Volatility Dynamics In Indian Financial Market: A Quantitative Analysis Of Macroeconomic Influences

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Abstract

This study evaluates the influence of important macroeconomic factors on market volatility in the Indian context and investigates the volatility dynamics of the Nifty 50 index. Six macroeconomic indicators—the call money rate, consumer price index (CPI), economic policy uncertainty (EPU) index, exchange rate, index of industrial production (IIP), and crude oil prices—are included in the analysis, which uses monthly data from April 2010 to March 2025. To ascertain the order of integration, the Augmented Dickey-Fuller (ADF) approach is used to construct the Nifty 50 return series and test it using unit root. To capture the baseline volatility structure and asymmetric effects, both alone and with individual stationary macroeconomic variables, a thorough econometric framework is used, starting with the Exponential GARCH (EGARCH) model. The Autoregressive Distributed Lag (ARDL) model is used to analyze the short- and long-term relationships between volatility and the chosen macroeconomic variables. The Error Correction Model (ECM) is then used to estimate the rate of adjustment toward equilibrium. The CUSUM plot is used to assess structural stability, and the Markov Switching model is used to identify volatility regime shifts. Furthermore, the time–frequency domain interactions between macroeconomic factors and market volatility are examined using wavelet transform analysis. The empirical findings underscore the significant role of macroeconomic fundamentals in shaping equity market volatility and demonstrate the relevance of advanced econometric techniques in capturing the complex dynamics of financial markets in emerging economies.

JEL Classification: G12, C22, C24, C32, E37, E44, G15

Keywords: Volatility Dynamics; Nifty 50; Macroeconomic Variables; EGARCH Model; ARDL Approach; Economic Policy Uncertainty; Markov Switching Model; Wavelet Analysis; Indian Stock Market; Emerging Markets.

2 Introduction

In emerging markets like India, where financial systems are frequently typified by structural inefficiencies, changing regulatory frameworks, and increased vulnerability to both internal and international shocks, volatility modelling is especially important. Emerging markets are more vulnerable to sudden swings caused by shifts in policy, investor mood, and external economic conditions than developed markets, which typically behave in a more steady and predictable manner. Understanding and simulating volatility in these kinds of environments is therefore essential for both scholarly research and real-world decision-making. In risk management, precise volatility estimates are essential because they help financial institutions and investors create sensible asset allocation plans and efficient hedging techniques.

Furthermore, volatility is a crucial factor in determining the price of financial instruments, especially derivatives, where miscalculation can result in significant losses. From a policy standpoint, keeping an eye on volatility enables central banks and regulators to evaluate the stability of the financial system and take the necessary action during times of excessive uncertainty. Additionally, volatility patterns can serve as early warning indicators for market distress or more significant economic crises and frequently mirror the state of the economy. Robust volatility modelling is necessary to improve market efficiency, promote well-informed policymaking, and cultivate investor confidence in an economy like India's, which is characterized by rapid growth, growing global integration, and exposure to changeable macroeconomic conditions.

This study targets to find the Nifty 50 index's volatility patterns and evaluate the impact of particular macroeconomic factors on its behaviour. The Nifty 50 is used as a measure of general market sentiment and economic activity since it is a benchmark index that shows the performance of the top 50 large-cap businesses listed on the National Stock Exchange of India. Policymakers that care about financial stability as well as analysts and investors must comprehend its volatility characteristics. Numerous domestic and international macroeconomic factors frequently impact stock market volatility, especially in developing nations like India. This study looks at how the volatility of Nifty 50 returns is affected by six important macroeconomic indicators: the call money rate, consumer price index (CPI), economic policy uncertainty index (EPU), exchange rate, index of industrial production (IIP), and crude oil prices. The study attempts to capture both the short-term variations and the long-term correlations between macroeconomic conditions and market volatility by utilizing sophisticated econometric techniques as wavelet analysis, ARDL, ECM, EGARCH modelling, and Markov Switching. This method makes it possible to fully comprehend how macroeconomic shocks affect the volatility of one of the most significant stock indices in India.

The study employs monthly data from April 2010 to March 2025, capturing a broad spectrum of economic and financial developments in India, including major policy shifts, global market shocks, and the economic disruption caused by the COVID-19 pandemic. This 15-year timeframe ensures a sufficiently long and recent period for reliable econometric modelling of volatility dynamics. The dependent variable is the monthly return series of the Nifty 50 index, computed as log returns of the closing values, which reflects the variability in market performance over time and serves as the basis for volatility modelling.

To examine the macroeconomic influences on market volatility, six key independent variables have been selected based on theoretical relevance and their prevalence in empirical studies. These include the call money rate, which represents short-term interest rates and reflects liquidity conditions in the financial system; the consumer price index (CPI), a primary measure of inflation that affects real returns and investor confidence; and the economic policy uncertainty (EPU) index, which captures the effects of ambiguous or unstable policy environments on financial decision-making. Additionally, the exchange rate (INR/USD) is considered, as it influences external competitiveness and investor flows; the index of industrial production (IIP), which serves as a proxy for real economic activity and cyclical trends; and crude oil prices (Brent), a globally significant commodity that impacts inflation, corporate costs, and trade dynamics. These variables collectively offer a well-rounded view of the macroeconomic landscape and are expected to significantly influence the volatility patterns of the Nifty 50 index.

The remainder of the paper is structured as follows. Section 2 presents a review of relevant literature on volatility modelling and the influence of macroeconomic variables in emerging markets, with a focus on the Indian context. Section 4 describes the data used in the study, detailing the selection of variables, their sources, and the rationale for their inclusion. It also outlines the methodological framework, including the econometric techniques employed such as EGARCH, ARDL, ECM, Markov Switching models, and wavelet analysis. Section 5 reports the empirical results derived from these models, discussing both the standalone volatility patterns of the Nifty 50 and the impact of each macroeconomic variable. This section also provides a discussion of the findings, drawing comparisons across models and interpreting their implications in light of existing theory and literature. Finally, Section 6 concludes the paper by summarizing the key insights, highlighting policy and investment implications, and suggesting directions for future research.

3 Literature Review

Volatility in financial markets has been a widely studied phenomenon, particularly in the context of emerging economies, where markets are often more susceptible to external shocks, policy uncertainty, and structural inefficiencies. In the Indian context, several studies have analysed stock market volatility using various econometric models. For instance, **Mukherjee and Mishra (2005)** employed GARCH-type models to examine the volatility of Indian stock indices and found evidence of volatility clustering and persistence, reflecting the presence of long-memory processes. Building upon this basis, there has been a notable advancement in the creation of volatility modelling frameworks. The Autoregressive Conditional Heteroskedasticity (ARCH) model was developed by Engle

(1982) and takes into consideration time-varying volatility in financial time series. However, more reliable alternatives were developed as a result of the ARCH model's practical limitations, specifically its sensitivity to lag length and parameter instability. The Generalized ARCH (GARCH) model was first presented by **Bollerslev (1986)** and includes both the autoregressive and moving average components of volatility. GARCH(1,1) is simple in nature and it can capture volatility in a straightforward manner; that's why it has established itself as a standard in volatility measurement.

