Major Research Project on

INDIA'S WHOLESALE INFLATION RATE: AN EXAMINATION OF VOLATILITY CLUSTERING AND LEVERAGE EFFECTS

Submitted By

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23/DMBA/076

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CERTIFICATE

This is to certify that **Nakul Sharma**, Roll No. **23/DMBA/76**, has submitted the major research project report titled **“India's Wholesale Inflation Rate: An Examination of Volatility Clustering and Leverage Effects”** in partial fulfilment of the requirements for the award of the degree of **Master of Business Administration (MBA)** from **Delhi School of Management, Delhi Technological University, Delhi** during the academic year **2024–2025**.

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DECLARATION

I, **Nakul Sharma**, hereby declare that the Major Research Project Report entitled **"India's Wholesale Inflation Rate: An Examination of Volatility Clustering and Leverage Effects",** submitted to **Delhi Technological University,** is a record of my original work. This project report is submitted in partial fulfilment of the requirements for the award of the degree of **MBA in Finance and Business Analytics**.

I also declare that this project report has not been submitted to any other university or institute for the award of any degree or diploma.

Nakul Sharma
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Date:

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ABSTRACT

The Volatility in inflation rates is a significant concern for policymakers, economists, and financial analysts due to its profound impact on economic planning, investment decisions, and price stability. This study aims to investigate the existence of volatility clustering and leverage effects in India's Wholesale Inflation rate over a span of eighteen years, from January 2005 to June 2022. The research employs the monthly Wholesale Price Index (WPI) inflation data, a crucial indicator for wholesale-level price movements in the Indian economy, sourced from the Government of India's official data repository.

Volatility clustering refers to the phenomenon where high-volatility events tend to cluster together, followed by periods of relative calm, indicating persistence in volatility. Leverage effects, on the other hand, reflect the asymmetric relationship between past returns and future volatility, typically suggesting that negative shocks have a greater impact on volatility than positive ones of similar magnitude. Identifying these characteristics in inflation dynamics is essential for designing accurate predictive models and developing informed policy responses.

The study begins by testing the stationarity of the WPI inflation series using the Augmented Dickey-Fuller (ADF) test. The findings confirm that the data series is non-stationary at level but achieves stationarity at the first difference, implying that the statistical properties of the series such as mean and variance become constant after differencing. This transformation is a necessary precondition for applying volatility modelling techniques effectively.

Following the stationarity check, the Autoregressive Conditional Heteroskedasticity (ARCH) model is employed to detect the presence of heteroskedasticity and to examine leverage effects. The ARCH model is particularly useful for modelling time-varying volatility by capturing the influence of past forecast errors on current volatility. In the context of this study, it was used to analyse whether past inflation shocks, both positive and negative, influence the future volatility of wholesale inflation rates. The results from the ARCH model suggest that while volatility clustering is present, the leverage effect is minimal. This indicates a relatively symmetric response of volatility

to inflation shocks, suggesting that positive and negative shocks have a comparable impact on future volatility.

To understand more about the the asymmetry and persistence of volatility, the study further applies the Exponential GARCH (EGARCH) model, an advanced variant of the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family that explicitly accounts for asymmetric effects. The EGARCH model allows for a more refined understanding of volatility patterns by incorporating the possibility that volatility may respond differently to positive and negative shocks, and also allows for logarithmic specification to ensure non-negativity of variance without constraints.

However, the application of the EGARCH model yielded results that support the earlier findings—although there is evidence of volatility clustering, the impact of past volatility on current wholesale inflation is statistically insignificant. This suggests that past high-volatility episodes in India's WPI inflation do not necessarily result in increased volatility in the current period, highlighting a weaker persistence of volatility and an absence of strong leverage effects in the dataset studied.

Overall, the findings of this research provide valuable insights into the nature of inflation volatility in India. The limited presence of leverage effects and insignificant influence of lagged volatility suggest that India's wholesale inflation rate is more likely influenced by real-time economic shocks and external macroeconomic factors rather than its own past behaviour. These insights can be crucial for central banks and policymakers in refining inflation targeting strategies and ensuring economic stability.

This study also contributes to the growing literature on inflation volatility modelling in emerging economies by demonstrating the usefulness and limitations of ARCH-type models in capturing the nuanced dynamics of inflation volatility. Further research may explore structural models or incorporate external macroeconomic variables to enhance the predictability of wholesale inflation trends in India.

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1. INTRODUCTION

Macroeconomic indicators play a pivotal role in analysing the health and dynamics of an economy. Among these, the Wholesale Price Index (WPI) has emerged as one of the most crucial metrics for understanding inflationary trends, especially in emerging and developing economies like India. The WPI measures the average change in the prices of goods at the wholesale level and serves as a critical barometer for policy decisions, business forecasting, and economic planning. Over the years, its significance has grown not only in policy-making circles but also in academic research, owing to its sensitivity to various economic shocks and its influence on other macroeconomic indicators such as consumer price index (CPI), interest rates, and GDP growth.

The fluctuations in WPI have long attracted attention from economists and policymakers, who seek to understand the underlying patterns and causes behind its volatility. One of the most widely observed characteristics in time-series data of macroeconomic indicators, including the WPI, is the presence of volatility clustering—a phenomenon where large changes in prices are followed by further large changes, and small changes are succeeded by more small changes, regardless of the direction of change. This pattern suggests that while price level changes may appear random, the degree of variability in those changes—commonly referred to as volatility—can follow a predictable pattern. This observation has been supported by empirical studies across financial and economic domains and is now considered a fundamental feature of time-series data.

The concept of volatility clustering was first brought into mainstream economic literature through the pioneering works of Mandelbrot (1963) and later popularized in financial econometrics through models such as ARCH (Engle, 1982) and GARCH (Bollerslev, 1986). These models provided a quantitative framework to examine and forecast the time-varying nature of volatility. In the context of inflation or price indices, volatility clustering has significant implications. For instance, persistent high inflation volatility may lead to uncertainty in investment decisions, destabilize consumer confidence, and disrupt long-term planning for businesses and governments alike.

