

A Study on Volatility Persistence and Spillover Effect Between Nifty and Nifty Futures

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Abstract

This study investigates whether a significant spillover effect exists between the NIFTY spot and futures markets. Further, as the purpose of the study, we also determine whether volatility persistence and asymmetry exist in both markets. As the methodology, the ten-year daily closing prices of the Nifty 50 and Nifty Futures Indices were collected, and GARCH (1,1), EGARCH, and DCC GARCH were used for the analysis. From the study, we found that a high level of volatility persists in both spot and futures markets, and the EGARCH test results reveal a significant volatility asymmetry in both spot and futures markets. The spillover effects analysis using the GARCH DCC model shows that a significant long-term and short-term volatility spillover effect is present between the two markets. We conclude that these results will be of immense use for traders and investors to have a direction on volatility asymmetric effect, persistence, and volatility spillover effect between spot and futures markets. We also state that the study can be extended to stock futures, Bank Nifty indices, etc., and other GARCH methods can be employed in further studies.

Keywords: Volatility; Spillover Effect; Asymmetry; GARCH Models; Spot and Futures Markets; Volatility Persistence, **JEL Classification:** G02; G11.

Introduction

The financial market plays a vital role in facilitating the smooth operation of capitalist economies by allocating resources and creating liquidity for businesses. The stock market is a part of the financial market in which people buy and sell financial instruments, including equities, bonds, currencies, and derivatives. It allows companies to raise money by offering shares and corporate bonds. It also enables investors to participate in the financial achievements of companies, profit through capital gains, and earn income through dividends. The stock market works as a platform through which the savings and investments of individuals are significantly channelled to productive investment opportunities, which results in returns to investors but sometimes creates huge losses due to volatility in the market. Investors in spot markets consider futures markets as a platform for hedging, since the stock market is volatile and earns profits from this opportunity. This hedging process helps investors mitigate their losses in volatile markets. This encourages the study of the interdependence between the spot and futures markets.

In this study, we investigate the interdependence between the spot and futures markets by analysing whether a volatility spillover effect exists between the Nifty spot and futures markets. We also explore the presence of volatility persistence and asymmetry in the spot and futures markets. This study

contributes to the existing literature by focusing on the following objectives: First, it analyses the nature of Nifty and Nifty Futures returns. Second, to determine the optimal hedge ratio. Third, we determine the volatility persistence in the Nifty and Nifty Futures. Fourth, we check for asymmetry in both markets. Finally, we determine the volatility spillover between the Nifty spot and Nifty futures markets.

The results reveal that a significant volatility asymmetry is present in both the spot and futures markets, indicating that negative news has a higher impact on volatility than positive news. The test results also reveal long- and short-term volatility spillover effects between the spot and futures markets. This study helps investors understand the significance of hedging in the futures market.

The rest of the research paper is categorized as follows: section 2 explains the review of the literature, section 3 describes data and methodology, section 4 shows the analysis and interpretations, and Section 5 shows the conclusions of the study.

Review of Literature

Chou (1988) investigated how volatility persistence, unexpected increases in investments and changes in risk premiums affect stock market dynamics. The GARCH results reveal that shocks to stock returns exhibit a high level of volatility persistence. **Vevek et al. (2022)** analysed the volatility persistence of the Nifty 50's daily returns in the Indian Stock Market using different GARCH models. They showed that the Indian secondary market experienced unanticipated volatility.

Bubak et al. (2011) examined the volatility dynamics between Central European (CE) currencies and the EUR/USD foreign exchange rate. The findings reveal statistically significant intra-regional volatility spillovers within the Central European foreign exchange markets. **Erten et al. (2012)** analysed the magnitude and presence of the volatility transmissions in the emerging market. A multivariate BEKK methodology was used, and the results indicate that significant volatility spillovers exist between the emerging markets. **Magkonis & Tsouknidis (2017)** examined the existence, severity and direction of time-varying spillover effects across

petroleum-based commodities, and the results reveal the existence of significant and time-varying spillovers among the spot and future volatilities across petroleum-based commodities.

Hasan et al. (2019) examined the spillover effect between the KSE 100 and S&P indexes. GARCH and EGARCH models were used for the study, and the findings highlight that shocks to the volatility of the indices have asymmetrical and persistent effects. They also revealed that there is no spillover effect between the indices. **Kara et al. (2022)** investigated the relationship between Turkey's spot and futures markets. The DCC-GARCH and GJR-GARCH models found a bidirectional volatility spillover between the markets and the impact of positive and negative shocks on market volatility. **Yadav et al. (2023)** examined the transmission of volatility spillovers between the Indian and global stock markets. The DCC-GARCH model was employed, and the findings revealed that in the short run, a spillover effect is present from global markets to Indian stock markets.

