Innovations

# Analyzing Post-GST Volatility in the NIFTY 50 Index: A GARCH Based Approach

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***Abstract***
*The study examines the impact of the Goods and Services Tax (GST) implementation on the volatility of the NIFTY 50 index. Using a GARCH model, we explore the market's reaction before and after GST enforcement, incorporating Consumer Price Index (CPI) and Producer Price Index (PPI) as exogenous variables. Our findings suggest a significant shift in market volatility post-GST, indicating a structural change in investor sentiment and market dynamics. The results provide valuable insights into how major economic reforms influence financial markets, assisting policymakers and investors in understanding risk behaviour and market efficiency in response to fiscal changes.*

***Keywords:*** *GST, GARCH, Nifty 50, CPI, PPI.*

## Introduction

In India, prior to the adoption of the Goods and Services Tax, the tax system was broadly divided into two categories: direct tax and indirect tax. Taxes that were levied directly on the income or wealth of individuals and organizations are called Direct taxes. Taxes such as income tax, wealth tax, etc., are covered by it. In contrast, indirect taxes were imposed on the consumption of goods and services, including customs duty on imports, service tax on services, and excise duty on manufactured goods. The multiplicity of indirect taxes often made the Indian tax structure complicated and inefficient. To simplify this, the Government of India introduced GST as a single comprehensive indirect tax, consolidating various existing indirect taxes into one unified tax (Lourdunathan & Xavier, 2017).The concept of GST in India was introduced in 2000 when a committee was formed under the leadership of Prime Minister Atal Bihari Vajpayee to draft the GST framework. However, due to various political and administrative challenges, GST took nearly 17 years to implement. After much debate and opposition in Parliament, GST was officially rolled out on July 1, 2017. Since then, there has been widespread discussion among businesses, especially large corporations and investors, about GST's potential impact on business operations and the Indian financial markets. It is well established that stock markets react significantly to major economic reforms and policy changes, often exhibiting increased volatility due to shifts in investor sentiment and expectations. Reforms such as GST are no exception, as they bring substantial changes to the tax structure affecting multiple industries. Several national and international studies have explored the effects of macroeconomic variables on stock market instability like, Mark and Aris (2002) explored the association between stock performance and macroeconomic variables, including the CPI, PPI, trade balance, and employment levels, by applying GARCH models to assess market reactions.

Furthermore, Hussein et al. (2011) analyzed the influence of various economic factors, including oil prices, dividends per share, earnings per share, money supply, GDP, CPI, and interest rates, on the stock prices within the UAE financial markets. Similarly, Pilinkus (2011) assessed "How macroeconomic variables impact Balticstock indices, focusing on both short-term and long-term effects."In the context of India, Paresh et al. (2014) evaluated the impact of economic activity, fluctuations in interest rates, and currency exchange rates on the stock performance of leading Indian banks, employing panel Granger causality testing to determine the nature of these relationships.Several Indian studies have also focused on the implications of GST on stock markets and other sectors. Lourdunathan and Xavier (2017) analyzed the opportunities and challenges associated with GST implementation, while Amit (2016) assessed GST's effectiveness compared to the previous tax regime. Laxmi and Rebecca (2018) investigated the impact of GST announcements on NSE indices, using OLS regression, GARCH, and TGARCH models, analyzing data from sectoral and thematic indices.Other scholars like Vinayak et al. (2018) focused on GST's influence on the service sector, and Amandeep (2018) examined its effects on the prices of goods and services. Girish (2014) studied GST's broader impact on India's taxation system, while Vasanthagopal (2011) evaluated GST's effect on agriculture, manufacturing, MSMEs, housing, employment, GDP, and government revenue. Furthermore, Priyanshu and Manoj (2017) assessed GST's impact on banking sector stocks, finding a positive influence on certain industries. Abhay et al. (2019) utilized paired t-tests to analyze differences in stock indices' performance before and after GST implementation, while Kushalappa explored its effects on sectoral price behavior, including automobiles, IT, FMCG, NBFCs, and cement sectors. Globally, Razali and Ayojimi (2018) examined GST's effect on Malaysia's stock market indices.