In recent decades, the behaviour of macroeconomic variables has become increasingly erratic due to both domestic and global factors such as oil price shocks, fiscal imbalances, changes in monetary policy regimes, and more recently, global financial crises and pandemics. These developments have further heightened interest in understanding not just the direction of inflation but also the dynamics of its volatility. Researchers are particularly concerned with identifying patterns in inflation volatility that may aid in building more accurate predictive models and formulating robust economic policies, particularly in developing economies where inflation can have a disproportionately large impact on the vulnerable population segments.

Plosser (2009) notes that macroeconomic variables, including price indices, have exhibited notable fluctuations in recent years, prompting scholars to explore their underlying causes and consequences more deeply. These fluctuations have led to debates on whether such volatility is purely random or if it reflects underlying structural characteristics of the economy. One key debate centers around whether inflationary shocks are symmetrical in nature—do both positive and negative shocks have similar effects on future volatility? This brings into discussion another important concept known as the leverage effect, which indicates that negative shocks tend to increase volatility more than positive shocks of the same magnitude. While leverage effects are more commonly discussed in the context of financial markets, recent studies have attempted to examine their relevance in macroeconomic indicators as well.

According to Gaunersdorfer and Hommes (2007), although price changes themselves often appear unpredictable and follow no clear linear trend, their magnitude—whether measured through absolute returns or squared returns—demonstrates a certain degree of predictability. This predictability manifests as periods of intense fluctuation being followed by similarly volatile periods, and calm periods being succeeded by relative price stability. Such behaviour suggests that volatility in macroeconomic indicators is not entirely random but can exhibit temporal dependence, thereby allowing for econometric modelling and forecasting.

Understanding the nature and drivers of such volatility is particularly critical for developing economies like India. In such economies, inflation can have far-reaching consequences on interest rates, employment, fiscal discipline, and poverty levels. Hence, comprehending whether WPI volatility follows a clustered pattern or responds asymmetrically to different shocks can equip policymakers with more effective tools for inflation targeting and monetary policy formulation.

Given the economic importance of the WPI and the broader implications of its volatility patterns, this research seeks to examine the presence of volatility clustering and leverage effects in India's wholesale inflation rate. By using econometric techniques suited for time-series analysis, such as ARCH and GARCH models, the study attempts to shed light on whether volatility in the WPI is persistent and asymmetric in nature, and what this means for future economic policy and research.

1.1. Background of the Study

The Inflation has long been a critical focus of macroeconomic research and policy-making. It reflects the rate at which the general level of prices for goods and services rises, eroding the purchasing power of a currency. In India, the Wholesale Price Index (WPI) has traditionally served as a key measure of inflation, especially in the context of industrial and production-oriented sectors. The WPI measures price changes at the wholesale level and has been instrumental in influencing monetary policy, investment planning, and price stability strategies. Unlike the Consumer Price Index (CPI), which reflects changes in retail prices, the WPI captures broader shifts in producer and distributor costs, making it an important tool for understanding supply-side inflationary pressures.

Over the years, numerous studies have been conducted to understand the drivers of inflation, but recent research has increasingly turned toward understanding the behaviour of inflation volatility, particularly in developing economies. This is because inflation volatility, and not just inflation itself, can have serious implications for the economy. High volatility in inflation reduces economic predictability, discourages investment, and complicates monetary policy transmission. Policymakers, therefore, need to go beyond average inflation rates and investigate the patterns and causes of its volatility.

A key concept in this line of research is volatility clustering, a phenomenon where periods of high volatility tend to follow other high-volatility periods, while periods of low volatility are followed by similarly tranquil periods. This concept, originating from financial markets, has been found to hold true for various macroeconomic variables, including inflation. The presence of volatility clustering implies that shocks to inflation are not isolated but have lingering effects over time. Identifying such clustering behaviour in inflation can provide deeper insights into how economic shocks affect price levels and how persistent such effects can be.

Another important but often underexplored concept in the context of macroeconomic variables is the leverage effect. Originally observed in stock market data, the leverage effect implies that negative shocks tend to increase volatility more than positive shocks of similar magnitude. In simpler terms, bad news creates more uncertainty than good news. In inflation data, such an effect would suggest that unexpected deflationary trends or negative economic shocks might have a larger impact on future price uncertainty than inflationary pressures. While this idea has been well-documented in financial literature, its application to inflation studies, particularly in the context of developing countries like India, is still in the early stages and warrants further exploration.

India presents a compelling case for such a study due to its dynamic economic structure and exposure to various internal and external shocks over the years. From changes in monetary policy frameworks to global commodity price fluctuations, exchange rate movements, and fiscal policy reforms, India's inflation dynamics have evolved significantly. Moreover, the country's transition from using WPI as the primary measure of inflation to adopting CPI for monetary policy targeting by the Reserve Bank of India (RBI) in recent years has opened new discussions on the relevance and behaviour of wholesale inflation trends.

Despite the shift toward CPI, WPI continues to be a crucial indicator, especially for analysing trends in production costs, intermediate goods pricing, and the transmission of global commodity shocks. Studying the volatility and asymmetric behaviour of WPI inflation can thus offer valuable insights into how producers, industries, and policymakers respond to changing economic conditions.

This research attempts to fill the gap in the existing literature by focusing on the volatility clustering and leverage effects present in India's WPI inflation over a long-term period. By applying econometric models such as ARCH and EGARCH, this study seeks to understand whether past volatility significantly impacts current price behaviour and whether inflation responds asymmetrically to economic shocks. The findings are expected to enhance our understanding of inflation dynamics in India and contribute to more informed and resilient economic policy frameworks in the future. industry.

1.2. Problem Statement

In Inflation remains a central concern for policymakers, economists, and financial institutions due to its profound influence on economic stability, purchasing power, and overall growth. In developing economies like India, inflation management poses a greater challenge owing to frequent structural shifts, volatile global commodity prices, and a large dependency on monsoon-driven agricultural outputs. Among various inflation indicators, the Wholesale Price Index (WPI) has traditionally served as a vital measure for capturing the movement of prices at the wholesale level, reflecting the cost trends faced by producers and intermediaries.

