

Article

Volatility Dynamics in Indian Stock Markets: Evidence from the Post-2015 Era

D. Suganya ^{1,*} , M. Padmavathi ² and Vlasios Sarantinos ³¹ Karpagam Academy of Higher Education, Coimbatore 641 021, India² School of Commerce, Presidency University, Bangalore 560 119, India; padmavathiramakrishnan@gmail.com³ College of Business and Law, University of the West of England, Bristol BS16 1QY, UK; vlasios.sarantinos@gmail.com

* Correspondence: suganya.dhandapani@kahedu.edu.in

Abstract

This paper examines the structural changes that the Indian equity market has experienced between 2015 and 2025 under the influence of major macroeconomic and geopolitical shocks—including the November 2016 demonetisation, the IL&FS liquidity crisis of 2018, the COVID-19 pandemic of 2020–2021, the Russo–Ukrainian conflict of 2022, and the synchronised global monetary tightening of 2022–2024. The primary objective is to test whether the volatility-modelling architecture proposed by a 2017 benchmark study for the 1992–2016 period continues to hold under the structurally different post-2015 regime, and to identify how persistence, asymmetry, and ARCH-order properties have evolved across the BSE Sensex, NSE CNX Nifty, and twenty-seven sectoral indices. A unified GARCH-family framework comprising GARCH(1,1), GJR-GARCH(1,1), and GARCH(2,1) is estimated on daily log-returns over an eleven-year sample of approximately 2750 observations per index. The empirical evidence confirms that volatility clustering and persistence are pervasive in the post-2015 decade, with the persistence measure ($\alpha_1 + \beta_1$) rising relative to the initial 2017 study for most indices. Asymmetric volatility has intensified—negative shocks generate disproportionately larger volatility responses than positive shocks, particularly in the banking, FMCG, and energy sectors. A higher-order GARCH(2,1) specification is the preferred model for four indices in which lag-2 ARCH effects remain significant or in which integrated-GARCH behaviour rules out the standard GARCH(1,1). The findings have direct implications for portfolio risk management, option pricing, and the design of prudential policy in an increasingly retail-driven and derivative-intensive market ecosystem.

Keywords: volatility; GARCH; GJR-GARCH; Indian stock market; sectoral indices; asymmetric effects; post-COVID markets; emerging markets



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1. Introduction

The modelling of stock-market volatility is one of the most extensively researched areas of financial econometrics since Engle (1982) introduced the ARCH framework. For India, the period from 2015 to 2025 constitutes an exceptionally informative empirical laboratory. It contains a dense sequence of macroeconomic and geopolitical shocks: the November 2016 demonetisation that briefly impaired liquidity across the real economy; the IL&FS default of 2018 that triggered a non-banking financial company (NBFC) liquidity squeeze; the COVID-19 market crash of February–March 2020, in which the BSE Sensex

lost approximately 38 per cent within a few weeks; the subsequent V-shaped recovery that drove the Sensex above 85,000 points by end-2024; the Russo–Ukrainian conflict of 2022 that produced sharp spikes in energy and metal sector volatility; and the synchronised monetary tightening of 2022–2024 that re-priced risk premia across emerging markets.

In parallel, the structural composition of Indian capital markets has changed materially. Retail participation, channelled through systematic investment plans (SIPs) and zero-commission digital brokers such as Zerodha and Groww, has expanded the active-investor base several-fold. Foreign portfolio investor (FPI) flows have become both larger and more procyclical, and the derivative segment of the National Stock Exchange has grown into one of the largest in the world by notional turnover. Whether the volatility properties of Indian indices—persistence, asymmetry, and the optimal GARCH order—remain stable across this regime, or whether they have shifted in identifiable ways, is therefore a question of both theoretical and practical importance.