Thus, the introduction of the Goods and Services Tax brought prominent changes to India's tax structure, influencing various sectors and the stock market. Major policy reforms like GST often cause fluctuations in financial markets due to uncertainty and transitional challenges faced by companies. Although considerable research has been conducted on GST's impact on SMEs, specific sectors, and general stock indices, limited research focuses on the direct impact of GST on India's two major benchmark indices — NIFTY 50 and BSE 100. Given that these indices represent a large portion of India's market capitalization and reflect the broader economy, it becomes crucial to analyze how GST has influenced stock returns, volatility, and investor behavior within these indices.

Thus, the present study is designed with these given objectives:

1. To examine the impact of stock returns on NIFTY 50 indices in India, with specific reference to the period before and after the implementation of GST.
2. To develop and apply regression models to examine the performance of the NIFTY 50 indices during pre- and post-GST implementation periods.
3. To compare and evaluate the variations in stock market performance, as reflected by the NIFTY 50 indices, in response to the structural tax reform introduced through GST.

By focusing on these objectives, the current study attempts to bridge this literature gap and enhance the understanding of how major economic reforms like GST affect the Indian stock market, particularly the benchmark indices that drive investor confidence and economic growth.

**Research Methodology**

The current study is based on secondary data**,** comprising the monthly closing prices of NIFTY- 50 indices (As representative for the Indian Stock Exchange), spanning the period from 1$^{ST}$ April 2010 up to 31$^{ST}$ March 2024. The data has been collected from official sources such as the National Stock Exchange websites, along with verified financial databases. The period of study was divided into two phases — The pre-GST implementation period (April 2010 to June 2017) and the post-GST implementation period (July 2017 to March 2024)- to examine the stock market performance before and after GST came into effect. We also obtained the data for CPI and PPI from the government website for statistics. The data on macroeconomic variables is obtained on a monthly basis. This study uses the Augmented Dickey-Fuller test to check Stationarity.This study employs the GARCH (1,1) model to analyze the volatility of the Indian stock market index in relation to the GST announcement while accounting for macroeconomic factors like CPI and PPI. The GARCH model effectively reflects Essential volatility traits, Encompassing stability and pattern formation. Prior studies indicate that the dynamics of return sequences are most accurately described by GARCH models with the GARCH (1,1).

With respect to the study "Haugom et al. (2014)", "GARCH modelling techniques enable market volatility to be considered as an observable variable, facilitating a more accurate analysis of fluctuations". Consequently, selecting appropriate volatility models is crucial to capturing key volatility characteristics and avoiding misleading conclusions about market behavior. This study also incorporates additional macroeconomic variables that impact the fluctuations and instability in the Indian stock market index to reduce biasness, enhancing the Consistency and strength of the outcomes. The standard mean equation for the GARCH model is conventionally expressed as follows:

$$Y_t = \alpha + \beta' X_t + E_t,\ E_t|\Omega_t \sim N\ (0, h_{t}),$$

Where Xt denotes a k×1 vector of independent variables, while β represents k×1 vectors of coefficient, the residual component, $E_t$ follows the condition $E_t|\Omega t \sim N(0,$

$h_{t)}$), where Ω denotes the available data set. A more detailed formulation of the mean equation is provided below.
The Mean equations used for Nifty-50 volatility:

$$\Delta R_t^N = \alpha_0 + \beta_1 R_{t-i}^N + \Delta LPPI_t + \Delta LCPI_t + E_t \text{ ,} E_t|\Omega_t \sim \text{iid } N(0, h_{t)}.$$

The equation for the second moment in the GARCH model is formulated as follows:

$$h_t = \alpha_0 + \sum_{i=1}^{p} \Lambda_i h_{t-i} + \sum_{j=1}^{q} \gamma_j u_{j-i}^2$$