While average inflation levels have been widely studied and understood, less attention has been given to the dynamic behaviour of inflation volatility—particularly its persistence and asymmetry. Price volatility affects investment decisions, financial planning, inventory management, and, most importantly, policy formulation. For instance, a sudden spike in inflation volatility could mislead central banks in framing interest rate policies or managing inflation expectations. It becomes imperative to analyse not just the levels of inflation but also its pattern of fluctuation over time.

One of the most observable yet underexplored phenomena in this domain is volatility clustering, wherein periods of high inflation volatility tend to follow other high-volatility periods, and low-volatility periods follow one another. This indicates that inflation shocks are not random or isolated but tend to persist over time. Despite the theoretical support for this concept, few empirical studies have assessed its applicability in the context of India's WPI.

Another complex, yet relevant, phenomenon is the leverage effect, which reflects the asymmetric response of volatility to positive and negative shocks. Originally developed in financial market studies, this concept is gaining traction in macroeconomic analysis. If such asymmetry exists in WPI data, it implies that negative inflation shocks (e.g., sudden deflation or a drop in wholesale prices) might result in greater volatility than positive shocks of the same magnitude. This has direct implications for economic forecasting and risk management, particularly in sectors vulnerable to price swings.

Despite the significance of these phenomena, there is a clear research gap in applying asymmetric GARCH models, such as EGARCH, to study volatility clustering and leverage effects in India's WPI over a long-term period. Most existing studies focus predominantly on the Consumer Price Index (CPI), largely due to the Reserve Bank of India's adoption of CPI as the main inflation targeting tool since 2016. However, WPI remains crucial in understanding upstream price behaviour and cost-push inflation trends, which often precede retail-level inflation.

Furthermore, there is limited empirical evidence regarding whether past volatility in WPI significantly influences current or future price movements, and whether these shocks behave symmetrically or asymmetrically. Understanding these dynamics is critical for designing effective inflation-control policies, especially during periods of economic uncertainty, such as global oil price shocks, pandemic disruptions, or supply chain bottlenecks.

Therefore, this study aims to investigate the presence and extent of volatility clustering and leverage effects in India's WPI-based inflation using advanced time-series econometric models. By bridging the empirical gap in this area, the research seeks to contribute to the broader understanding of inflation behaviour in India and to support more responsive and forward-looking macroeconomic policymaking. management.

1.3. Objectives of the Study

The primary objective of this research is to analyse the volatility clustering and leverage effect in India's Wholesale Price Index (WPI) rate over the period from January 2005 to June 2023, using monthly data. The study aims to understand whether periods of high volatility in the WPI rate tend to be followed by further high-volatility periods, and whether negative shocks exert a stronger influence on future volatility than positive ones—a phenomenon known as the leverage effect.

To facilitate this analysis, the study begins by assessing the stationarity of the time series data through the Augmented Dickey-Fuller (ADF) test, which is a crucial prerequisite for accurate time-series modelling. Following this, the research employs Ordinary Least Squares (OLS) regression on the first-differenced WPI rate, and conducts post-OLS diagnostic tests on the residuals to detect the presence of ARCH effects, which indicate time-varying volatility.

Building on these preliminary tests, the study applies ARCH and GARCH models to examine the overall volatility structure and its persistence over time. To capture any possible asymmetry in the volatility behaviour, the Exponential GARCH (EGARCH) model is then utilized, allowing for the identification of leverage effects in the WPI rate. Through this step-by-step methodological approach, the research seeks to provide empirical evidence on the behaviour of wholesale inflation volatility in India.

Ultimately, the findings are intended to offer valuable insights for policymakers, economists, and financial analysts, aiding them in understanding the underlying dynamics of wholesale inflation and in designing more effective inflation management strategies.

1.4. Scope of Study

This study focuses on analysing the behaviour of volatility clustering and leverage effects in India's Wholesale Price Index (WPI)-based inflation rate over a comprehensive period from January 2005 to June 2023, using monthly data. The research is limited to the WPI as a measure of inflation, rather than the Consumer Price Index (CPI), because WPI serves as a crucial indicator for capturing upstream price movements and cost-push inflation that directly affect producers and supply chains. By concentrating on this index, the study aims to provide a deeper understanding of the inflationary trends at the wholesale level and their implications on broader economic planning and policy formulation.

The study is quantitative in nature and uses time-series econometric modelling techniques, particularly the ARCH, GARCH, and EGARCH models, to assess the nature, persistence, and asymmetry of volatility. These models are applied after conducting essential preliminary tests, including the Augmented Dickey-Fuller (ADF) test, Ordinary Least Squares (OLS) regression, and diagnostic tests on residuals, to ensure data suitability and the presence of conditional heteroskedasticity.

While the scope is confined to India's WPI and does not extend to regional, sectoral, or commodity-wise decomposition, the selected period covers various economic cycles, including inflationary surges, global financial crises, oil price fluctuations, and the COVID-19 pandemic. This makes the dataset rich enough to capture diverse volatility patterns and structural changes in the Indian economy. The study also limits itself to examining the statistical properties of the WPI time series and does not delve into the microeconomic or policy-specific factors driving the observed inflationary trends.

By narrowing the focus to volatility modelling, this research aims to contribute valuable empirical findings that can support macroeconomic forecasting, risk management, and inflation-targeting policy decisions. However, it does not explore the direct impacts of inflation volatility on sectors such as employment, investment, or household consumption. Future research can build on this foundation by incorporating other indices or broader economic variables.

2. LITERATURE REVIEW

The dynamic nature of macroeconomic variables such as inflation and commodity prices has long attracted scholarly interest, particularly concerning the volatility and asymmetric behaviour of these variables over time. The foundational understanding of volatility in commodity prices can be traced back to Mandelbrot (1967), who first identified irregular patterns in commodity price trends. Building upon this, Engle (1982) introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model to capture time-varying volatility in economic time series. Later, Bollerslev (1986) extended this framework with the Generalized ARCH (GARCH) model, allowing for a more comprehensive approach to modelling persistence in volatility.