International studies of volatility in evolving markets by **Bekaert and Harvey (1997)** and **Aggarwal et al. (1999)** have emphasized the role of market liberalization and global spillovers in driving volatility, especially in times of economic turbulence. In India, **Kumar (2005)** demonstrated that oil prices and industrial production significantly impact equity volatility, while **Dash and Mahakud (2013)** showed that global financial uncertainty also plays a critical role. These findings underscore the importance of accounting for both domestic macroeconomic indicators and global factors when modelling volatility in emerging markets. Collectively, the literature suggests that volatility in these markets is not only driven by internal fundamentals but also highly sensitive to policy shifts and global developments, justifying the use of advanced econometric models to capture these complex dynamics.

In financial econometrics, the use of advanced models like EGARCH, ARDL, and wavelet analysis has gained prominence due to their ability to capture the complex and dynamic nature of financial time series. The Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model, introduced by **Nelson (1991)**, is particularly useful for modelling asymmetric volatility, where negative shocks may have a greater impact on market volatility than positive ones. Unlike traditional GARCH models, EGARCH does not impose non-negativity constraints on parameters and allows for a logarithmic specification of conditional variance, making it more flexible and better suited to capturing volatility clustering and leverage effects commonly observed in financial markets.

The Autoregressive Distributed Lag (ARDL) model, developed by **Pesaran and Shin (1998)**, is widely applied in macro-financial research to examine both short-run dynamics and long-run equilibrium relationships between variables. One of the main advantages of the ARDL framework is that it can be applied irrespective of whether the variables are I(0), I(1), or a combination of both, provided none are I(2). This makes it especially useful in empirical studies where the integration order of macroeconomic variables may vary. The Error Correction Model (ECM) derived from ARDL further captures the speed at which variables return to equilibrium after a shock, offering deeper insights into the temporal interactions between macroeconomic indicators and financial volatility.

Wavelet analysis, on the other hand, provides a powerful non-parametric tool for time frequency decomposition of financial time series. Unlike traditional time series techniques that operate either in the time domain or frequency domain, wavelet transforms allow for simultaneous localization in both domains. In recent years, wavelet-based approaches have been increasingly used to analyse co-movements between financial and macroeconomic variables, as well as to detect periods of instability or regime shifts.

Together, these models offer a comprehensive econometric toolkit for understanding the volatility behaviour of financial markets, especially in the context of emerging economies like India, where both macroeconomic fundamentals and external fluctuations significantly contribute to market dynamics.

Past research has extensively explored the role of macroeconomic variables in driving stock market volatility, particularly in the context of emerging markets where economic fundamentals and policy changes tend to have a pronounced impact. Numerous studies have identified interest rates, inflation, exchange rates, industrial production, and global commodity prices as key determinants of market volatility. For example, **Flannery and Protopapadakis (2002)** found that macroeconomic announcements, particularly related to inflation and interest rates, significantly affect stock returns and volatility. In the Indian context, studies such as **Bhattacharya et al. (2003)** and **Arun Giri** and **Pooja Joshi (2017)** showed that macroeconomic indicators like the interest rate and industrial production index have a significant influence on the volatility of equity markets. Exchange rate fluctuations have also been shown to contribute to market uncertainty, as they affect import-export dynamics and investor confidence, especially in globally integrated economies.

More recent studies have emphasized the growing impact of economic policy uncertainty. For instance, **Arouri et al. (2016)** found that rising policy uncertainty tends to amplify volatility in both developed and emerging stock markets. In India, evidence from studies such as **Sahoo and Sethi (2017)** suggests that uncertainty surrounding fiscal and monetary policies can significantly disturb market expectations and lead to heightened volatility. Similarly, oil prices—often considered a global macroeconomic variable—have been shown to affect emerging market volatility through their influence on inflation, input costs, and the balance of payments. The inclusion of these macroeconomic factors in volatility modelling is therefore not only empirically justified but also crucial for understanding the transmission channels through which economic shocks affect financial markets.

4 Research Objective

The primary objective of this research is to examine the volatility dynamics of the Indian stock market index (Nifty 50) and to analyse how key macroeconomic variables influence market volatility over time. Financial markets in emerging economies like India often experience heightened sensitivity to both domestic and global shocks, making an understanding of volatility behaviour essential for policymakers, investors, and financial analysts. While volatility is an inherent feature of equity markets, its magnitude, persistence, and responsiveness to macroeconomic fundamentals carry significant implications for risk management, asset pricing, and investment strategies.

This study aims to contribute to the existing literature by adopting a multi-model econometric framework to capture both the short-term fluctuations and long-term relationships between macroeconomic indicators and market volatility. Specifically, it seeks to evaluate how variables such as interest rates, inflation (CPI), exchange rate movements, industrial output (IIP), economic policy uncertainty, and crude oil prices influence the volatility structure of the Indian equity market.

By integrating traditional models like EGARCH and ARDL with advanced techniques such as Markov Switching and wavelet analysis, the study endeavours to provide a robust and nuanced understanding of volatility transmission mechanisms. Ultimately, the research intends to inform market participants and decision-makers about the macro-financial linkages that underpin market instability and to offer insights for forecasting and managing volatility in the Indian stock market.

5 Data and Methodology

5.1 Data

This study utilizes monthly data spanning from April 2010 to March 2025, comprising 156 observations for each variable. The dependent variable is the return series of the Nifty 50 index, calculated as the logarithmic difference of monthly closing prices, effectively capturing market volatility over time. The Nifty 50 index serves as a representative benchmark for the Indian equity market, consisting of 50 of the most liquid and large-cap stocks listed on the National Stock Exchange (NSE).

To evaluate the impact of macroeconomic fundamentals on stock market volatility, six key independent variables are selected: the call money rate, Consumer Price Index (CPI), Economic Policy Uncertainty (EPU) index, exchange rate (INR/USD), Index of Industrial Production (IIP), and crude oil prices (Brent). These variables have established theoretical linkages with financial market behaviour and have shown empirical relevance in the context of emerging markets. Data are sourced from reputable databases such as the Reserve Bank of India (RBI), Ministry of Statistics and Programme Implementation (MOSPI), Federal Reserve Economic Data (FRED), NSE India, and PolicyUncertainty.com.