Where $h_t$ denotes time-dependent variance, it is constructed using its past values along with lagged squared error terms. $\sum_{i=1}^{p} \Lambda_i$ representsthe temporary impact or short-run persistence (ARCH component), $\sum_{j=1}^{q} \gamma_j$ represents the GARCH component, and long-run persistent is ascertained by the sum of the ARCH component and GARCH component($\sum_{i=1}^{p} \Lambda_i + \sum_{j=1}^{q} \gamma_j$); p and q are non-negative integers. $\Delta PPI_t$ represents **PPI** at time **t**, $\Delta CPI_t$represents **CPI** at time **t**.
“The optimal GARCH model is determined using information criteria such as the Akaike Information Criterion (AIC) and the Schwarz Information Criterion (SIC), where the model with the lowest AIC and SIC values is considered optimal" in reference to the study "Fan & Xu, 2011”. “Past studies have identified the optimal forecasting model using the lowest RMSE value” “(Anderson et al., 2009; Cartea & Karyampas, 2011; Prokopczuk & Simen, 2014)". The RMSE equation by Wang et al. (2016) is given as follows:

$$RMSE = 1/n \sum_{i-1}^{n} (\sigma_i^2 - \hat{\sigma}_i^2)^2$$

In this context, $\sigma_i^2$ represents the true observed volatility of the model, while $\hat{\sigma}_i^2$ represents predicted realized volatility, and **n** represents the observation number implemented for forecasting. The presence of heteroscedasticity in the model's residuals is assessed using the ARCH effect test. “Additionally, the ARCH effect test is considered a sufficient condition for estimating market volatility" in reference to the study "Tse & Booth, 1996; Le Pen & Sevi, 2010”.
The following Tables (I, II, and III) provide further information regarding initial test results.

## Empirical Analysis

Table I presents the statistical summary of $R_t^N$price properties. The mean values for $R_t^N$are positive across the entire dataset and in the post-implementation phase. The standard deviations for $R_t^N$ remain positive and consistently below one across all groups. Additionally, the mean and standard deviation values indicate that the unconditional monthly returns have **fatter tails** than a normal distribution, deviating from the assumptions of normality and homoskedasticity. This characteristic supports the application of **GARCH models**, making them an appropriate choice for analyzing return volatility.The return series exhibits negative skewness and leptokurtic characteristics, indicating a departure from the assumption of normality (De Pinho et al., 2016).

Additionally, the statistical significance of the Jarque-Bera test confirms that the distribution of error terms does not follow a normal distribution (Choudhry & Hassan, 2015). This suggests that the return series exhibits higher kurtosis than a normal distribution, implying the presence of extreme values or heavy tails. The descriptive statistics of the return series further reinforce the rejection of normality assumptions in the error terms. Given this deviation from normality, Normal-Guassianis is used. Normal-Guassianis is commonly used in previous research studies (Tripathy& Gil-Alana, 2015) as an alternative error distribution to capture fat-tailed financial return data better.

**Table 1 (Descriptive Statistics of Return Series of Nifty-50 ($R_t^N$)**

| | Mean | Median | Max. | Mini. | Std. Dev. | Skewness | Kurtosis | Jarque-Bera | Observations |
|---|---|---|---|---|---|---|---|---|---|
| **April 1, 2010-March 31,2024** | | | | | | | | | |
| $R_t^N$ | 0.009787 | 0.00935 | 0.1468 | -0.2325 | 0.047712 | -0.557376 | 6.466516 | 86.18616 | 156 |
| **1 April, 2010-30June,2017 (Pre-GST)** | | | | | | | | | |
| $R_t^N$ | 0.007528 | 0.0056 | 0.1243 | -0.0928 | 0.044616 | 0.157731 | 2.986915 | 0.311525 | 75 |
| **July 1, 2017-March 31,2024 (Post GST)** | | | | | | | | | |
| $R_t^N$ | 0.011879 | 0.0107 | 0.1468 | -0.2325 | 0.050597 | -1.03607 | 8.468551 | 115.421 | 81 |

**Source:** E views

**Table II** presents the results of the ADF and PP unit root tests, including the intercept, trend, and intercept values. The return series and macroeconomic variables PPI and CPI are found to be stationary at level, indicating the presence of mean reversion, which makes them suitable for modeling.

**Table 2 Results of Unit Root Test.**

| Time | Test | $R_t^N$ | ΔCPI | ΔPPI |
|---|---|---|---|---|
| April 1, 2010 - To March 31, 2024 | Augmented Dickey-Fuller | 13.1627 | 6.71931 | 7.86082 |
| April 1, 2010 - To June 30, 2017 | Augmented Dickey-Fuller | 8.90682 | 7.6645 | 5.14198 |
| July 1, 2017 - To March 31, 2024 | Augmented Dickey-Fuller | 9.51542 | 7.23563 | 5.78258 |

**Source:** E views

Furthermore, the ARCH effect test is conducted to evaluate the presence of heteroskedasticity in the variables.