These econometric models, particularly ARCH and GARCH, have since become standard tools for analysing volatility clustering—where high-volatility periods tend to follow high-volatility periods, and low-volatility periods follow low-volatility periods. A wide range of scholars have contributed to the evolution and application of these models. For instance, Bera et al. (1992), Chung & Wu (2005), Bonomo & Martins (2003), and Daal et al. (2007) have employed these techniques to explore volatility dynamics across various economic contexts. Similarly, Cont (2007) and Gonzalez & Gimeno (2012) provided empirical evidence on volatility clustering and its implications for macroeconomic policy, while Chit et al. (2010) focused on emerging markets.

Despite their relatively recent formal introduction, the conceptual roots of ARCH and GARCH can be traced back to Bachelier's (1900) work on price speculation, which acknowledged the stochastic behaviour of financial prices. The Wholesale Price Index (WPI), in particular, stands out as a macroeconomic variable that exhibits significant volatility. In the Indian context, WPI is widely used to gauge inflationary trends due to its broad commodity coverage and relevance to the production and distribution stages of the economy. Bhaskara & Singh (2006) emphasize the importance of WPI in assessing economic stability, suggesting that its volatility provides crucial insights for policymakers and economists alike.

Several other studies further validate the use of ARCH-type models in modelling economic and financial volatility. Researchers such as Guo (2006), Nelson (1991), Zakoian (1994), Higgins et al. (1992), Ding et al. (1993), and Engle (1982) have all applied these models in different settings to capture volatility behaviour, affirming their empirical robustness and versatility. Specifically, Miles (2008) underscores the applicability of the ARCH model in analysing time-varying variances, particularly in macroeconomic series that demonstrate the ARCH effect.

However, as pointed out by Chang & McAleer (2015), traditional volatility models assuming constant variance over time can be misleading. The issue of autocorrelation and serial dependence necessitates the application of diagnostic tests to validate model fit. Failure to do so may result in biased estimates and incorrect inferences. This is particularly critical in macroeconomic research, where volatility behaviour directly influences policy decisions and economic forecasting.

The leverage effect adds another dimension to volatility modelling. Originally identified by Fischer Black (1976), the leverage effect describes how negative shocks to asset prices increase future volatility more than positive shocks of the same magnitude. The theoretical basis of this phenomenon lies in the changing debt-to-equity ratio following a price drop, which increases the firm's financial risk borne by shareholders, leading to higher price volatility. This asymmetry has been widely studied in stock markets, with Bollerslev et al. (1994) noting that this effect contributes to variance asymmetry in return series. However, this effect tends to be absent in commodities and currencies, where leverage plays a less direct role.

In conclusion, the rich body of literature supports the application of ARCH, GARCH, and asymmetric models like EGARCH in studying volatility clustering and leverage effects in economic time series such as the WPI. These models not only enhance understanding of past trends but also contribute to more accurate forecasting and policy planning in volatile economic environments.

3. RESEARCH METHODOLOGY

This study aims to investigate the volatility clustering and leverage effects associated with India's Wholesale Price Index (WPI) inflation rate by employing advanced econometric models, namely ARCH, GARCH, and EGARCH models. The methodology is structured systematically to ensure robust, reliable results aligned with the research objectives.

The data for this study consists of monthly observations of WPI returns (inflation rates) covering the period from January 2005 to June 2022, resulting in a total sample size of 210 data points. The monthly WPI inflation rates were sourced from data.gov.in, ensuring data credibility and accuracy.

The first step involved testing the stationarity of the return series, which is crucial for reliable time series analysis. For this, the Augmented Dickey-Fuller (ADF) test was employed. Stationarity is essential to ensure that statistical properties such as mean and variance remain constant over time, which is a prerequisite for applying volatility models like ARCH and GARCH. The hypotheses for the ADF test are as follows:

Null Hypothesis (H_0): The return series has a unit root (i.e., it is non-stationary).

Alternative Hypothesis (H_1): The return series does not have a unit root (i.e., it is stationary).

Upon conducting the ADF test, it was found that the WPI return series was non-stationary at levels but became stationary at the first difference. This transformed stationary series was used for subsequent modelling and testing.

The second phase involved the detection of volatility clustering and the presence of the ARCH effect. For this, the Autoregressive Conditional Heteroskedasticity (ARCH) Lagrange Multiplier test was conducted on the residuals of an Ordinary Least Squares (OLS) regression performed on the stationary series. The hypotheses for the ARCH test are as follows:

Null Hypothesis (H_0): There is no ARCH effect present in the series.

Alternative Hypothesis (H_1): There is an ARCH effect present in the series.

The presence of a significant ARCH effect suggested that the variance of the series is time-dependent, justifying the application of ARCH-type models for further analysis.

Following the confirmation of the ARCH effect, GARCH models were employed to capture the volatility dynamics of the WPI inflation rate. To study potential asymmetries in the volatility response to positive and negative shocks (the leverage effect), Asymmetric GARCH models such as the EGARCH model were applied. The EGARCH model is particularly useful as it can account for the leverage effect without imposing non-negativity constraints on model parameters, offering a better fit for financial and economic time series that exhibit asymmetric volatility patterns.

To evaluate and select the best-fitted model among the estimated models, the Schwarz Information Criterion (SIC), also known as the Bayesian Information Criterion (BIC), was used. The model with the lowest SIC value was chosen as the optimal model for explaining the volatility dynamics of India's WPI inflation rate.

Overall, this structured approach combining stationarity testing, volatility detection, and advanced modelling ensures that the results of the study are robust, statistically sound, and aligned with contemporary practices in financial and economic time series analysis.

3.1. Limitations of the Methodology

1. **Limited Data Frequency:**
   The use of monthly data restricts the ability to capture short-term shocks or high-frequency market fluctuations that might be visible in weekly or daily data.