Prior to modelling, all time series variables were tested for stationarity using the Augmented Dickey-Fuller (ADF) test. The return series, CPI, and EPU index were found to be stationary at level [I(0)], while the call money rate, exchange rate, IIP, and crude oil prices were integrated of order one [I(1)]. First differencing was applied to non-stationary variables to ensure stationarity before model estimation. To capture the inherent volatility characteristics in the Nifty return series, the study initially employs the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model, which accounts for volatility clustering and asymmetric effects. In the next step, each I(0) macroeconomic variable is introduced individually into the EGARCH framework to examine its direct influence on conditional volatility.

Subsequently, the Autoregressive Distributed Lag (ARDL) model is applied to assess both long-run and short-run relationships between Nifty 50 return volatility and the macroeconomic indicators. For combinations of variables that satisfy the ARDL bounds testing criteria, Error Correction Models (ECM) are estimated to quantify the speed at which deviations from long-run equilibrium are corrected after short-term disturbances.

To detect structural stability, the CUSUM plot is used to check for parameter constancy over time. A Markov Switching model is also incorporated to identify volatility regime shifts, which could correspond to periods of heightened economic or financial uncertainty.

Finally, wavelet transform analysis is employed to investigate the time–frequency behaviour of macroeconomic influences on volatility. This allows for the identification of co-movement patterns and relationships that vary across different time scales.

This multi-method econometric approach enables a comprehensive understanding of the volatility dynamics in the Indian equity market and the evolving role of macroeconomic variables in shaping these dynamics.

5.2 Methodology

This research adopts a multi-stage econometric and time series modelling approach to capture the volatility dynamics of the Nifty 50 index and the influence of selected macroeconomic variables. Each method is chosen for its ability to address specific analytical questions, collectively offering a holistic understanding of market behaviour. The analysis begins with the application of the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model, initially estimated without macroeconomic variables. This serves as the baseline model to capture inherent characteristics such as volatility clustering and asymmetry (leverage effects) in the Nifty 50 return series—phenomena commonly observed in financial time series.

Following the baseline estimation, EGARCH models are extended by incorporating each stationary (I(0)) macroeconomic variable—specifically, the Consumer Price Index (CPI) and the Economic Policy Uncertainty (EPU) index—one at a time. This enables an assessment of the individual impact of these variables on conditional volatility while maintaining the asymmetric properties of the model.To explore broader macro-financial interactions, the Autoregressive Distributed Lag (ARDL) model is employed. The ARDL framework is particularly suited for datasets comprising a mix of I(0) and I(1) variables. It facilitates estimation of both short-run dynamics and long-run relationships between Nifty 50 volatility and macroeconomic indicators. Bounds testing is used to determine the existence of cointegration among the variables. In cases where a long-run relationship is established through ARDL, the Error Correction Model (ECM) is estimated. The ECM captures short-run deviations from equilibrium and quantifies the speed of adjustment back to the long-run path after a shock, as reflected by the coefficient of the error correction term.

To assess structural stability, the CUSUM (Cumulative Sum of Recursive Residuals) plot is utilized. If the plot remains within the critical bounds, the model is considered structurally stable over time. Furthermore, the Markov Switching model is applied to detect regime changes in market volatility, capturing non-linear dynamics and allowing for probabilistic identification of high- and low-volatility states.

Finally, Wavelet Analysis is conducted to explore time–frequency co-movement between macroeconomic variables and Nifty 50 volatility. Unlike conventional time series models, wavelet transforms enable localized examination of relationships across multiple time scales, revealing dynamic and scale-specific effects that evolve over time.

6 Empirical Results

6.1 Descriptive Statistics

The behaviour of the Nifty 50 returns and important macroeconomic factors between April 2010 and March 2025 is summed up by the descriptive statistics. With a modest monthly mean of 0.81%, high volatility (standard deviation of 3.93%), negative skewness (-1.48), and excess kurtosis (10.31), characteristic of financial return series, the Nifty 50 return series shows frequent downward movements and fat tails. At the 1% level, non-normality is confirmed by the Jarque-Bera statistic.

The Call Money Rate (CMR), one of the macroeconomic indicators, has a moderate variation (standard deviation of 1.58%) and a slight left skewness, averaging 6.30%. Moderate but erratic inflation is reflected in the CPI's positive skewness and leptokurtosis, which average 6.07%.

Strong positive skewness and kurtosis, along with the EPU index's high volatility (standard deviation of 49.13), point to periods of extreme policy uncertainty.

The USD/INR exchange rate has a near-normal distribution and moderate volatility, averaging 67.05. With an average of 122.18 and low skewness and kurtosis close to 3, the IIP shows steady industrial activity. The dynamics of the commodity market are reflected in the high variability (standard deviation of 20.96), low skewness, and subnormal kurtosis of crude oil prices.

Table 1: Descriptive Statistics of the Variables

Statistic	Return50	CMR	CPI	EPU	Exrate	IIP	Oilp
Mean	0.008169	6.303697	6.066072	100.0883	67.04667	122.1896	71.70225
Median	0.014303	6.472693	5.590000	85.97074	67.20763	121.7000	71.74000
Maximum	0.095828	9.971509	13.90728	283.6891	87.06649	164.8000	111.6061
Minimum	-0.235926	3.135995	1.460000	23.35276	44.36813	54.00000	24.07667
Std. Dev.	0.039260	1.583012	2.319989	49.13265	11.41451	17.61820	20.96281
Skewness	-1.479120	-0.435793	0.689274	1.199404	-0.290424	-0.028885	-0.044994
Kurtosis	10.30943	2.759213	3.238707	4.613667	2.322306	3.161195	1.987550
Jarque-Bera	463.7512	6.098238	14.59876	62.33825	5.941718	0.218688	7.705600
Probability	0.000000	0.047401	0.000676	0.000000	0.051259	0.896422	0.021220
Sum	1.462302	1128.362	1085.827	17915.80	12001.35	21871.94	12834.70
Sum Sq. Dev.	0.274356	446.0550	958.0580	429695.1	23191.81	55251.34	78220.22
Observations	179	179	179	179	179	179	179

Source: Author's calculation using EViews 11

6.2 Stationarity

The Augmented Dickey-Fuller (ADF) test was employed to examine the stationarity properties of the Nifty 50 return series and selected macroeconomic variables at level. The results indicate that the return series is stationary at level with a highly significant test statistic ($t = -11.06$, $p < 0.01$), suggesting it is integrated of order zero, I(0). Similarly, the Consumer Price Index (CPI) and Economic Policy Uncertainty (EPU) index are found to be stationary at level, rejecting the null hypothesis of a unit root at the 5% level. In contrast, the Call Money Rate (CMR), Exchange Rate (EXRATE), Index of Industrial Production (IIP), and Crude Oil Prices (OILP) are non-stationary at level, as the null hypothesis could not be rejected, indicating they are integrated of order one, I(1). These mixed orders of integration justify the use of an Autoregressive Distributed Lag (ARDL) framework for modelling long- and short-run relationships.