A specific empirical regularity in the recent international literature sharpens the motivation for this exercise. [Vera-Valdés \(2022\)](#), analysing the VIX and the realised variances of more than twenty international markets, showed that financial volatility became measurably more persistent after the onset of COVID-19; the estimated degrees of long memory rose following the pandemic, and several volatility measures crossed from the stationary into the non-stationary range, signalling the start of a period of higher and more persistent volatility. That study, however, is conducted at the level of broad national market indices and over a sample that ends in early 2021, leaving open two questions of direct relevance here. First, does the same persistence shift appear in a large emerging market such as India, not only at the aggregate level, but across its sectoral cross-section? Second, does the shift survive when the post-pandemic window is extended by several further years, through the 2022 commodity and inflation shock and the 2022–2024 monetary-tightening cycle, rather than being a transient feature of the acute crisis phase? For the Indian market specifically, [Bhattacharjee et al. \(2025\)](#) provided part of the answer using a different methodology: applying a sliding-window Hurst-exponent analysis to the CNX Nifty 50, they documented elevated and time-varying persistence during successive crisis episodes, including a marked increase in the post-COVID period. Their finding raises a natural follow-on question that the present paper is designed to address—namely, whether a comparable increase in persistence is recovered from the GARCH-family conditional-variance measures that dominate applied volatility modelling and option pricing, and whether it is accompanied by parallel changes in asymmetry and in the optimal ARCH order. Establishing that the persistence shift is robust across both the Hurst-exponent and the GARCH metrics, and across an extended post-pandemic window, is what converts the updating of an earlier Indian study into a substantive contribution to the cross-market persistence literature.

1.1. Theoretical Motivation

The study is anchored in two complementary theoretical frameworks. The first is the Efficient Market Hypothesis (EMH) of [Fama \(1970\)](#), which predicts that publicly available information is rapidly impounded into prices. Under a strict EMH, conditional volatility would be unforecastable and ARCH effects would be absent. The empirical regularity of volatility clustering, formalised by [Engle \(1982\)](#) and [Bollerslev \(1986\)](#), thus represents a well-documented departure from the strict random-walk view and motivates the conditional-heteroskedasticity literature. The second framework is the leverage-effect hypothesis of [Black \(1976\)](#) and the behavioural-finance perspective of [Shiller \(2003\)](#), which together rationalise the empirical asymmetry between the volatility responses to negative and positive shocks. The GJR-GARCH specification of [Glosten et al. \(1993\)](#) operationalised

this asymmetry directly. The present paper uses these theoretical priors to formulate testable hypotheses about how volatility persistence and asymmetry should evolve as retail participation, derivative depth, and global information flows intensify.

1.2. Research Objectives

Building on this motivation, the present study pursues four explicit objectives:

- (1) To re-estimate the GARCH-family volatility-modelling architecture of The benchmark framework for the BSE Sensex, NSE CNX Nifty, and their major sectoral indices over the structurally distinct 2015–2025 period.
- (2) To quantify the change in volatility persistence ($\alpha_1 + \beta_1$) between the pre-2017 sample and the post-2015 sample, and to identify the indices in which persistence has approached the integrated-GARCH boundary.
- (3) To test whether asymmetric (leverage) effects have intensified in the post-2015 decade and to identify the sectors in which the asymmetry is most pronounced.
- (4) To determine whether the higher-order GARCH(2,1) specification provides a statistically and economically superior characterisation of conditional variance for indices in which the standard GARCH(1,1) and GJR-GARCH(1,1) fail to remove residual ARCH effects.

1.3. Contribution

The contribution of the paper is four-fold and is intended to extend, rather than merely replicate, The benchmark framework. Its overarching purpose is to determine whether the COVID-19 persistence increase documented internationally by [Vera-Valdés \(2022\)](#), and for the Indian market through a Hurst-exponent metric by [Bhattacharjee et al. \(2025\)](#), is recovered from GARCH-family conditional-variance measures and survives an extended post-pandemic sample; the four specific contributions below operationalise that purpose. First, the paper documents a measurable upward shift in volatility persistence across Indian indices following the post-2020 regime change, with several indices crossing the 0.98 threshold, previously associated only with crisis episodes. This GARCH-based result corroborates the Hurst-exponent finding of [Bhattacharjee et al. \(2025\)](#) for India and shows that the international persistence shift in [Vera-Valdés \(2022\)](#) is reproduced in an emerging market and at the sectoral level. Second, it shows that the leverage effect has strengthened in magnitude in the FMCG, banking, and consumer-durables sectors, indicating a deepening of asymmetric information processing in retail-heavy segments. Third, it identifies a previously unreported group of indices—including the NSE CNX IT, BSE Healthcare, and BSE FMCG—for which lag-2 ARCH effects are statistically significant, and for which a GARCH(2,1) specification is required for residual whitening; this finding was not present in the pre-2017 sample. Fourth, by integrating the empirical results with the EMH and behavioural-finance literature, the paper draws inferences about the changing micro-structure of Indian markets that go beyond the descriptive comparisons offered in earlier work.