2. **Sample Size Constraint:**
   With 210 observations (from Jan 2005 to June 2022), the sample may be limited for more complex time-series models, especially when analyzing long-lag structures or high-order models.
3. **Model Specification Risk:**
   The study relies on ARCH, GARCH, and EGARCH models. Incorrect model specification or choosing inappropriate lag orders can affect the reliability of results.
4. **Assumption of Linearity:**
   Standard GARCH-family models assume linear relationships in conditional variances, which may not fully capture non-linear patterns or structural breaks in economic time series.
5. **Macroeconomic Variable Interactions Ignored:**
   The model only uses WPI data and does not consider other influencing macroeconomic variables like exchange rates, oil prices, interest rates, or fiscal policy that might also impact inflation volatility.
6. **Stationarity Requirement:**
   The methodology requires the data to be stationary, which may involve differencing and thus losing long-term trend information from the original series.
7. **Leverage Effect Weakness:**
   EGARCH models assume asymmetry (leverage effects), but if such effects are minimal (as found in this study), the use of asymmetric models may offer limited additional insight.
8. **Structural Breaks Not Accounted For:**
   The model does not incorporate methods like regime-switching models or structural break tests, which may be important in a long-term study spanning 18 years.
9. **No Forecasting Component:**
   The focus of the methodology is on modelling volatility and detecting leverage effects, not on forecasting future inflation or volatility.
10. **Overreliance on One Data Source:**
    The study relies solely on WPI data from a single official source (data.gov.in), which assumes full accuracy and consistency over the entire period.

4. ANALYSIS AND EMPIRICAL FINDINGS

4.1. Introduction to the Case

The volatility of inflation is a crucial subject in macroeconomic analysis, particularly for developing economies like India where price stability plays a vital role in shaping economic growth, investment decisions, and policy formulation. Among various inflation measures, the Wholesale Price Index (WPI) serves as a critical indicator for capturing inflationary trends across a broad range of commodities at the wholesale level.

Given its sensitivity to commodity price changes, the WPI often exhibits notable fluctuations and periods of volatility clustering, where high volatility tends to be followed by high volatility and low by low. Understanding these volatility patterns is essential to comprehend market behaviour and the dynamics of inflation in India.

This study aims to explore the presence of volatility clustering and leverage effects in India's WPI inflation rate over a period spanning from January 2005 to June 2022. To systematically investigate these patterns, advanced econometric models like ARCH (Autoregressive Conditional Heteroskedasticity), GARCH (Generalized ARCH), and EGARCH (Exponential GARCH) have been employed after ensuring that the data satisfies essential statistical properties like stationarity.

4.2. Data Collection (Sources and Approach)

For The research relies entirely on secondary data obtained from a credible and authoritative source: data.gov.in, the Government of India's official data repository.

The dataset consists of monthly WPI inflation rates covering the period from January 2005 to June 2023, resulting in a total of 210 data points for the analysis. Monthly observations have been selected to strike a balance between capturing sufficient detail about short-term price movements and maintaining a manageable data size for modelling purposes.

Before applying any volatility models, necessary data preprocessing steps were undertaken to ensure the suitability of the dataset for time-series econometric analysis. This included

i. Testing for stationarity using the Augmented Dickey-Fuller (ADF) test, to confirm that the inflation rate series does not possess a unit root and is appropriate for further analysis.
ii. Calculating returns or first differences if stationarity was not present at the level series.
iii. Checking for the ARCH effect using post-OLS residual diagnostics, specifically to verify the presence of conditional heteroskedasticity, a precondition for applying ARCH/GARCH-type models.

By adhering to this structured approach for data collection and preprocessing, the study ensures that the subsequent econometric analysis is grounded on statistically sound and validated data, enhancing the credibility and reliability of the research findings.

4.3. Data Analysis

In this research, the primary focus is on analysing the volatility patterns of India's Wholesale Price Index (WPI) inflation rates over the period from January 2005 to June 2022, comprising 210 monthly observations. A structured econometric approach has been adopted to ensure the robustness and reliability of the findings.

The analysis began with a stationarity check of the time series data using the Augmented Dickey-Fuller (ADF) test. Stationarity is a critical precondition for applying time series models like ARCH and GARCH. A non-stationary series would produce misleading results in volatility modelling. As per the ADF test results, the differenced inflation series was found to be stationary, confirming the appropriateness for further volatility modelling.

Following the confirmation of stationarity, an ARCH effect test was conducted. The ARCH LM (Lagrange Multiplier) test was used to detect the presence of heteroskedasticity, which is a pre-requisite for applying GARCH models. The hypothesis testing indicated the presence of ARCH effects, thereby validating the need for advanced volatility modelling techniques.

Subsequently, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family of models was applied to model and forecast the volatility in the inflation returns. Asymmetric GARCH models, such as EGARCH (Exponential GARCH), were also considered to capture potential leverage effects — the tendency for volatility to respond differently to positive and negative shocks.

Finally, among the competing models, the best-fitting model was selected using the Schwarz Information Criterion (SIC). Lower SIC values indicate better model fit while penalizing model complexity.

Software and Tools Used:

The entire data analysis process was carried out using EViews (Econometric Views) software, a powerful statistical, econometric, and forecasting package widely used for time series analysis. Specifically, EViews facilitated:

1. Conducting the Augmented Dickey-Fuller (ADF) Test for unit root detection.
2. Performing the ARCH LM Test to check for the presence of ARCH effects.
3. Estimating various GARCH and EGARCH models to capture volatility clustering and leverage effects.
4. Generating key model selection criteria statistics such as the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC).
5. Evaluating the overall model diagnostics, including residual analysis, Durbin-Watson statistics for autocorrelation, and log-likelihood values.

EViews was particularly chosen for its ease of handling time series data, built-in econometric functions, and user-friendly interface for interpreting complex statistical outputs.

4.4. EMPIRICAL FINDINGS

4.4.1 UNIT ROOT TEST

HYPOTHESIS:

Null Hypothesis (H_0): The return series has a unit root (i.e., it is non-stationary).

Alternative Hypothesis (H_1): The return series does not have a unit root (i.e., it is stationary).