Table 2: ADF Test Result at Level

Variables (At level)	t-statistics	p-value	Null Hypothesis	Characteristics
Return50	-11.05605	0.0000*	Rejected	I(0) and stationary
CMR	-1.981341	0.2949	Accepted	I(1) and non-stationary
CPI	-3.393754	0.0022*	Rejected	I(0) and stationary
EPU	-3.619107	0.0063*	Rejected	I(0) and stationary
EXRATE	-0.862323	0.7982	Accepted	I(1) and non-stationary
IIP	0.233527	0.9740	Accepted	I(1) and non-stationary
OILP	-2.307690	0.1707	Accepted	I(1) and non-stationary

Note: * indicates significance at the 5% level.
Source: Author's calculation using EViews 11.

Table 3: ADF Test Result at First Difference on Selected Variables

Variables (First Difference)	t-statistics	p-value	Null Hypothesis	Characteristics
Return50	-11.05605	0.0000*	Rejected	Stationary
CMR_D	-10.20381	0.0000*	Rejected	Stationary
CPI	-3.39375	0.0022*	Rejected	Stationary
EPU	-3.61911	0.0063*	Rejected	Stationary
EXRATE_D	-10.96877	0.0000*	Rejected	Stationary
IIP_D	-5.96416	0.0000*	Rejected	Stationary
OILP_D	-10.15137	0.0000*	Rejected	Stationary

Note: * indicates significance at the 5% level.
Source: Author's calculation using EViews 11.

To address the non-stationarity observed in certain macroeconomic variables, the Augmented Dickey-Fuller (ADF) test was reapplied after first differencing. The Nifty 50 return series, along with Consumer Price Index (CPI) and Economic Policy Uncertainty (EPU), were found to be stationary at level, confirming they are integrated of order zero, I(0). For the remaining variables—Call Money Rate (CMR), Exchange Rate (EXRATE), Index of Industrial Production (IIP), and Crude Oil Prices (OILP)—stationarity was achieved upon first differencing, as indicated by highly significant t-statistics and p-values below 0.01. This confirms that these variables are integrated of order one, I(1).

6.3 GARCH Model

The return series was first subjected to the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model in order to start simulating the volatility dynamics of the Nifty 50 index. Bollerslev (1986) developed the GARCH framework, which is ideal for capturing time-varying volatility, persistence, and volatility clustering—all of which are frequently seen in financial return data. The GARCH(1,1) specification, which assumes that the current conditional variance depends on both the past squared error term (ARCH effect) and past conditional variance (GARCH effect), was used to model the Nifty 50 return series, which was determined to be stationary. The presence of strong volatility persistence in the Indian equity market was indicated by the statistical significance of the estimated model parameters. This outcome demonstrates that historical shocks continue to impact present volatility, which is a hallmark of the behaviour of emerging markets.

$$r_t = \mu + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \sigma_t^2) \tag{1}$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{2}$$

Table 4: GARCH(1,1) Estimation Results for Return Series

Variable	**Coefficient**	**Std. Error**	**Z-value**	**p-value**
μ	0.008109*	0.003503	2.314791	0.0206
ω	0.000283	0.002530	0.111845	0.9100
ε_{t-1}^2	0.007183	0.042566	0.168748	0.8660
σ_{t-1}^2	0.806848	1.704510	0.473361	0.6360

Note: * indicates significance at the 5% level.
Source: Author's calculation using EViews 11.

The volatility structure of the Nifty 50 return series was estimated using the GARCH(1,1) model. A small but positive average monthly return is indicated by the statistically significant mean equation coefficient. However, the high p-values of the variance equation coefficients indicate that they are statistically insignificant: the constant ($\omega = 0.000283$), the GARCH term ($\beta = 0.8068$), and the ARCH term (α). This implies that the volatility clustering or persistence in the data may not be adequately captured by the conventional GARCH(1,1) model. Furthermore, the relatively high GARCH term and low ARCH coefficient suggest that volatility is typically persistent, but that previous shocks have little immediate effect on current volatility.

6.4 EGARCH Model

a. Taking only Return

The Exponential GARCH (EGARCH) model was initially estimated using just the return data in order to better represent the volatility dynamics of the Nifty 50 return series. The ability of this baseline model to simulate volatility asymmetries—more especially, the varying effects of positive and negative shocks—led to its selection over the conventional GARCH model. The return-only EGARCH(1,1) model's findings showed a significant leverage effect, suggesting that bad news has a greater effect on volatility than good news, and strong evidence of volatility clustering, where large shocks are typically followed by more large shocks.

$$\log\left(\sigma_t^2\right) = \omega + \alpha\left|\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}}\right| + \gamma\left(\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}}\right) + \beta\log\left(\sigma_{t-1}^2\right) \tag{3}$$

Table 5: EGARCH Result on Return

Variable	Coefficient	Standard Deviation	Z-values	p-values
μ	0.008077*	0.002450	3.296242	0.0010
ω	-0.147013*	0.023848	-6.164478	0.0000
$\left\|\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}}\right\|$	-0.158688*	0.026423	-6.005769	0.0000
$\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}}$	-0.068161*	0.032743	-2.081732	0.0374
$\log\left(\sigma_{t-1}^2\right)$	0.958523*	0.000109	8802.413	0.0000

Note: * indicates significance at the 5% level.
Source: Author's calculation using EViews 11

To create a baseline structure of market volatility, the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model was initially estimated using only the Nifty 50 return series. A statistically significant positive coefficient ($\mu = 0.0081$, $p = 0.0010$) was obtained from the mean equation, suggesting a modest average return during the study period. Important aspects of the volatility dynamics in the Indian equity market are revealed by the variance equation. A comparatively low base level of conditional volatility is reflected in the significant negative constant term.

Additionally negative and statistically significant is the ARCH term, which accounts for the influence of lagged squared residuals (shock magnitude). This implies that significant shocks, regardless of their direction, have a tendency to lower volatility—an unusual outcome that might be a reflection of particular structural features of the Indian market.