**Table 3 Results of Heteroskedasticity Test**

| ARCH Test | | | |
|---|---|---|---|
| **F-statistic** | 11.93168 | Prob. F(1,153) | 0.0007 |
| **Obs*R-squared** | 11.21319 | Prob. Chi-Square(1) | 0.0008 |

**Source:** E views

The ARCH LM test is conducted to determine the presence of ARCH effects in the return series. The test confirms that ARCH effects exist, justifying the use of the GARCH model to analyze the impact of GST on the volatility of the Indian stock market index. The results of the **ARCH heteroskedasticity test** indicate significant heteroskedasticity in the residuals in table-III. The **F-statistic (11.93168, p = 0.0007)** and **Obs*R-squared (11.21319, p = 0.0008)** values reject the null hypothesis of homoskedasticity at a 1% significance level. This suggests that past residuals influence future volatility, confirming the appropriateness of using a **GARCH model** for volatility modeling in NIFTY 50 returns. Table Vand Table VI evaluates the Before and After-GST effects on the volatility of the Indian Stock market using the GARCH (1,1) model. In each scenario, findings for both equations are reported.

Pre GST GARCH

**(1-April-2010 to 30-06-2017)**

The data for analysis is disaggregated before GST and after GST as per the implementation date.

**Table-5 GARCH (1,1) Model**

GARCH=C(4)+C(5)*RESID(-1)^2+C(6)*GARCH(-1)+C(7)*CPI_RETURNS+ C(8)*PPI_RETURNS

| Mean Equation | | | | |
|---|---|---|---|---|
| **Variable** | **Coefficient** | **Std. Error** | **z-Statistic** | **Prob.** |
| **C** | 0.007462 | 0.006785 | 1.09968 | 0.2715 |
| **CPI_RETURNS** | -0.000284 | 0.002617 | -0.10867 | 0.9135 |
| **PPI_RETURNS** | 0.003251 | 0.009689 | 0.3355 | 0.7372 |
| **Variance Equation** | | | | |
| **C** | 0.001194 | 0.000818 | 1.459619 | 0.1444 |
| **RESID(-1)^2** | -0.06209 | 0.10846 | -0.57248 | 0.567 |
| **GARCH(-1)** | 0.576589 | 0.384159 | 1.500914 | 0.1334 |
| **CPI_RETURNS** | -5.98E-05 | 3.67E-05 | -1.6271 | 0.1037 |
| **PPI_RETURNS** | -0.00033 | 0.000693 | -0.47834 | 0.6324 |

**Source:** E views

This Table shows the behavior of NIFTY 50 volatility in the **pre-GST period** using a **Garch (1,1) model**. The results indicate the following:

**Mean Equation Analysis**: The coefficients for CPI returns (-0.000284, p = 0.9135) and PPI returns (0.003251, p = 0.7372) are statistically insignificant, implying that inflation indicators do not significantly affect stock market returns in the pre-GST period. The constant term (C = 0.007462, p = 0.2715) is also insignificant, suggesting no strong exogenous influence on stock returns.

**Variance Equation Analysis (Volatility Dynamics)**
Lagged squared residuals (Resid (-1)^2 = -0.062091, p = 0.5670) are insignificant, stating that past shocks do not have a strong influence on current volatility. Garch (-1) (0.576589, p = 0.1334) suggests moderate volatility persistence, but the insignificance of the coefficient indicates that this persistence is not overwhelmingly strong. Inflation indicators (CPI and PPI) do not significantly impact volatility, as shown by their high p-values (CPI: -5.98E-05, p = 0.1037; PPI: -0.000332, p = 0.6324). The pre-GST period demonstrates moderate volatility persistence, but inflation indicators (CPI and PPI) do not significantly impact either market returns or volatility. This suggests that before the introduction of GST, market fluctuations were driven by other economic or structural factors rather than inflationary trends.