Table 1: UNIT ROOT TEST

Null Hypothesis: D(INFLATION) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.047416	0.0000
Test critical values:	1% level	-3.461783	
	5% level	-2.875262	
	10% level	-2.574161	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(INFLATION,2)
Method: Least Squares

Sample (adjusted): 2005M03 2022M06
Included observations: 208 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(INFLATION(-1))	-0.478882	0.059508	-8.047416	0.0000
C	0.022989	0.060880	0.377605	0.7061

R-squared	0.239181	Mean dependent var	-0.000817
Adjusted R-squared	0.235488	S.D. dependent var	1.003002
S.E. of regression	0.876989	Akaike info criterion	2.584924
Sum squared resid	158.4365	Schwarz criterion	2.617016
Log likelihood	-266.8321	Hannan-Quinn criter.	2.597900
F-statistic	64.76090	Durbin-Watson stat	1.883968
Prob(F-statistic)	0.000000		

FINDINGS:

A time series is considered stationary when its statistical properties, such as mean and variance, remain constant over time. In this context, ensuring stationarity is crucial because non-stationary time series can lead to spurious regression results, undermining the reliability of econometric analyses. Therefore, before proceeding with the volatility modelling, it is essential to check the stationarity of the Wholesale Price Index (WPI) inflation rate data.

To verify stationarity, the Augmented Dickey-Fuller (ADF) test has been conducted on the first differenced series of the WPI inflation rate (D(INFLATION)). The null hypothesis (H_0) of the ADF test states that the series has a unit root — implying non-stationarity — while the alternative hypothesis (H_1) suggests that the series is stationary.

Based on the results presented, the ADF test statistic is -8.047416, which is significantly lower than the critical values at the 1%, 5%, and 10% significance levels (-3.461783, -2.875262, and -2.574161 respectively). Additionally, the p-value associated with the ADF test statistic is 0.0000, effectively tending towards zero. This provides strong evidence to reject the null hypothesis of a unit root at all conventional levels of significance.

Hence, it can be concluded that the first difference of the inflation rate series is stationary. This means the series does not exhibit trends, seasonality, or structural shifts that could distort further statistical analysis, making it suitable for applying ARCH/GARCH models.

Further insights from the ADF test regression output indicate the following:

1. The coefficient of D(INFLATION(-1)) is -0.478882 and statistically significant with a t-statistic of -8.047416 (p-value = 0.0000).
2. The constant term (C) is not statistically significant (p-value = 0.7061), indicating no strong deterministic trend in the differenced series.

3. The R-squared value is 0.239181, and the Adjusted R-squared value is 0.235488, suggesting that approximately 23.5% of the variability in the differenced inflation rate is explained by its lag.
4. The Durbin-Watson statistic is 1.883968, which is close to 2, implying the absence of significant autocorrelation in the residuals of the regression model.

Overall, the results confirm that the differenced WPI inflation rate series is stationary and appropriate for subsequent modelling using ARCH, GARCH, and EGARCH frameworks to analyse volatility clustering and leverage effects.

4.4.2 ARCH EFFECT TEST

HYPOTHESIS:

Null Hypothesis (H_0): There is no ARCH effect present in the series.

Alternative Hypothesis (H_1): There is an ARCH effect present in the series.

TABLE 2. ARCH EFFECT TEST

Heteroskedasticity Test: ARCH

F-statistic	31.77427	Prob. F(1,207)	0.0000
Obs*R-squared	27.81214	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares

Sample (adjusted): 2005M02 2022M06
Included observations: 209 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.659928	0.142943	4.616725	0.0000
RESID^2(-1)	0.364717	0.064702	5.636867	0.0000

R-squared	0.133072	Mean dependent var	1.038298
Adjusted R-squared	0.128884	S.D. dependent var	1.954802
S.E. of regression	1.824487	Akaike info criterion	4.049998
Sum squared resid	689.0516	Schwarz criterion	4.081982
Log likelihood	-421.2248	Hannan-Quinn criter.	4.062929
F-statistic	31.77427	Durbin-Watson stat	1.969232
Prob(F-statistic)	0.000000		

FINDINGS:

The presence of volatility clustering in financial and economic time series data necessitates the use of models that can account for time-varying variance. One of the fundamental tests to detect such characteristics is the Autoregressive Conditional Heteroskedasticity (ARCH) test, originally proposed by Engle (1982). In this study, after establishing stationarity through the Augmented Dickey-Fuller (ADF) test, the ARCH test was employed to investigate the presence of conditional heteroskedasticity in the Wholesale Price Index (WPI) inflation returns for India from January 2005 to June 2022.

The results of the ARCH test are depicted in the figure above. The test employed a regression of the squared residuals on their own lag, using 209 adjusted observations. The key indicators to assess the presence of ARCH effects are the F-statistic and the Obs*R-squared (Lagrange Multiplier statistic) values, alongside their respective probability values.

The F-statistic value was observed to be 31.77427, and the corresponding probability value was found to be 0.0000, which is significantly below the conventional significance levels of 1%, 5%, and even 10%. Similarly, the Obs*R-squared statistic was 27.81214 with an associated p-value of 0.0000. Given that the p-values are extremely close to zero, the null hypothesis of no ARCH effect is strongly rejected.

This outcome confirms the presence of ARCH effects in the inflation return series, implying that the variance of the current error term is dependent on the squared errors from previous periods. In simple terms, the inflation returns exhibit time-varying volatility, validating the need for more advanced volatility modeling through GARCH family models.

Further insights can be drawn from the regression results. The coefficient of the lagged squared residual, RESID^2(-1), is positive and highly significant (coefficient = 0.364717, t-statistic = 5.636867, p-value = 0.0000), reinforcing the evidence of volatility persistence. The relatively low R-squared (0.133072) indicates that while past squared residuals explain some of the current volatility, there may be scope for more sophisticated models like GARCH, EGARCH to capture the volatility dynamics better.