Conventionally, the asymmetry coefficient is negative and significant, indicating that there is a leverage effect, meaning that negative shocks affect volatility more than positive ones. A high level of volatility persistence and clustering over time is indicated by the GARCH term's proximity to unity.

b. Taking Macroeconomics Variables

By adding each of the stationary macroeconomic variables—the Consumer Price Index (CPI), the Economic Policy Uncertainty (EPU) index, and the different forms of the call money rate (CMR_D), exchange rate (EXRATE_D), index of industrial production

(IIP_D), and crude oil prices (OILP_D)—individually into the variance equation, six extended EGARCH models were estimated, building on the initial analysis. An independent evaluation of the precise influence that each macroeconomic variable has on the volatility of financial markets was made possible by this modeling approach.

$$\log\left(\sigma_t^2\right) = \omega + \alpha\left|\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}}\right| + \gamma\left(\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}}\right) + \beta\log\left(\sigma_{t-1}^2\right) + \lambda X_t \tag{4}$$

Where $X_t \ \forall\ t = \text{CPI}, \text{EPU}, \text{CMR\_D}, \text{EXRATE\_D}, \text{IIP\_D}, \text{OILP\_D}$

The effects of including these macroeconomic factors varied. Interestingly, it was discovered that the EPU index considerably raised conditional volatility, indicating that policy uncertainty raises risk in financial markets. The market's sensitivity to inflationary pressures was reflected in the CPI's quantifiable impact on volatility. The moderate influence of other variables, like the exchange rate and crude oil prices, suggests that domestic market dynamics are also influenced by external and global shocks. The effects of including these macroeconomic factors varied. Interestingly, it was discovered that the EPU index considerably raised conditional volatility, indicating that policy uncertainty raises risk in financial markets. The market's sensitivity to inflationary pressures was reflected in the CPI's quantifiable impact on volatility. The moderate influence of other variables, like the exchange rate and crude oil prices, suggests that domestic market dynamics are also influenced by external and global shocks.

Table 6: EGARCH Output Taking Macroeconomic Variables

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
ω	-9.269604*	-3.852433*	-4.157137*	-9.204526*	-6.385462*	-10.35136*
$\left\lvert\varepsilon_{t-1}\sqrt{\sigma_{t-1}^2}\right\rvert$	0.525501*	1.022612*	1.091795*	0.171106	-0.133979	0.381542
$\varepsilon_{t-1}\sqrt{\sigma_{t-1}^2}$	-0.250685*	-0.624112*	-0.522884*	-0.020027	-0.001235	-0.004667
$\log\left(\sigma_{t-1}^2\right)$	-0.354427*	0.612522	0.571147*	-0.344826*	0.005094	-0.520093*
$\alpha + \beta$	0.171074	1.635134	1.662942	-0.173720	-0.128885	-0.138551
CMR_D_t	0.813331*					
CPI_t		0.079361				
EPU_t			0.004684*			
EXRATE_D_t				0.498643*		
IIP_D_t					-0.032337*	
OILP_D_t						-0.054719*

Note: * indicates significance at the 5% level.
Source: Author's calculation using EViews 11

The EGARCH models incorporating individual macroeconomic variables (Model 1 to Model 6) provide deeper insights into how specific economic indicators influence the volatility dynamics of the Nifty 50 index. A low baseline level of conditional volatility is highlighted by the constant term (ω), which stays negative and statistically significant across all models. Different models have different ARCH (α) and GARCH (β) coefficients, which reflect how previous shocks and volatility levels affect current volatility. Both α and β are significant and positive in Models 1 through 3, indicating strong volatility persistence. These coefficients, on the other hand, show mixed signs and decreased significance in Models 4 through 6, suggesting that memory effects in the volatility process are weaker.

In the first three models, the asymmetry term (γ), which captures the leverage effect, is negative and statistically significant, indicating that negative shocks have a greater effect on volatility than positive shocks. The asymmetry effect, however, is minimal or insignificant in Models 4 through 6, suggesting that the impact of bad news is lessened when specific macro variables are taken into account. The impact of each macroeconomic variable on volatility is shown by the λ coefficients. Tighter monetary conditions increase market volatility, as evidenced by the call money rate (Model 1), which has a large and significant positive coefficient ($\lambda = 0.8133$). The exchange rate (Model 4) and the EPU index (Model 3) are also positively and significantly correlated with volatility, indicating that increased policy uncertainty and currency market swings fuel market instability. Conversely, there are negative and significant effects of both crude oil prices (Model 6) and industrial production (Model 5), suggesting that lower oil prices and higher industrial output tend to stabilize equity market volatility.

These results highlight the heterogeneous and context-dependent nature of the effects of macroeconomic fundamentals on financial market volatility. The Indian equity market's sensitivity to financial and economic policy signals is highlighted by the noteworthy role of monetary and policy uncertainty variables.

6.5 ARDL Approach

The Autoregressive Distributed Lag (ARDL) approach is suitable since your variables are a combination of I(0) and I(1). The ARDL model is especially helpful for estimating both short-run dynamics and long-run equilibrium relationships between variables, and it is robust for handling mixed integration orders (apart from I(2)).

There is no long-term cointegration between the dependent and independent variables, according to the Bounds Test null hypothesis. The presence of a long-term relationship is indicated by the rejection of the null hypothesis if the computed F-statistic is greater than the upper bound critical value. The null cannot be rejected if the F-statistic is less than the lower bound, which suggests that there is no cointegration. The outcome is inconclusive if the statistic falls between the bounds.

Table 7: ARDL Bounds F-Test Results

F-Bound Test	**Value**	**Significance Level**	**I(0)**	**I(1)**
F-statistic	30.39260	10%	1.99	2.94
K (number of regressors)	6	5%	2.27	3.28
		2.5%	2.55	3.61
		1%	2.88	3.99

Source: Author's calculation using EViews 11

The F-Bounds Test results clearly show that the chosen macroeconomic variables and Nifty 50 volatility have a long-term relationship. At all standard levels of significance (1%, 2.5%, 5%, and 10%), the computed F-statistic of 30.39 substantially surpasses the upper bound critical values.

By confirming that at least one of the explanatory macroeconomic variables is cointegrated with the dependent variable over the long term, this enables the rejection of the null hypothesis that there is no level relationship. As a result, the ARDL model is confirmed to be an appropriate method for investigating both short-term and long-term dynamics in this research. The best ARDL lag structure chosen by applying the Akaike Information Criterion (AIC) serves as the foundation for the estimated ECM specification. The six macroeconomic indicators act as regressors for the dependent variable, which is the volatility of the Nifty 50 return. To quantify the rate at which a short-run disturbance is adjusted back to long-run equilibrium, the error correction term (ECT), which is derived from the lagged residuals of the long-run ARDL model, is included.