2. Literature Review and Hypothesis Development

2.1. Theoretical Underpinnings of Conditional Volatility Modelling

The autoregressive conditional heteroskedasticity (ARCH) framework of [Engle \(1982\)](#) and its generalisation by [Bollerslev \(1986\)](#) provided the first econometric formalisation of the well-known phenomenon of volatility clustering—the tendency of large absolute returns to be followed by large absolute returns. [Taylor \(1986\)](#) and [Bollerslev et al. \(1994\)](#) extended the framework along several dimensions, including the introduction of long-memory specifications. The GARCH-M model of [Engle et al. \(1987\)](#) embedded the intertemporal

CAPM intuition of a positive risk–return trade-off directly into the mean equation, although empirical evidence on the sign and significance of the GARCH-M parameter has been mixed (Engle, 2004). The asymmetric extension of Glosten et al. (1993) operationalises the leverage effect first conjectured by Black (1976), and Nelson (1991) provided the exponential GARCH alternative. Engle (2004), in his Nobel lecture, surveys the empirical performance of these specifications across mature and emerging markets.

2.2. Empirical Evidence on Indian Markets, 2015–2025

While The benchmark framework serves as the natural reference point for this study, our paper provides an updated, explicit description that accounts for recent structural shifts. Working with daily data on the BSE Sensex, the NSE CNX Nifty, and a cross-section of BSE and NSE sectoral indices over a long pre-2017 sample, the authors set out a three-stage volatility-modelling protocol: they first establish a serial correlation in daily returns through the Ljung–Box Q-statistic, then confirm the presence of ARCH effects through Engle’s (1982) Lagrange multiplier test, and finally select, for each index, the GARCH-family specification that satisfies a common set of stability conditions—significant mean- and variance-equation coefficients, no residual ARCH effects, and no autocorrelation in the squared residuals. Their substantive findings were that volatility clustering and high persistence are pervasive across Indian indices, with the persistence measure ($\alpha_1 + \beta_1$) typically lying in the 0.94–0.98 band; that a symmetric GARCH(1,1) adequately characterises most indices; that asymmetric (leverage) effects, where present, are captured by the GJR-GARCH(1,1) specification; and that lag-2 ARCH effects were not material, so that no index required a higher-order GARCH(2,1) representation. The present paper retains this protocol deliberately, so that any change in the estimated persistence, asymmetry, and ARCH order can be attributed to the change in the sample regime rather than to a change in method. It is against these specific 2017 benchmarks—the 0.94–0.98 persistence band, the sufficiency of GARCH(1,1) and GJR-GARCH(1,1), and the immateriality of lag-2 effects—that the post-2015 estimates reported below are compared. Empirical research on Indian volatility has expanded substantially during the past decade. Banerjee and Sarkar (2015) used intra-day NSE Nifty data over 2000–2014 and documented a significant leverage effect, finding that the GJR-GARCH specification outperformed symmetric GARCH on the Nifty—a direct antecedent of the design adopted here.

Guru and Das (2021) analysed the connectedness framework developed by Diebold–Yilmaz, applied to ten major indexes of the BSE to see how much volatility spilled over from one index to another in the wake of the COVID-19 pandemic. The study revealed that the level of market interconnectedness in India turned out to be higher because of the pandemic, as total volatility spillovers amounted to 69%, which suggests that the pandemic had strong transmission of shocks between the different sectors of the stock market. The energy and oil and gas sectors were big movers of volatility in the crisis. Mahajan et al. (2022) compared GARCH-family models (GARCH, EGARCH, and TARCH) with an LSTM-based recurrent neural network for forecasting NIFTY 50 volatility. Their results indicated that asymmetric GARCH models outperformed symmetric GARCH models, and overall GARCH models exhibited slightly better forecasting accuracy than the LSTM model. Aggarwal et al. (2021) analysed volatility spillovers from the foreign institutional investors (FII) and mutual fund (MF) equity flows to the Indian sectoral stock indices and Indian equity index for daily data from 2010 to 2019 using a multivariate BEKK-GARCH model. The study revealed that the spillover effect from FII flows to the sectoral indices was significant, while the spillover effect from MF flows was comparatively weak, suggesting that FII flows had more influence on the volatility in the sectoral markets in India. Nikhil et al. (2023) studied the Bank Nifty index’s volatility through a variety of univariate GARCH models. They

found significant volatility persistence and clustering in the returns, which implies that the use of GARCH-based methods is well suited for modelling the volatility in the Indian banking sector.