Data and Methodology

Data

For this study, secondary data were utilised, with information sourced from the NSE website, encompassing daily closing prices of the Nifty 50 and Nifty Futures Index from 1 April 2014 to 31 March 2024. The analysis involved utilising the Mean, Median, Skewness, Kurtosis and Jarque-Bera test results to understand the nature of the data, and various GARCH models, such as GARCH (1,1), EGARCH, and DCC GARCH, were employed to examine the market volatility effects. Returns were calculated using the following formula:

$$R_t = \ln \left[\frac{P_t}{P_{t-1}} \right] * 100$$

Where R_t is the return at time t , P_t is the closing price at time t , and P_{t-1} is the lagged value of the closing price at time t .

Models Used

Garch (1,1) Model

This model extends the basic ARCH model by incorporating autoregressive and moving average terms to capture volatility dynamics in time series

data. The GARCH (1,1) model is used to identify volatility persistence in time series data. It also models the relationship between past and current volatility levels through its autoregressive and moving average terms. The formula for the GARCH (1,1) model is as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2$$

Where σ_t^2 is the conditional variance at time t , u_{t-1}^2 is the lagged square of error terms and σ_{t-1}^2 is the conditional variance of the lagged term.

Egarch Model

The EGARCH model is a type of GARCH model used to analyse and forecast the volatility of financial data. Unlike traditional GARCH models, the EGARCH model allows for asymmetry in the volatility response to positive and negative shocks. This means that the model can capture the tendency for volatility to increase more after negative shocks than after positive shocks, a phenomenon known as the leverage effect. The EGARCH model is beneficial in financial modelling, where such asymmetries are often observed, allowing for more accurate estimation and prediction of volatility in asset prices and other financial variables.

The formula for the EGARCH model is as follows:

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{(u_{t-1})}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right]$$

Where γ is the asymmetry coefficient, β is the ARCH coefficient, ω is the intercept term, α is the GARCH term, σ_t^2 is the conditional variance at time t , u_{t-1} is lagged squares of error terms, σ_{t-1}^2 is the conditional variance of lagged term

DCC Garch Model

The correlation in volatility between two variables, conditioned on past data and dynamic in nature, is referred to as the Dynamic Conditional Correlation (DCC) GARCH model. The DCC offers the advantage of utilising only the α and β parameters. The process involves two stages: initially conducting standard GARCH estimation for each variable and calculating the DCC alpha and beta. This iterative process requires multiple iterations to achieve

convergence. Hence, α signifies short-term volatility spillover, while β denotes long-term volatility spillover, indicating its importance.

Analysis of Data

Descriptive statistics

Table 4.1 shows the descriptive statistics of the returns of the Nifty 50 and Nifty 50 futures indices. Future returns have the highest mean (0.045148) and median (0.069184) values among the variables. Both Nifty 50 and Nifty 50 futures returns are negatively skewed. The kurtosis value is greater than 3 for future and spot returns, thus forming a leptokurtic distribution. The standard deviation is used as a measure of volatility. Future returns have the highest standard deviation of 1.110705. Jarque-Bera is used to test non-normality. The test results show a significant value at the 5% significance level, confirming that the returns of both indices are not normal. A unit root test was also performed using the Augmented Dicky Fuller test (ADF). Since the p-value is less than 0.05, we reject the null hypothesis and conclude that the data are stationary.

Table 4.1 Descriptive statistics of Nifty and Nifty futures based on returns

	Future Returns	Spot Returns
Mean	0.045148	0.045112
Median	0.069184	0.065907
Maximum	9.338546	8.400295
Minimum	-14.0257	-13.90376
Std. Dev.	1.110705	1.089143
Skewness	-1.149105	-1.224162
Kurtosis	20.67536	20.50944
Jarque-Bera	32656.91	32130.07
Probability	0.0000	0.0000
Observations	2467	2467
ADF	0.0000	0.0000

Source: Computed Data

Time Series Plot based on Returns

The following graph shows the returns of Nifty and Nifty Futures.

