0+\beta_1 \cdot BankNifty_t+\beta_2 \cdot FinNifty_t+\beta_3 \cdot MidcapNiftyt+\varepsilon_t$$

Results show that [Table 2] banknifty returns and midcap nifty returns significantly impact the returns of Nifty50. But Fin nifty result shows that it is statistically in significant as the P value is more than .05. hence it can be concluded that out of the three sectoral indices, two sectoral indices (bank nifty and midcap nifty) can significantly explain the mean behaviour of Nifty50 returns with a predictive power of 81%, with Durbin Watson statistic of 2.2. [Figure 1] shows the volatility pattern of Nifty50 returns over the past one year. Proceeding further to check whether sectoral indices affect the conditional volatility of Nifty50 returns, GARCH (1,1) model is used since the ARCH effect was established with F statistic of 45.4011 and P value being significant with .000. [Table 3] shows the result of GARCH (1,1) model. It is noted that GARCH effect is not significant as the P value is greater than .05. Since GARCH is insignificant at .3049, ARCH model is adopted further with each independent variable as regressor. [Table 4] explains the result of ARCH model with regressors. It shows that there is significant presence of ARCH effect which means past shocks effect the current volatility. The model reveals a statistically significant ARCH effect ($\alpha = 0.434$, $p < 0.01$), confirming volatility clustering. However, the log term of sectoral indices returns does not significantly impact the volatility. This shows that conditional variance is predominantly influenced by its on lagged shocks rather than sectoral return movements. Volatility dynamics are sufficiently captured by ARCH terms. It can be inferred that volatility in Nifty50 over the past one year significantly respond to recent shocks or sudden changes because of the presence of ARCH effect but does not persist over time in a predictive manner as GARCH effect is insignificant. Further EGARCH Model is used for capturing the asymmetry in volatility known as leverage effect. Result of EGARCH exhibited in [Table 5] shows that volatility is significantly affected by both the size and sign of past shocks. Significant and large coefficient value ($\beta = .673$) of EGARCH result, indicates that volatility is persistent. ARCH effect term shows larger shocks regardless of direction will affect volatility. The negative coefficient on asymmetric term ($C(4)\,(\gamma) = -.2337$) indicates the leverage effect that negative returns increase volatility that the positive ones.

Table 1

Result of ADF Test

Variable	ADF T Statistic	5% critical value	P Value	Result	Order
log_nifty50 returns	-17.01459	-2.89	.000	stationary	I(0)

log_finnifty	-11.28561	-2.89	.000	stationary	I(0)
log_banknifty	-18.47290	-2.89	.000	stationary	I(0)
log_midcapnifty	-17.03656	-2.89	.000	stationary	I(0)

Table 2

Result of OLS Regression

Variable	Coefficient (β)	Std. Error	t statistic	P Value
log_banknifty	.4956	.0404	12.26	.0000
log_finnifty	.0003	.0014	.2662	.7903
log_midcapnifty	.2653	.0316	8.39	.0000
Intercept (β_0)	-.0009	.0295	-.003	.9971
R^2 = .8127 DW Statistic = 2.2				

Figure 1

Volatility of Nifty50 returns

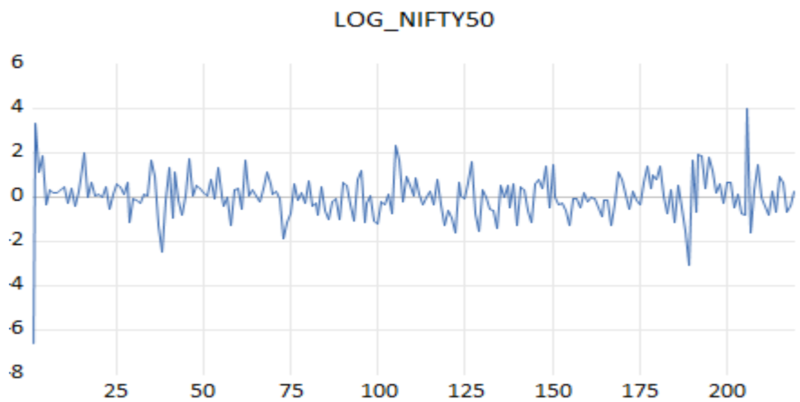

Table 3

Result of GARCH (1,1) Model

Variable	Coefficient	Std. Error	z-Statistic	Prob.
LOG_BANKNIFTY	0.493192	0.042836	11.51342	0.0000
LOG_FINNIFTY	0.000345	0.002206	0.156611	0.8756
LOG_MIDCAP	0.266975	0.030648	8.711087	0.0000
C	0.001564	0.032133	0.048688	0.9612
Variance Equation				
C	0.038623	0.134552	0.287050	0.7741
RESID(-1)^2	0.021448	0.045988	0.466391	0.6409
GARCH(-1)	0.771971	0.752395	1.026019	0.3049