6.6 ECM Estimation

To investigate the short-term dynamics and long-term adjustment mechanism between the Nifty 50 returns and specific macroeconomic variables, the ARDL-based Error Correction Model (ECM) was estimated. The chosen model, ARDL(1, 0, 0, 0, 1, 2, 1), was estimated from April 2010 to March 2025 and was defined using the Akaike Information Criterion (AIC).

$$\begin{aligned}\Delta\mathrm{Return50}_t = {} & \alpha_0 + \beta_1\Delta\mathrm{Return50}_{t-1} + \gamma_0\Delta\mathrm{CMR}_t + \delta_0\Delta\mathrm{CPI}_t + \theta_0\Delta\mathrm{EPU}_t \\ & + \varphi_0\Delta\mathrm{EXRATE}_t + \varphi_1\Delta\mathrm{EXRATE}_{t-1} + \psi_0\Delta\mathrm{IIP}_t + \psi_1\Delta\mathrm{IIP}_{t-1} \\ & + \psi_2\Delta\mathrm{IIP}_{t-2} + \kappa_0\Delta\mathrm{OILP}_t + \kappa_1\Delta\mathrm{OILP}_{t-1} + \lambda\mathrm{ECT}_{t-1} + \varepsilon_t \end{aligned} \tag{5}$$

The coefficient of the exchange rate (D(EXRATE)) is negative and statistically significant at the 1% level (-0.0216; $p < 0.01$), suggesting that a short-term decline in the value of the domestic currency has a negative impact on stock market returns. This illustrates how currency-driven valuation pressures affect industries that rely on imports and foreign investment. For Industrial Production Index (D(IIP) and D(IIP(-1))) the one-period lag is positive and significant (0.000828; $p < 0.01$), indicating a delayed positive impact of industrial activity on equity returns, even though the contemporaneous value of IIP is statistically insignificant. In the short term, rising crude oil prices are linked to higher market returns, according to the positive and statistically significant coefficient (0.001351; $p < 0.01$). This might be a reflection of sectoral dynamics in energy-sensitive stocks or growth expectations linked to oil prices.

The presence of a long-term equilibrium relationship between the variables is confirmed by the negative and highly significant error correction term (CointEq(-1)) (-0.9291; $p < 0.01$). A strong and quick rate of adjustment is implied by the coefficient's magnitude, which indicates that about 93% of the departure from the long-run equilibrium is fixed in the following month.

Table 8: ARDL Error Correction Regression Result

Variable	**Coefficient**	**Std. Error**	**t-statistic**	**p-value**
D(EXRATE)	-0.021566*	0.002323	-9.282883	0.0000
D(IIP)	-0.000122	0.000279	-0.439400	0.6609
D(IIP(-1))	0.000828*	0.000284	2.911922	0.0041
D(OILP)	0.001351*	0.000424	3.186488	0.0017
CointEq(-1)*	-0.929133*	0.058369	-15.91835	0.0000
Model Summary				
R-squared	0.651008			
Adjusted R-squared	0.642939			
S.E. of regression	0.029922			
Sum squared resid	0.154890			
Log likelihood	374.5961			
Akaike info criterion	-4.152765			
Schwarz criterion	-4.063389			
Hannan-Quinn criterion	-4.116521			
Durbin-Watson stat	1.854834			
Mean dependent var	0.000211			
S.D. dependent var	0.050075			

* indicates statistical significance at 5% level.

Source: Author's Calculation Using EViews 11.

With the included variables accounting for 65.1% of the variation in return changes, the model's R-squared of 0.651 indicates a good fit. There appears to be no significant autocorrelation, according to the Durbin-Watson statistic (1.85). The robustness and parsimony of the model are also supported by the Akaike and Schwarz information criteria. This estimate demonstrates that there is a substantial long-term co-movement between macroeconomic fundamentals and equity market volatility, even though some macroeconomic shocks (such as changes in the exchange rate and oil prices) have an immediate impact on returns.

6.7 Model Stability – CUSUM Test

The CUSUM (Cumulative Sum of Recursive Residuals) plot was used to analyze the stability of the estimated coefficients over the sample period. Plotting the cumulative sum of the recursive residuals against time, together with the 5% significance boundaries, allows the CUSUM test to visually verify structural stability.

The findings suggest that the model coefficients are structurally stable and that there is no indication of parameter instability because the CUSUM plot stays within the 5% confidence bands for the duration of the sample. This confirms the ARDL model's dependability and guarantees that the estimated correlations between macroeconomic factors and stock market returns hold true over time.

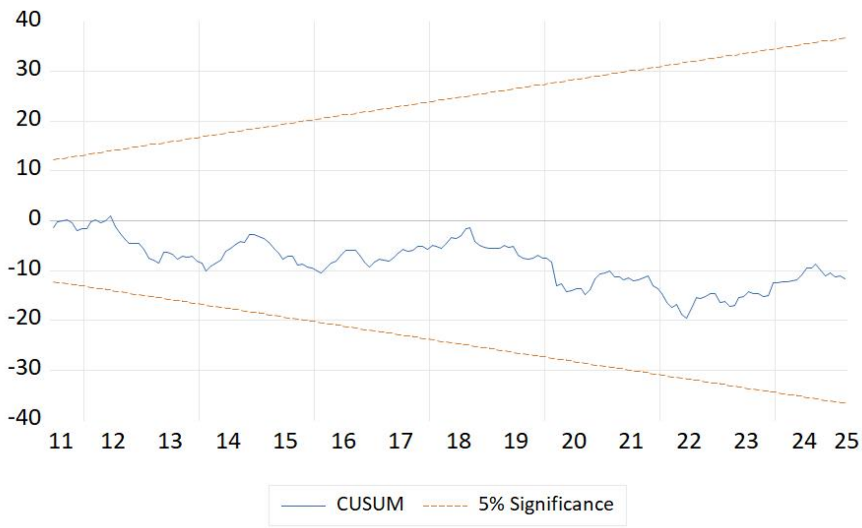

Figure 1: CUSUM Plot for Model Stability

6.8 Markov Switching Model

A Markov Switching model (MSM) was used to take into consideration possible structural breaks and nonlinear dynamics in the volatility behavior of the Nifty 50 return series. With regime transitions controlled by a first-order Markov process, the MSM makes it possible to identify discrete regimes in the time series, each of which is distinguished by unique means and variances.

Low-volatility and high-volatility states were represented by a two-regime Markov Switching model that was estimated. With Regime 1 reflecting times of comparatively stable market conditions and Regime 2 reflecting increased volatility, which frequently corresponds to episodes of economic or policy uncertainty, the model results show a notable regime differentiation.The model's transition probabilities point to high persistence within each regime, meaning that once the market reaches a particular volatility state, it usually stays there for a long time. The model's ability to accurately identify regime shifts is confirmed by the smoothed regime probabilities, which closely match known economic events and market disruptions.