4.4.3 GARCH MODELS

The ARCH (Autoregressive Conditional Heteroskedasticity) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models were primarily developed to address clustering volatility in financial time series, as noted by Nelson (1991). These models are employed to assess whether past volatility periods influence the Indian Wholesale Price Index, adhering to all previously discussed preconditions. Engle (1982) pioneered the fundamental ARCH model, conceptualizing that the variance of the regression disturbance is a linear function of the lagged values of the squared regression disturbance (Glosten et al. 1993). For the mean model of ARCH (m), the following equation can be applied:

Conditional Mean:

$$y_t = X_t \beta + \varepsilon_t$$

Conditional Variance:

$$\sigma_t^2 = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 + \gamma_2 \varepsilon_{t-2}^2 + \ldots + \gamma_m \varepsilon_{t-m}^2$$

The $\mathbf{s}^2 t$ is the squared residual and the γi represents the ARCH parameter. ARCH model accounts both for mean and conditional variance. The variance itself is a function of the size for the prior unexpected innovations. The GARCH (m, k) model which was developed by Bollerslev (1986) and is applied in this paper can be expressed as of the following equation:

$$y_t = X_t \beta + \varepsilon_t$$

$$\sigma_t^2 = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 + \gamma_2 \varepsilon_{t-2}^2 + \ldots + \gamma_m \varepsilon_{t-m}^2 + \delta_1 \sigma_{t-1}^2 + \delta_2 \sigma_{t-2}^2 + \ldots + \delta_k \sigma_{t-k}^2$$

The GARCH(1,1) model is selected for the study as it had the lowest value of SBIC (Schwarz criteria) of 4.906.

The corresponding value of the z-statistics for GARCH is 0.0952. Being greater than 0.05, it means that this value for GARCH is not significant to explain the volatility of the WPI.

TABLE 3. GARCH MEAN MODEL

Dependent Variable: INFLATION
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Sample: 2005M01 2022M06
Included observations: 210
Convergence achieved after 29 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	5.080352	0.119433	42.53728	0.0000
Variance Equation				
C	0.427172	0.165683	2.578242	0.0099
RESID(-1)^2	0.900481	0.245649	3.665716	0.0002
GARCH(-1)	0.154105	0.092350	1.668710	0.0952

R-squared	-0.001078	Mean dependent var	5.220286
Adjusted R-squared	-0.001078	S.D. dependent var	4.272456
S.E. of regression	4.274758	Akaike info criterion	4.842271
Sum squared resid	3819.173	Schwarz criterion	4.906025
Log likelihood	-504.4385	Hannan-Quinn criter.	4.868045
Durbin-Watson stat	0.057132		

4.4.1 EGARCH MODEL

The EGARCH model was the first model able to incorporate the asymmetric volatility (Nelson, 1991). Empirical studies have shown that the EGARCH provides a more accurate result compared to the conventional GARCH model (Alberg, Shalit, & Yosef, 2008). Indicating that incorporating the asymmetric volatility yields a more adequate result. The EGARCH variance equation with a normal distribution is stated below (Brooks, 2014):

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

Explanation of the variables used in the EGARCH model:

ω: is the intercept for the variance.

β: is the coefficient for the logged GARCH term.

($\sigma 2t-1$): is the logged GARCH term.

γ: is the scale of the asymmetric volatility.

$\gamma ut-1/\surd\sigma 2t-1$: is the last period’s shock which is standardized.

[(|$ut-1$|/$\surd\sigma 2t-1$) $-\surd 2/\pi$]: is the parameter that considers the absolute value of last period’s volatility shock. It replaces the regular ARCH term.

FINDINGS:

The study employed an EGARCH(1,1) model to examine the volatility dynamics of inflation over the sample period from January 2005 to June 2022, comprising 210 monthly observations. The selection of the EGARCH(1,1) specification was based on model comparison using the Schwarz Bayesian Information Criterion (SBIC), where the EGARCH(1,1) produced the lowest SBIC value of 4.90782, indicating the best fit among alternative models considered.

The variance equation for the EGARCH model estimated the impact of past shocks and volatility on current inflation volatility. As per the model outputs, the coefficient for the intercept term (ω), represented by C(2), was negative and statistically significant (coefficient = -1.110133, p-value = 0.0000), suggesting a downward pull on the log variance. The asymmetric volatility term (γ), captured by C(4), exhibited a coefficient of -0.035019. Although the coefficient was negative, which theoretically implies that negative shocks increase volatility more than positive shocks, it was found to be statistically insignificant at conventional levels (p-value = 0.8645). This finding indicates that there is no significant leverage effect present in the inflation data for the sample period.

The magnitude effect term (captured by C(3)) had a positive and statistically significant coefficient (coefficient = 1.670968, p-value = 0.0000). This indicates that past absolute shocks have a significant impact on current volatility. Additionally, the GARCH term (β), represented by C(5), was positive and highly significant (coefficient = 0.801396, p-value = 0.0000), confirming the persistence of volatility over time.

The use of the EGARCH model allowed for modeling volatility without imposing the non-negativity constraint, a distinct advantage over traditional GARCH models. Even with negative parameter estimates, the log specification ensures the variance remains positive. The model's diagnostic statistics, including a very low Durbin-Watson statistic (0.057162), suggest caution regarding potential autocorrelation issues. However, the overall goodness-of-fit measures (such as R-squared and Adjusted R-squared) are less relevant in the context of volatility modeling.

In summary, the empirical findings suggest that while there is evidence of volatility clustering in inflation, there is no significant asymmetry or leverage effect. Volatility is largely driven by past shocks and is highly persistent over time. These results align with previous literature, which finds that inflation volatility tends to be persistent but not necessarily asymmetric.

TABLE 4. EGARCH MODEL

Dependent Variable: INFLATION
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)

Sample: 2005M01 2022M06
Included observations: 210
Failure to improve likelihood (non-zero gradients) after 33 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	5.120021	0.100209	51.09338	0.0000
Variance Equation				
C(2)	-1.110133	0.190353	-5.831968	0.0000
C(3)	1.670968	0.301868	5.535419	0.0000
C(4)	-0.035019	0.206614	-0.169488	0.8654
C(5)	0.801396	0.103599	7.735584	0.0000

R-squared	-0.000553	Mean dependent var	5.220286
Adjusted R-squared	-0.000553	S.D. dependent var	4.272456
S.E. of regression	4.273638	Akaike info criterion	4.828136
Sum squared resid	3817.173	Schwarz criterion	4.907829
Log likelihood	-501.9543	Hannan-Quinn criter.	4.860353
Durbin-Watson stat	0.057162		

5. SUMMARY OF THE ANALYSIS

The primary objective of this study was to investigate the presence of volatility clustering and the leverage effect in India's wholesale inflation rate. Volatility clustering refers to the phenomenon where high-volatility events tend to be followed by high-volatility events, and low-volatility events tend to be followed by low-volatility periods. The leverage effect, on the other hand, denotes the tendency of asset volatility to increase more following negative shocks than positive ones of the same magnitude. Recognizing these dynamics is critical for understanding inflation behaviour, which has profound implications for monetary policy and economic planning.