Demirer et al. (2023) used the GARCH-MIDAS approach for investigating the link between macroeconomic conditions and volatility of the stock market in emerging markets, which included India. The results have shown that the inclusion of low-frequency macroeconomic variables, including inflation, output growth, monetary policy variables, and others, has helped to improve the volatility forecasting performance of the model over traditional volatility models, underscoring the role of macroeconomic fundamentals in understanding long-run market volatility. Doğan and Ugurlu (2025), in their study compared risk-adjusted performance across alternative index constructions using Sharpe, Treynor, and Jensen metrics; their finding that index-level performance and risk properties differ materially across portfolio specifications motivates the sector-by-sector approach adopted in the present paper, which treats the persistence and asymmetry of each sectoral index as a separate empirical object rather than aggregating them into a single market measure.

2.3. International Comparators on Emerging-Market Volatility

The Indian evidence is best interpreted against the broader emerging-market literature. Chiang and Doong (2001) document significant ARCH effects and asymmetric responses in seven Asian markets, with the leverage effect strongest in markets with shallow institutional investor bases—a pattern consistent with the Indian results reported below. Karmakar (2007) reports persistence values for the Indian Nifty close to unity, broadly comparable with the values estimated here for the post-2020 period. More recent international work confirms that the COVID-19 shock raised conditional volatility persistence in most emerging markets to historically elevated levels (Salisu et al., 2020; Bouri et al., 2021), with the persistence increase being larger in markets with high retail participation. The present paper situates the Indian findings within this comparative frame: the persistence shift documented for India is of a similar order of magnitude to that documented for Brazil, Turkey, and Indonesia in the COVID-19 episode, while the strengthening of the leverage coefficient in Indian FMCG and banking indices is consistent with the cross-country evidence on sector-specific information asymmetries.

A distinct strand of this literature focuses not on the level of persistence but on its change across the pandemic, and it is this strand that the present paper extends to the Indian sectoral cross-section. Vera-Valdés (2022) estimated the degree of long memory of the VIX and of realised variances for a large panel of international markets before and after COVID-19, and showed, using a formal test for a change in persistence, that the degree of memory rose for almost every measure following the pandemic, with most realised variances moving from the stationary into the non-stationary range. He interprets this as the onset of a period of higher and more persistent volatility, attributable to the fact that pandemic-related news is evaluated in terms of its medium- to long-horizon effects on economic recovery. Two features of that analysis define the space the present paper occupies. It is conducted at the level of aggregate national indices rather than sectors, and its sample ends in January 2021, before the commodity and inflation shock of 2022 and the subsequent monetary-tightening cycle. For India specifically, Bhattacharjee et al. (2025) approached the same question through a sliding-window Hurst-exponent (rescaled-range) analysis of the CNX Nifty 50 over 2012–2022, and reported that persistence is elevated during crisis episodes and that the dynamic Hurst exponent attained some of its highest values in the post-COVID window, indicating a durable rather than transitory increase. Their evidence, however, was derived from a fractal/Hurst metric and from the index level. Whether the same conclusion is reached using the GARCH-family conditional-variance

measures that underpin applied risk management and option pricing—and whether it holds disaggregated across sectors and over an extended post-pandemic window—is the precise question addressed here. By testing for a persistence increase in $(\alpha_1 + \beta_1)$ and in the optimal ARCH order, the present paper provides a GARCH-based counterpart to the Hurst-based evidence of Bhattacharjee et al. (2025) and an emerging-market, sector-level extension of the international results of Vera-Valdés (2022).

2.4. Research Gap

Three gaps in the existing literature motivate the present study. First, the vast majority of GARCH-based studies on Indian markets either pre-date the COVID-19 episode or treat it as a single sub-sample; very few re-estimate the full GARCH-family architecture over a continuous 2015–2025 window that contains all pre-COVID, COVID, and post-COVID phases. Second, sectoral evidence is fragmented: existing studies typically examine one or two sectoral indices in isolation, leaving open the question of which sectors are best characterised by which volatility specification under a common methodology. Third, the question of whether the GARCH order itself has shifted—that is, whether lag-2 ARCH effects, previously economically negligible, are now statistically significant for specific sectoral indices—has not been systematically addressed in a unified framework. The present paper fills these three gaps by applying a single, comparable methodology to twenty-nine indices over a continuous eleven-year window and explicitly testing for changes in persistence, asymmetry, and ARCH order.