Figure 1. Spot Returns

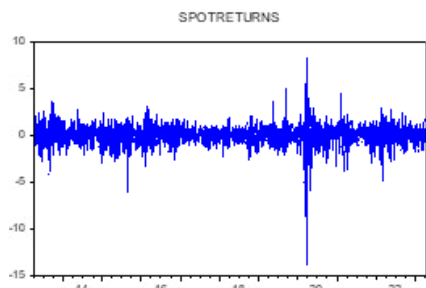
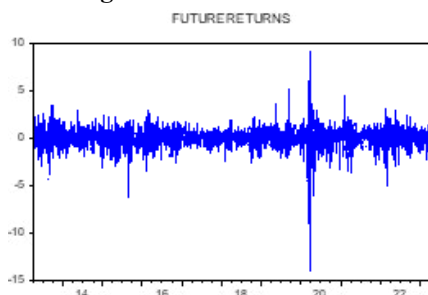


Figure 2. Future Returns



Determination of Optimal Hedge Ratio

The optimal hedge ratio, also known as the minimum variance hedge ratio, is determined by the ratio of spot trades to futures trades. Table 4.2 shows that the cost of carry, represented by the intercept, is 3.217873, and furthermore, the future price is statistically significant with a p-value of less than 0.05. The coefficient for the future price is 0.99, indicating that the spot-to-future ratio is one. This means that changes in the spot price closely correspond to changes in future prices.

Table 4.2 Descriptive statistics of hedging ratio based on Nifty and Nifty Futures

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.217873	1.758298	1.830106	0.0674
NIFTY_FUTURE	0.997814	0.000153	6527.394	0.0000
R-squared	0.999942	Mean dependent var		10888.67
Adjusted R-squared	0.999942	S.D. dependent var		3638.273
F-statistic	42606875	Durbin-Watson stat		0.423703

Source: Computed Data

ARCH LM Test

The ARCH LM test is a statistical method used to detect and analyse the presence of autoregressive conditional heteroscedasticity in time-series data. The test assesses whether past squared residuals have a significant impact on the current variance of the residuals, implying the presence of ARCH effects. If the p-value is less than 0.05, it indicates that the null hypothesis (No ARCH Effect) will be rejected. This implies that the time series have an ARCH effect.

Table 4.3 presents the results of the ARCH-LM test. The test results show a significant p-value of less than 0.05, indicating the rejection of the null hypothesis (no ARCH effect). Thus, it shows that the returns of Nifty and Nifty futures have an Autoregressive Conditional Heteroscedasticity (ARCH) effect.

Table 4.3 ARCH-LM Test Results

Returns	ARCH LM Test Results	
	F Statistics	P Value
SPOT	81.27546	0.0000
FUTURE	101.86	0.0000

Source: Computed Data

Checking Volatility Persistence using GARCH (1,1) Model

Volatility persistence in the market is determined by adding the coefficients of the ARCH and GARCH terms. If the sum of the ARCH and GARCH coefficients is close to 1, then volatility is persistent in the market. The results show that the sum of the ARCH and GARCH terms is 0.9772 for spot returns and 0.9798 for future returns, which is close

to 1. Hence, these results prove that a high level of volatility persists in both the spot and futures markets. This result aligns with the results of Chou (1988) and Hasan et al. (2019), who also found high volatility persistence in their study.

The ARCH LM test is performed after the GARCH analysis to check whether the model is sufficient. The ARCH LM test result following volatility modelling with the GARCH (1,1) model reveals a p-value greater than 0.05, suggesting the

non-rejection of the null hypothesis for both spot and futures returns. This result confirms that there is no ARCH effect in the residuals of both the spot and futures return series. This outcome from the ARCH LM test supports the suitability of the GARCH (1,1) model in effectively capturing volatility in both markets. Hence, the GARCH (1,1) model is appropriate for capturing volatility persistence in the spot and futures markets.