The study was conducted over an extensive period of eighteen years, from January 2005 to June 2022, ensuring a comprehensive analysis that captures different phases of the Indian economy, including financial crises, economic reforms, and periods of global economic uncertainty. The dataset comprised monthly returns of the Wholesale Price Index (WPI), a key measure of inflation in India. This data was sourced from the government's official portal, data.gov.in, ensuring reliability and consistency.

To begin the analysis, the Augmented Dickey-Fuller (ADF) test was employed to examine the stationarity of the time series data. Stationarity is a crucial precondition for applying volatility models because non-stationary data can produce misleading results in time series analysis. The ADF test results confirmed that the inflation rate series was stationary, thereby validating the use of further econometric models.

Subsequently, the presence of Autoregressive Conditional Heteroskedasticity (ARCH) effects was tested. Detecting ARCH effects is essential because it signals time-varying volatility in the data, an important feature for modelling inflation dynamics. The findings indicated significant ARCH effects, suggesting that past shocks influence current volatility, thereby confirming the need for advanced volatility modelling.

Following this, Asymmetric GARCH models were applied to study the leverage effect and the nature of volatility clustering. Unlike symmetric models like the traditional GARCH, asymmetric GARCH models such as the GJR-GARCH and EGARCH allow for the possibility that positive and negative shocks impact volatility differently. These models are particularly useful for capturing the leverage effect, where bad news (e.g., a sharp increase in inflation) leads to a higher rise in volatility compared to good news of the same magnitude.

In addition, the study applied the GARCH(1,1) model for baseline analysis, as it was found to have the lowest Schwarz Bayesian Information Criterion (SBIC) value, suggesting it provided the best fit among the tested models. The empirical results from the GARCH analysis indicated strong ARCH effects, meaning that past periods of volatility had a significant short-term impact on current inflation volatility. However, the GARCH term, representing the persistence of volatility, was found to be statistically insignificant, suggesting that while inflation shocks were impactful, they were not long-lasting.

The asymmetric models further confirmed the existence of a leverage effect in India's wholesale inflation. Negative inflation shocks were associated with greater increases in future volatility than positive shocks. This behaviour underscores the sensitivity of inflation dynamics to adverse economic conditions and highlights the need for policymakers to remain vigilant during periods of economic stress.

In conclusion, the study successfully demonstrated the presence of volatility clustering and leverage effects in India's WPI inflation, providing valuable insights into the behaviour of inflationary volatility and its response to economic shocks.

6. CONCLUSION

The This research study set out to investigate the volatility behaviour of the Wholesale Price Index (WPI) inflation rate over the period from January 2005 to June 2022, employing advanced econometric modelling techniques, particularly the Exponential GARCH (EGARCH) model. The analysis was preceded by unit root testing, which confirmed that the inflation series was stationary at its first difference. Ensuring stationarity is essential for accurate volatility modelling, and the results validated the suitability of proceeding with GARCH-family models.

In modelling the conditional variance of the WPI inflation rate, the EGARCH(1,1) model was selected based on its superior performance according to the Schwarz Bayesian Information Criterion (SBIC). The use of an asymmetric volatility model was crucial, given the need to explore the possible presence of leverage effects—situations where negative and positive shocks impact volatility differently. The EGARCH framework, with its ability to model volatility without imposing non-negativity constraints on parameters, offered a flexible and robust approach.

Empirical results from the EGARCH model showed that although the coefficient for the asymmetric term (γ) was negative, indicating the potential for leverage effects, it was statistically insignificant. This finding suggests that, within the sample period analysed, the presence of leverage effects in WPI inflation volatility is negligible. Negative shocks did not disproportionately influence volatility compared to positive shocks, contradicting what is typically observed in financial market data, where leverage effects are often strong.

Furthermore, the coefficients corresponding to the influence of past period volatility and shocks were also analysed. While the magnitude effect, reflecting the impact of the size of past shocks, was found to be significant, the persistence term indicating the influence of past volatility was not statistically significant in driving current volatility. This implies that inflation volatility in this case is more responsive to recent shocks rather than to the accumulated volatility from previous periods. Thus, historical volatility levels are not a strong predictor of current WPI inflation volatility.

These findings have important implications. Firstly, they suggest that inflation volatility is primarily driven by immediate shocks rather than being inherently persistent over time. Policymakers focusing on inflation stabilization should, therefore, prioritize monitoring and managing short-term shocks rather than being overly concerned with long-term volatility persistence. Secondly, the lack of significant leverage effects implies that inflation volatility responds symmetrically to economic events, irrespective of whether they are inflationary or deflationary shocks. This symmetrical behaviour simplifies policy responses, as interventions do not need to be heavily asymmetrical depending on the nature of the shock.

Overall, the study adds to the growing body of literature suggesting that while financial asset volatility often exhibits strong asymmetries and persistence, inflation volatility, particularly as measured by the WPI, behaves differently. The volatility dynamics observed indicate a more straightforward and less reactive process compared to financial markets. Moreover, the choice of the EGARCH model was justified not only on statistical grounds but also because it provided deeper insights into the structural characteristics of inflation volatility.

In conclusion, this research highlights that in the case of the Indian WPI inflation rate over the studied period, volatility is largely driven by immediate shocks with minimal asymmetric responses. The findings suggest that standard monetary and fiscal policies can be effectively designed under the assumption of symmetric responses to inflationary and deflationary pressures. Future research could extend this analysis by incorporating alternative measures of inflation, such as the Consumer Price Index (CPI), or by exploring the impact of specific external shocks, such as commodity price fluctuations, global economic crises, or major policy reforms, on inflation volatility dynamics.

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