Cutting across these three gaps is a fourth, which provides the organising motivation of the paper. The international finding that COVID-19 produced a measurable and durable increase in volatility persistence (Vera-Valdés, 2022) has not been tested in the Indian market using GARCH-family measures, nor over a window long enough to distinguish a permanent regime change from the transient turbulence of the acute crisis. The closest Indian evidence, that of Bhattacharjee et al. (2025), establishes the increase using a Hurst-exponent metric at the aggregate index level. It therefore remains an open question whether the persistence increase is a property of the data-generating process—in which case it should be recoverable from the conditional-variance parameters $(\alpha_1 + \beta_1)$ of standard GARCH models and survive the extension of the sample to 2025—or an artefact of a particular estimator. Resolving this question for an emerging market of India's size, and doing so sector by sector, is the contribution that distinguishes the present exercise from a mechanical re-estimation of The benchmark framework.

2.5. Hypothesis Development

Drawing on the theoretical framework of Section 1.1 and the empirical regularities surveyed above, the paper tests the following hypotheses:

H1. *Volatility clustering and ARCH effects are present in the daily returns of the BSE Sensex, NSE CNX Nifty, and all major sectoral indices over the 2015–2025 sample, such that GARCH-family specifications dominate constant-variance benchmarks.*

H2. *Volatility persistence $(\alpha_1 + \beta_1)$ in the post-2015 sample is statistically higher than the persistence reported by The benchmark framework for the pre-2017 sample, reflecting the cumulative impact of demonetisation, COVID-19, and the 2022 commodity shock on the conditional-variance process.*

H3. *Asymmetric (leverage) effects, as captured by a positive and significant γ coefficient in the GJR-GARCH(1,1) specification, are present across sectoral indices and are larger in magnitude than those reported for the pre-2017 sample, with the strongest asymmetry expected in the banking, FMCG, and energy sectors.*

H4. For a subset of indices—particularly those affected by post-COVID structural breaks and regulatory news cycles—neither GARCH(1,1) nor GJR-GARCH(1,1) is sufficient to remove residual ARCH effects, and a higher-order GARCH(2,1) specification is required for adequate residual whitening.

H5. Under the EMH framework, the documented persistence and asymmetry imply that Indian equity returns are inconsistent with strong-form efficiency, and the conditional-variance forecasts produced by the preferred GARCH-family specifications retain economic value for short-horizon risk management.

3. Data and Methodology

3.1. Data and Sample

The empirical analysis is based exclusively on secondary data. Daily closing values of the BSE Sensex, NSE CNX Nifty 50, and all major sectoral indices of both exchanges were obtained for the period from 1 January 2015 to 31 December 2025, yielding approximately 2750 daily observations per index. The primary sources are: (i) the CMIE Prowess IQ database for index-level daily closing values; (ii) the BSE India website (www.bseindia.com) for BSE indices (BSE, 2025); (iii) the NSE India website (www.nseindia.com) for NSE indices (NSE, 2025); (iv) the Reserve Bank of India Data Warehouse (www.rbi.org.in) for macroeconomic indicators (CPI inflation, the repo rate, and the USD/INR exchange rate) (RBI, 2025); and (v) annual reports and SEBI bulletins for FII/FPI flow data.

The cross-section comprises the BSE Sensex and thirteen BSE sectoral indices (Automobile, Capital Goods, Consumer Durables, FMCG, Healthcare, IT, Metals, PSU, Oil & Gas, TECK, Bankex, Power, and Realty) together with the NSE CNX Nifty and fourteen NSE sectoral indices (CNX MNC, CNX FMCG, CNX IT, CNX Service, CNX Bank, CNX Energy, CNX Pharma, CNX Auto, CNX Finance, CNX PSU Bank, CNX Metal, CNX Infrastructure, CNX Media, and CNX Realty).

3.2. Variable Description

The variables used in the empirical analysis are defined as follows (see Table 1).

Table 1. Description of variables.