Table 9: Markov-switching Dynamic Regression Result

Markov-switching Dynamic Regression

Sample: 2010M04 – 2025M03 **No. of Observations:** 179

Number of States: 2 **Log likelihood:** 288.87217

AIC: -3.1718 **HQIC:** -3.1357 **SBIC:** -3.0827

Return50	**Coefficient**	**Robust Std. Err.**	**z**	$p > \|z\|$	**[95% Conf. Interval]**
State 1					
_cons	-0.0533361	0.0226401	-2.36	0.018	[-0.0977098, -0.0089624]
State 2					
_cons	0.0270635	0.0102262	2.65	0.008	[0.0070205, 0.0471066]
Sigma	0.0383696	0.0077305			[0.0258519, 0.0569485]
P11	0.4828283	0.1805424			[0.1845512, 0.7938654]
P21	0.1275287	0.0803961			[0.0342511, 0.3759462]

Source: Author's Calculation Using Stata 14

In State 1, periods of bearish market conditions were characterized by a significantly negative mean return of -5.33% ($p < 0.05$). On the other hand, State 2 showed a significantly positive mean return of 2.71% ($p < 0.01$), which is a sign of a bull market. The transition probabilities show that State 1 is less common, occurring about 20% of the time, while State 2 is more persistent, with the market staying in this regime for about 80% of the time. Here p_{ij} = transitional probability, which implies if one in $state_i$ at current period then there is probability p_{ij} that it will switch to $state_j$ in next period.

$$\text{Prob}\,(\text{State}_1) = \frac{p_{21}}{p_{21} + 1 - p_{21}} \approx 0.199$$

$$\text{Prob}\,(\text{State}_2) = 1 - \text{Prob}\,(\text{State}_1) = \ 0.801$$

Both regimes showed stable conditional volatility, which was estimated to be around 3.8%. These results highlight the significance of taking nonlinear dynamics into account when modeling returns and offer compelling evidence of regime-switching behavior in the Indian equity market. Adding regime-dependent features to risk assessment and asset allocation plans can help investors and policymakers make stronger decisions in the face of shifting market conditions.

6.9 Wavelet-Based Time–Frequency Analysis

Wavelet analysis was used as a time-frequency domain method to investigate the dynamic behavior of return volatility in the Indian equity market in more detail. The return series can be broken down into various time scales using this method, which makes it possible to examine how market volatility changes over short-, medium-, and long-term time horizons.

According to the Continuous Wavelet Transform (CWT), times of high volatility were not evenly spaced out over time but rather manifested as localized outbursts that frequently accompanied significant policy or economic developments. In particular, times like the global commodity shock, demonetization, the COVID-19 pandemic, and the conflict between Russia and Ukraine were characterized by strong wavelet power. Persistent high-frequency volatility during these episodes suggested temporary market stress.

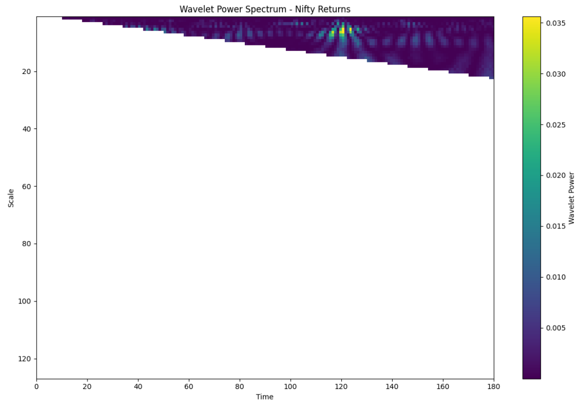

Figure 2: Wavelet Spectrum of Nifty50 return

Using the Continuous Wavelet Transform (CWT), the Wavelet Power Spectrum (WPS) of the Nifty 50 return series is shown in Figure 5.9.1. By breaking down the return series into time-scale space, this technique makes it possible to analyze localized volatility at various frequencies.

The Wavelet Power Spectrum shows that the majority of the power is concentrated at lower scales, suggesting that short-term (high-frequency) volatility dominates Nifty returns. This is in line with the usual market behavior caused by short-term shocks and trading noise. A sharp increase in power around time index 120 points to a brief period of high volatility that may have been caused by a macroeconomic or market event. At higher scales, power significantly decreases, suggesting limited persistence of long-term volatility and highlighting the short- to medium-term character of fluctuations during the observed period.

A bivariate Wavelet Coherence (WTC) analysis between the Nifty 50 return series and each chosen macroeconomic variable separately was carried out in order to investigate the dynamic interrelationship between stock market volatility and macroeconomic fundamentals. The WTC framework provides a thorough understanding of time-frequency localized correlations by allowing the evaluation of co-movements' strength and temporal evolution over a variety of time horizons and frequency bands.