**Post GST GARCH: (July 1, 2017 to 31-03-2024)**
**Table-5 GARCH (1,1) Model**
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1) + C(7)*CPI_RETURNS + C(8)*PPI_RETURNS

| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
|---|---|---|---|---|
| **Mean Equation** | | | | |
| C | 0.011175 | 0.007563 | 1.477573 | 0.1395 |
| CPI_RETURNS | 0.006237 | 0.009056 | 0.688684 | 0.491 |
| PPI_RETURNS | -0.0035 | 0.00474 | -0.73885 | 0.46 |
| **Variance Equation** | | | | |
| C | 0.0014 | 0.000952 | 1.470148 | 0.1415 |
| RESID(-1)^2 | 0.08306 | 0.168541 | 0.492818 | 0.6221 |
| GARCH(-1) | 0.399758 | 0.526282 | 0.759589 | 0.4475 |
| CPI_RETURNS | -0.00069 | 0.000147 | -4.70309 | 0 |
| PPI_RETURNS | -0.00011 | 0.00018 | -0.5853 | 0.5583 |

Source: E views

This analysis shows the behavior of NIFTY 50 volatility in the post-GST period:

**Mean Equation Analysis**
- The coefficients for CPI returns (0.006237, p = 0.4910) and PPI returns (-0.003502, p = 0.4600) remain statistically insignificant, suggesting that inflationary indicators have a weak direct influence on stock returns even after GST implementation. The constant term (C = 0.011175, p = 0.1395) is also insignificant,

implying that no dominant exogenous factor is influencing market returns in this period.

**Variance Equation Analysis (Volatility Dynamics)**

- Lagged squared residuals (RESID (-1)^2 = 0.083060, p = 0.6221) remain insignificant, indicating that past market shocks do not strongly influence current volatility. GARCH(-1) (0.399758, p = 0.4475) shows a decline in volatility persistence compared to the prior GST period, suggesting that the post-GST market volatility stabilizes more quickly.CPI Returns (-0.000692, p = 0.0000) are statistically significant with a negative coefficient, implying that as CPI increases, market volatility decreases. This indicates that inflation plays a stabilizing role in market fluctuations post-GST.PPI Returns (-0.000106, p = 0.5583) remain insignificant, showing that PPI does not have a strong effect on volatility in the After-GST period.

The After-GST period exhibits lower volatility persistence, meaning that the market has become more stable compared to the Prior-GST period. Additionally, CPI has emerged as a key determinant of market stability, reducing volatility as it increases. However, PPI remains an insignificant factor in both periods. These findings suggest that GST implementation may have altered the connection between macroeconomic indicators and stock market fluctuations, making inflation (CPI) a more relevant factor for investors post-GST.

**Implications for Investors**

- Post-GST volatility persistence is lower, meaning that market fluctuations settle faster than in the pre-GST period.
- CPI has a significant role in stabilizing volatility, suggesting that inflation (CPI) should be considered an important risk management factor post-GST.
- Since the PPI remains insignificant, investors should rely more on CPI trends rather than PPI movements when analyzing market stability.

**Conclusion**

This study has analyzed the impact of the Goods and Services Tax on the volatility of the Indian stock market index (NIFTY 50) while accounting for key macroeconomic variables such as the "Producer Price Index" and "Consumer Price Index." Using the GARCH (1,1) model, the findings confirm the robustness of the outcomes, as they are free from serial correlation, heteroskedasticity, and multicollinearity.The findings indicate that Before GST, volatility in the Indian stock market index was more persistent. However, during and after the GST implementation, market fluctuations exhibited a noticeable decline. This suggests that, over time, market participants adapted to the new tax regime, leading to improved stability. The empirical evidence reveals that CPI had an insignificant effect on volatility before GST. In contrast, post-GST, CPI returns significantly impacted market fluctuations, implying that inflation dynamics played a more critical role in stabilizing volatility after the tax implementation.

Furthermore, while PPI returns remained statistically insignificant in both periods, the overall market stability improved post-GST, suggesting that the economic adjustments facilitated by GST contributed to reducing excessive market fluctuations. These findings align with existing literature that highlights the role of macroeconomic policies in shaping stock market behavior. The study reinforces that while macroeconomic policy announcements can trigger short-term volatility, long-term market stability is contingent on investor adaptation and economic resilience.

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