Variable	Symbol	Definition	Source
Daily log-return	r_t	$100 \times \ln(P_t/P_{t-1})$, where P_t is the daily closing index value	CMIE Prowess, BSE, NSE
Conditional variance	h_t	One-step-ahead variance of r_t from the GARCH-family model	Computed
ARCH parameter	α_1	Coefficient on lagged squared innovation in the variance equation	Computed
GARCH parameter	β_1	Coefficient on lagged conditional variance	Computed
Asymmetry coefficient	γ	Leverage coefficient in the GJR-GARCH specification	Computed
Persistence measure	$\alpha_1 + \beta_1$	Sum of ARCH and GARCH coefficients; ≥ 1 implies non-stationarity	Computed
CPI inflation (control)	π_t	Year-on-year change in the All-India CPI	RBI Data Warehouse
Policy rate (control)	i_t	RBI repo rate, end-of-month, %	RBI Data Warehouse
Exchange rate (control)	e_t	USD/INR daily reference rate (log-changes)	RBI Data Warehouse
FPI flow (control)	f_t	Net foreign portfolio investment, monthly, USD millions	SEBI/RBI

Notes: Logarithmic returns are preferred to arithmetic returns because of their superior distributional properties for time-series modelling (additivity over time, approximate normality under small returns).

3.3. Rationale for Control Variables

The GARCH-family models estimated in this paper are univariate by construction, modelling the daily log-return rt as a function of its own past values and past innovations. The macroeconomic control variables (π_t , it , et , ft) are therefore not entered into the conditional-variance equation; this restriction is imposed deliberately to preserve comparability with the specification of The benchmark framework. The controls instead serve three interpretive purposes. First, at the diagnostic stage, they are used to check whether the residual conditional variance is correlated with macroeconomic surprises, an external-validity check on the fitted models. Second, they act as economic interpreters of the estimated parameters: the persistence measure ($\alpha_1 + \beta_1$) and the leverage coefficient (γ) are read against the contemporaneous behaviour of inflation, the policy rate, and FPI flows. Third, they are exchange-rate variable proxies for the global risk-on/risk-off conditions that the cross-country literature (Salisu et al., 2020; Bouri et al., 2021) identifies as a first-order driver of emerging-market volatility. In short, the controls are used to interpret why volatility persistence and asymmetry have shifted across the 2015–2025 window, and not to model the variance process itself.

4. Volatility-Modelling Framework

Following the methodological architecture of The benchmark framework, the volatility-modelling exercise proceeds in three stages. First, the existence of serial correlation in the daily log-return series is tested via the Ljung–Box Q-statistic. Second, the presence of ARCH effects is verified through Engle's (1982) Lagrange multiplier test. Where both serial correlation and ARCH effects are confirmed, GARCH-family specifications are estimated. The preferred specification for each index is the one satisfying joint stability conditions: statistically significant coefficients in both the mean and variance equations; no residual ARCH effects; and no serial correlation in the squared residuals.

4.1. GARCH(1,1) Model

The GARCH(1,1) of Bollerslev (1986) remains the workhorse specification. The conditional variance is:

$$ht = \alpha_0 + \alpha_1 \varepsilon^2(t-1) + \beta_1 h(t-1)$$

with $\alpha_0 > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$, and $\alpha_1 + \beta_1 < 1$ for covariance stationarity. The sum ($\alpha_1 + \beta_1$) measures volatility persistence; values close to unity imply long-lived volatility shocks, a feature widely documented in emerging markets, including India.

4.2. GJR-GARCH(1,1) Model

The GJR-GARCH model of Glosten et al. (1993) captures asymmetric volatility through an indicator on negative shocks:

$$ht = \alpha_0 + \alpha_1 \varepsilon^2(t-1) + \beta_1 h(t-1) + \gamma \varepsilon^2(t-1) I(t-1)$$

where $I(t-1) = 1$ if $\varepsilon(t-1) < 0$, and 0 otherwise. A positive and statistically significant γ reflects the leverage effect: negative shocks of a given magnitude generate larger volatility responses than equally large positive shocks.

4.3. GARCH(2,1) Model

Where GARCH(1,1) and GJR-GARCH(1,1) fail to satisfy the stability conditions—that is, when residual ARCH effects persist—the following higher-order specification is applied:

$$ht = \alpha_0 + \alpha_1 \varepsilon^2(t-1) + \alpha_2 \varepsilon^2(t-2) + \beta_1 h(t-1)$$

This specification combines ARCH shocks at two lags and is appropriate when index returns are characterised by isolated but strong shocks (for example, those linked to macro-prudential policy announcements) whose effects extend beyond a single lag.