Table 4

ARCH model with Regressors

Coefficient	Value	Interpretation
C (0.517355)	Significant as P value < .005	Baseline level of conditional variance
RESID(-1)^2 (0.434458)	Significant as P value < .005	Shows the presence of ARCH effect
log_banknifty (0.002528)	Not Significant as P Value (.9513)	Log return of Bank nifty do not significantly affect the Nifty50 Volatility
log_finnifty (0.002253)	Not Significant as P Value (.7667)	Log return of fin nifty do not significantly affect the Nifty50 Volatility
log_midcap (0.012203)	Not Significant as P Value (.6997)	Log return of midcap nifty do not significantly affect the Nifty50 Volatility

Table 5

Results of EGARCH

Variable	Coefficient	P Value	Interpretation
C(2) (ω)	-0.366556	.0007 (significant)	Low base volatility if no shocks
C(3) (α)	0.327298	.0061(significant)	Shows a significant result of volatility reacting to shock size
C(4) (γ)	-0.233738	.0006(significant)	Significant and negative which confirms the leverage effect.
C(5) (β)	0.673097	.0000(significant)	Volatility is persistent

Conclusion

This study concludes that even though sectoral indices significantly impact the Nifty50 returns, they do not contribute much in the volatility clustering of Nifty50. GARCH (1) result shows that there is no significant time varying conditional volatility ($\alpha = 0.0214$, $p = 0.6409$) in Nifty50returns but at the same time ARCH effect was statistically significant ($\alpha = 0.434$, $p < 0.01$) confirming volatility clustering. EGARCH results establishes the leverage effect and shows that negative shocks have higher impact on volatility when compared to positive shocks. To summarize, sectoral indices bank nifty and midcap nifty were significant in predicting returns but not volatility of Nifty50. Hence there is further scope for the study to assess the impact of macro-economic variables and other external factors which have more significant impact on volatility clustering,

References

Gupta, P. K. (2024). Analysing the dynamic interrelationship between Nifty Fifty and sectoral indices daily returns of NSE. *International Research Journal of Modernization in Engineering, Technology and Science,* 6(9), 3311–3323. https://www.irjmets.com/uploadedfiles/paper//issue_9_september_2024/61489/final/fin_irjmets1728275107.pdf

Mukherjee, T., & Mandal, S. (2024). Impact of market volatility on NIFTY 50 returns: An empirical study. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4964444 SSRNSSRN

Naveen Kumar, P., & Minithra, R. (2021). Estimation of price volatility of Nifty 50 index using ADF and GARCH (1,1). *Indian Journal of Economics and Development, 17*(2), 480–485. https://doi.org/10.35716/IJED/20286soed.in

Palanisamy, K., & Parthasarathy, K. (2016). Stock returns and volatility: Evidence from Nifty 50 index. *Asian Journal of Research in Social Sciences and Humanities, 6*(5), 434–442. https://doi.org/10.5958/2249-7315.2016.00127.1ResearchGate

Paientko, T., & Pundir, R. R. K. (2024). Volatility analysis of the Indian stock market: Insights from Bank Nifty index and futures trading. *Journal of Intercultural Management, 16*(4), 5–41. https://doi.org/10.2478/joim-2024-0013SciendoIDEAS/RePEc

Shankar, R., & Gopal, L. N. (2021). Volatility analysis of select blue-chip companies listed in Nifty 50 index of India. *Revista GEINTEC – Gestão Inovação e Tecnologias, 11*(4), 104–115. https://doi.org/10.47059/revistageintec.v11i4.2096

Sujyothi, M., & Suresh, A. S. (2024). Analysing the causal relationship between Nifty 50 and sectoral indices. *Journal of Emerging Technologies and Innovative Research, 11*(5), 256–264. https://www.jetir.org/view?paper=JETIR2405432

Vevek, S., Selvam, M., & Sivaprakkash, S. (2022). The persistence of volatility in Nifty 50. *Indian Journal of Research in Capital Markets, 9*(2–3), 8–18. https://doi.org/10.17010/ijrcm/2022/v9i2-3/172549