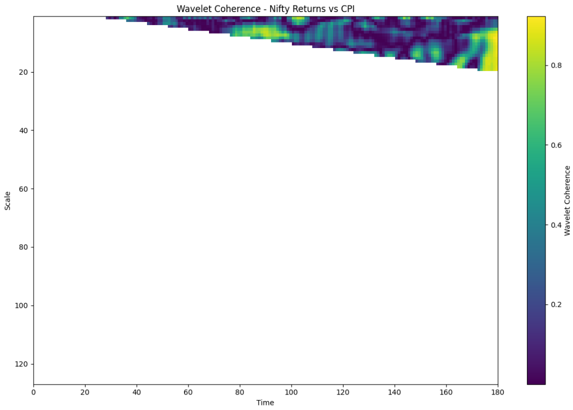

Figure 3: Nifty return vs CPI

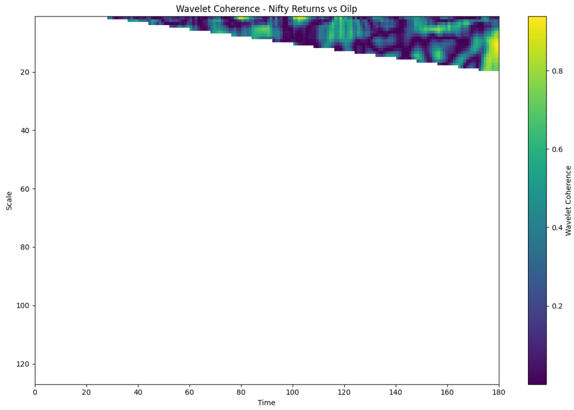

Figure 4: Nifty return vs Oilp

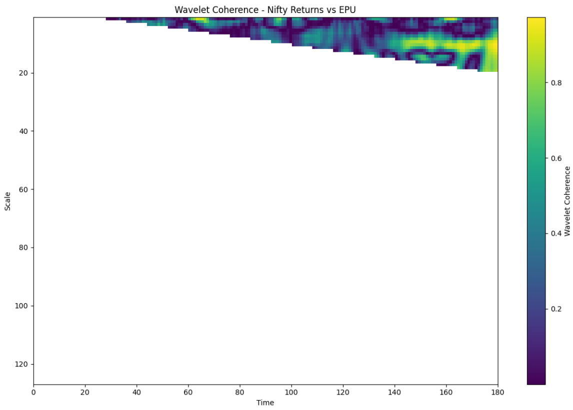

Figure 5: Nifty return vs EPU

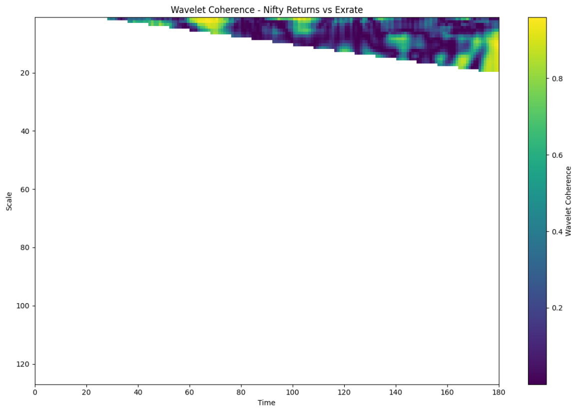

Figure 6: Nifty return vs Exrate

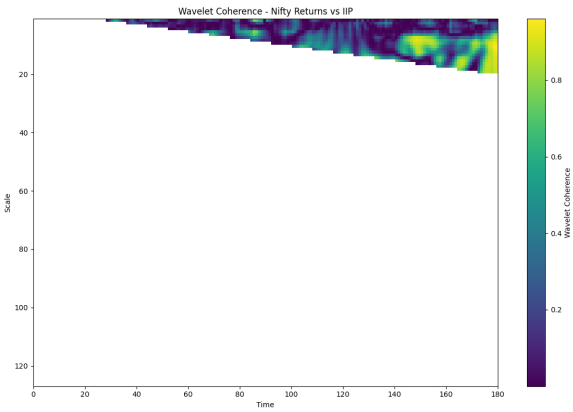

Figure 7: Nifty return vs IIP

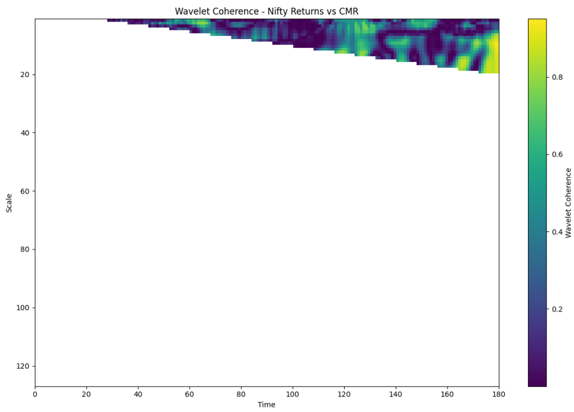

Figure 8: Nifty return vs CMR

The Consumer Price Index (CPI) and Nifty returns wavelet coherence plot reveals significant short-term co-movements that are concentrated at lower scales. Stronger coherence periods, particularly toward the end of the time series, indicate that the performance of the equity market is increasingly impacted in the short term by inflationary trends as measured by the CPI. At higher scales, the coherence is still weak, suggesting little long-term synchronization. This implies that inflation has a greater short-term impact on Nifty returns, highlighting the significance of keeping an eye on inflation shocks for immediate investment and policy choices.

Time-varying co-movements, mostly at lower scales, are revealed by the wavelet coherence plot between Nifty returns and oil prices, suggesting short-term interactions. Later times show a concentration of high coherence (yellow regions), indicating that the relationship gets stronger over time but stays mostly short-term. At larger scales, little coherence is seen, suggesting little long-term dependence. These results imply that changes in oil prices affect Nifty returns more quickly and directly, which is important for short-term market analysis and policy response.

Short-term co-movements are indicated by the wavelet coherence plot between Nifty returns and Economic Policy Uncertainty (EPU), which shows a time-varying relationship concentrated at lower scales. Significantly, the second half of the time series shows stronger coherence (shown by warmer colors), indicating that EPU started to have a greater impact on Nifty returns in more recent times. At higher scales, coherence is still weak, suggesting little long-term interaction. These findings suggest that any changes in policy uncertainty have an immediate short-term impact on the Indian equity market.

Wavelet coherence plot between Nifty returns and the exchange rate implies that exchange rate changes only have a short-term impact on Nifty returns. Throughout the time axis, there are sporadic notable pockets of higher coherence (yellow-green areas), especially around time points 40–60, 100–110, and 160–170. These suggest brief intervals of stronger short-term co-movement, perhaps during periods of macroeconomic events or currency volatility. Higher scales show no discernible coherence, suggesting that Nifty returns and the exchange rate have no lasting relationship.

Similarly, plot between Nifty returns and the Index of Industrial Production (IIP) implies that there are more short-term than long-term relationships between IIP and Nifty returns. Between time periods 140 and 170, there is a noticeable increase in coherence (green-yellow patches), which suggests that there was more short-term co-movement during that time, which could be a result of changes in industrial activity or economic shocks. On the other hand, the lack of structure at larger scales suggests that there is no long-term, consistent correlation between IIP and Nifty returns.

Nifty returns and the Call Money Rate (CMR) is concentrated at lower scales (roughly 1–30). Stronger short-term co-movements during this phase are likely due to monetary policy changes or financial stressors like the COVID-19 pandemic or RBI rate adjustments, as evidenced by the notable increase in coherence around the 130–170 time period. On the other hand, the lack of structure at larger scales indicates that CMR has no discernible long-term impact on Nifty returns.

7 Conclusion

This study used a variety of econometric techniques, such as GARCH, EGARCH, ARDL, ECM, Markov Switching models, and wavelet analysis, to examine the volatility behavior of the Nifty 50 index in light of important macroeconomic influences. The results demonstrate how well the EGARCH model captures the asymmetric reactions to shocks and the existence of volatility clustering in the Indian equity market.

The models' capacity to explain changes in market volatility has been greatly enhanced by the inclusion of macroeconomic variables such as the call money rate, consumer price index, exchange rate, industrial production index, crude oil prices, and the Economic Policy Uncertainty Index. According to the ARDL and ECM results, these variables showed both short-term and long-term relationships with market fluctuations. Furthermore, the wavelet approach demonstrated the scale-dependent influence of economic variables over time, whereas the CUSUM and Markov regime-switching models demonstrated structural changes in volatility. By highlighting the crucial role that economic fundamentals play in influencing market volatility, the study provides insightful information for risk managers, investors, and policymakers.

Volatility in the Indian equity market is dominated by short-term movements, with sharp or notable bursts linked to major economic and policy events such as demonetization, the COVID-19 pandemic, and geopolitical conflicts like the Russia–Ukraine War. Macroeconomic factors like inflation (CPI), crude oil prices, and economic policy uncertainty primarily influence Nifty returns over short time intervals, with their impact becoming more intense in recent years. This indicates that the stock market swiftly incorporates changes in these factors while exhibiting limited long-term synchronization with them. The weak or negligible long-term co-movements underscore the transient nature of these shocks, emphasizing the critical importance of focusing on short-term dynamics for effective investment strategies and policymaking.

Overall, the wavelet-based analysis provides a robust framework for capturing the evolving and time-dependent relationships between equity returns and macroeconomic indicators, offering valuable insights into the mechanisms through which short-term shocks affect the Indian financial markets. Future studies could enhance this analysis by extending it to other indices, incorporating global macroeconomic variables, or applying machine learning methods to further improve forecasting accuracy.

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