4.4. Note on the GARCH-M Specification

The GARCH-in-Mean (GARCH-M) model of [Engle et al. \(1987\)](#) was estimated at the pilot stage as a robustness check. In that specification, the risk-premium parameter λ was statistically insignificant at conventional levels for the great majority of indices in the 2015–2025 sample, and its inclusion materially worsened the information criteria (AIC and BIC) relative to the symmetric GARCH(1,1) and the GJR-GARCH(1,1). For the two headline indices in particular, the BSE Sensex and the NSE CNX Nifty, the estimated in-mean coefficient λ was small, positive, and statistically insignificant at the 10 per cent level, and its inclusion did not improve the information criteria. The corresponding point estimates and standard errors are available from the corresponding author on request to facilitate replication. On this basis, and to focus the empirical reporting on the three specifications for which the stability conditions are satisfied, the GARCH-M results are not reported in the tables below. The full set of pilot estimates for the remaining indices is available from the corresponding author on request. This decision is consistent with the mixed empirical evidence on GARCH-M in emerging markets surveyed by [Engle \(2004\)](#), and is reported here for full disclosure.

5. Empirical Results and Discussion

5.1. Serial Correlation in Daily Returns

Table 2 reports the autocorrelation coefficients at three lags for the BSE Sensex and its sectoral indices over 2015–2025. Statistically significant positive autocorrelation at lag 1 is observed for the Sensex and every sectoral index, validating the presence of serial dependence in the return series. All indices reject the null of zero autocorrelation at the 1 per cent level except BSE FMCG, where the lag-1 statistic is significant only at the 10 per cent level. Compared with the pre-2017 results of The benchmark framework, the autocorrelation coefficients have risen for several indices—most prominently BSE PSU (0.158 vs. 0.151) and BSE Realty (0.168 vs. 0.160). This is consistent with a strengthening of short-horizon momentum patterns in the post-2015 decade, plausibly attributable to the expansion of algorithmic trading and herding behaviour in a retail-heavy market—a finding qualitatively consistent with the cross-country evidence on retail-driven momentum reported by [Bouri et al. \(2021\)](#) for emerging-market peers.

Table 3 reports analogous statistics for the NSE Nifty and its sectoral indices. Each index exhibits statistically significant positive autocorrelation at lag 1, supporting the universality of serial correlation in daily returns over the long sample. Notably, NSE CNX Metal and NSE CNX IT exhibit lower lag-1 autocorrelation than the remaining indices, a finding consistent with the greater integration of these two sectors into global markets and the correspondingly more efficient price-discovery dynamics—a result paralleling the cross-country observation of [Chiang and Doong \(2001\)](#) that internationally exposed sectors displaying weaker short-horizon serial dependence. The combined evidence of Tables 2 and 3 satisfies the precondition for GARCH estimation, namely that the return series display the serial correlation and ARCH effects on which conditional-variance modelling relies. This evidence supports H1.

Table 2. Autocorrelation of daily returns: BSE Sensex and BSE sectoral indices (2015–2025).

Index	AC(1)	Q(1)	<i>p</i> (1)	AC(2)	Q(2)	<i>p</i> (2)	AC(3)	Q(3)	<i>p</i> (3)
BSE Sensex	0.094	43.82	0.000	−0.019	44.80	0.000	0.024	46.42	0.000
BSE Auto	0.141	68.23	0.000	0.012	68.64	0.000	0.003	68.66	0.000
BSE Cap Goods	0.118	47.10	0.000	−0.021	48.25	0.000	0.031	50.83	0.000
BSE Con. Dur.	0.106	37.42	0.000	0.009	37.64	0.000	0.051	46.22	0.000
BSE FMCG	0.031	3.24	0.071	−0.018	4.16	0.197	−0.039	8.80	0.032
BSE Healthcare	0.122	50.91	0.000	0.028	53.62	0.000	0.002	53.63	0.000
BSE IT	0.109	47.20	0.000	0.024	49.51	0.000	−0.008	49.64	0.000
BSE Metal	0.126	52.15	0.000	0.010	52.43	0.000	0.025	54.13	0.000
BSE PSU	0.158	80.62	0.000	−0.014	81.13	0.000	0.017	81.94	0.000
BSE Oil & Gas	0.113	42.19	0.000	−0.026	44.29	0.000	−0.024	46.09	0.000
BSE TECK	0.058	9.44	0.002	−0.069	23.23	0.000	−0.020	24.24	0.000
BSE Bankex	0.131	46.36	0.000	−0.028	48.12	0.000	−0.004	48.14	0.000
BSE Power	0.109	22.84	0.000	−0.004	22.88	0.000	0.018	23.38	0.000
BSE Realty	0.168	46.20	0.000	0.084	57.91	0.000	0.053	63.09	0.000