Table 4.4 GARCH (1,1) Output

RETURNS	GARCH (1,1) RESULTS				Diagnostic Test Results
	Intercept (p-value)	ARCH (p-value)	GARCH (p-value)	ARCH + GARCH	ARCH LM Test
					F stat (p-value)
Spot Returns	0.025026 (0.0000)	0.091119 (0.0000)	0.886143 (0.0000)	0.9772	0.459874 (0.4977)
Future Returns	0.023775 (0.0000)	0.089664 (0.0000)	0.890173 (0.0000)	0.9798	0.491347 (0.4834)

Source: Computed Data

Checking Asymmetric Effect using EGARCH Model

The coefficient gamma indicates the asymmetry. If the p-value of this coefficient is significant at a 5% level, it can be interpreted as there is an asymmetry, and if the coefficient value is negative or less than zero, it indicates that negative news has a higher impact than positive news

From the table, it is clear that the intercept term omega shows a significant negative value, which is less than zero for both spot and futures returns. The alpha term indicates the ARCH coefficient, which is significant in both the spot and futures markets. The beta term indicates the GARCH coefficient, which is also significant for returns in both the markets. The significance of these ARCH and GARCH terms suggests the presence of volatility in both the spot and futures markets, with the GARCH coefficient

value close to 1, indicating that volatility is persistent in both markets.

The asymmetry term gamma exhibits a negative and statistically significant coefficient for both spot and futures returns, indicating the presence of volatility asymmetry in both markets. With a coefficient value of less than 0, these test results suggest that negative news has a more significant impact on volatility than positive news in both the spot and futures markets. Thus, the results show volatility asymmetry in both the spot and futures markets. As asymmetry is determined, investors should be prudent in their investments. This result is consistent with the results of Rakshit et al. (2023) and Hasan et al. (2019), who also found the presence of asymmetry in their studies.

Table 4.5 EGARCH Output

	SPOT RETURNS		FUTURE RETURNS	
	Coefficient	P-Value	Coefficient	P-Value
Omega	-0.379384	0.00000	-0.381899	0.00000
Alpha	0.133694	0.00000	0.134162	0.00000

Gamma	-0.115144	0.00000	-0.116079	0.00000
Beta	0.970460	0.00000	0.970104	0.00000

Source: Computed Data

Volatility Spillover Analysis Using the DCC GARCH Model

The results of the GARCH DCC indicate a significant theta (1) value, suggesting short-term volatility spillover effects between the spot and futures markets. Similarly, a significant theta (2) indicates the presence of long-term volatility spillover effects between the spot and futures markets. In EViews, the parameters are theta (1) and theta (2). From the table, it is clear that the stability condition was

satisfied. The stability condition is that the sum of theta (1) and theta (2) should be less than one. Here, $\theta(1) + \theta(2) = 0.984537$, which is less than one, indicating that a long-term volatility spillover effect is present between the two markets. This result is consistent with the results of Bubak et al. (2011), Erten et al. (2012), Magkonis and Tsouknidis (2017), Kara et al. (2022), and Yadav et al. (2023). They also found significant volatility spillovers in their study.

Table 4.6 DCC Model Output

	Coefficient	Std. Error	z-statistics	p-value
C (1)	0.081569	0.016717	4.879329	0.0000
Theta (1)	0.022676	0.003726	6.086497	0.0000
Theta (2)	0.961861	0.006836	140.6998	0.000000

Source: Computed Data

Conclusion

The objectives of investing are wealth maximisation, capital preservation, and income generation, and the two main factors of investment are risk and returns. This study focused on volatility persistence, asymmetry, and spillover effects in spot and futures markets, which offer investors valuable insights into risk management, portfolio diversification, and long-term investment performance. The significant GARCH(1,1) coefficients confirm that volatility is persistent in both the spot and futures markets, and the EGARCH results prove a significant asymmetric effect, indicating that negative news has a more significant effect on volatility than positive news. The DCC GARCH model reveals short- and long-term volatility spillovers between the spot and futures markets. The sum of theta (1) and theta (2) is less than one, which indicates that long-term volatility spillover is present between the two markets. In short, this analysis highlights the complex dynamics of the Nifty and Nifty Futures markets, characterising their non-normality, volatility persistence, asymmetry in response to market shocks, and significant interdependence in volatility.

Policy Implications and suggestions

This study will help academicians and researchers identify the importance of volatility and spillover effects in the Nifty spot and futures markets, which should be considered while researching stock market performance. Understanding and modelling volatility persistence and asymmetry using GARCH (1,1) and EGARCH models can assist investors in making informed decisions by recognising how past volatility impacts future trends and how markets respond differently to positive and negative shocks.

Limitations and Suggested directions for future research

This study used data only for Nifty 50 and Nifty futures. It is also important to determine how other data behave with respect to volatility spillover and volatility persistence. Based on our experience, we suggest that researchers can extend this study by using stock futures, Bank Nifty indices, etc. Furthermore, researchers can use other GARCH models, such as FIGARCH and Diagonal BEKK GARCH, to analyse volatility persistence and spillover effects.

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