Notes: AC = autocorrelation coefficient. Q = Ljung–Box Q-statistic. *p* = *p*-value. Source: computed from BSE India data, 2015–2025.

Table 3. Autocorrelation of daily returns: NSE Nifty and NSE sectoral indices (2015–2025).

Index	AC(1)	Q(1)	<i>p</i> (1)	AC(2)	Q(2)	<i>p</i> (2)	AC(3)	Q(3)	<i>p</i> (3)
NSE Nifty	0.102	51.20	0.000	−0.037	57.92	0.000	0.024	59.55	0.000
NSE CNX MNC	0.099	40.11	0.000	−0.007	40.27	0.000	−0.011	40.63	0.000
NSE CNX FMCG	0.044	7.18	0.007	−0.027	9.88	0.007	−0.029	13.17	0.004
NSE CNX IT	0.035	4.88	0.027	0.005	4.96	0.084	0.001	4.96	0.175
NSE CNX Service	0.122	46.27	0.000	−0.016	47.01	0.000	−0.003	47.02	0.000
NSE CNX Bank	0.131	51.64	0.000	−0.035	55.09	0.000	−0.015	55.72	0.000
NSE CNX Energy	0.101	28.49	0.000	−0.029	30.62	0.000	−0.018	31.49	0.000
NSE CNX Pharma	0.088	21.98	0.000	0.010	22.21	0.000	0.022	23.61	0.000
NSE CNX Auto	0.136	37.61	0.000	−0.008	37.70	0.000	−0.030	39.56	0.000
NSE CNX Finance	0.140	39.96	0.000	−0.043	43.71	0.000	−0.010	43.96	0.000
NSE CNX Metal	0.024	3.46	0.063	0.004	3.50	0.174	0.001	3.50	0.320
NSE CNX PSU Bk	0.158	48.21	0.000	−0.030	50.01	0.000	−0.015	50.57	0.000
NSE CNX Infra	0.088	21.98	0.000	0.010	22.21	0.000	0.022	23.61	0.000
NSE CNX Media	0.133	26.74	0.000	0.044	29.58	0.000	0.018	30.05	0.000
NSE CNX Realty	0.122	18.89	0.000	0.049	21.68	0.000	0.025	22.57	0.000

Notes: AC = autocorrelation coefficient. Q = Ljung–Box Q-statistic. *p* = *p*-value. Source: computed from NSE India data, 2015–2025.

5.2. GARCH(1,1) Estimates

Table 4 reports the GARCH(1,1) estimates. The ARCH coefficient α_1 and the GARCH coefficient β_1 are statistically significant at the 1 per cent level for every index. The persistence measure $\alpha_1 + \beta_1$ ranges from 0.961 (BSE Capital Goods) to 0.992 (BSE Healthcare), confirming high persistence across the board. This range lies materially above the 0.94–0.98

band reported by The benchmark framework for the pre-2017 sample, supporting H2: volatility memory has lengthened in the post-2020 regime. The pattern is consistent with the cross-country findings of [Salisu et al. \(2020\)](#) for African and Asian emerging markets and with the COVID-19 persistence-shift evidence of [Bouri et al. \(2021\)](#). More directly, this upward shift in the GARCH persistence measure is the conditional-variance counterpart of the long-memory increase that [Vera-Valdés \(2022\)](#) documents internationally for the VIX and realised variances after COVID-19, and it confirms with a GARCH metric the persistence increase that [Bhattacharjee et al. \(2025\)](#) reported for the CNX Nifty 50 using a Hurst-exponent analysis. The agreement of the three distinct estimators—international long memory, Indian Hurst-exponent, and the Indian sector-level GARCH estimates reported here—and the fact that the increase is recovered over a sample extended to 2025 rather than ending in the acute crisis phase, indicate that the post-pandemic rise in persistence is a property of the data-generating process rather than an artefact of any single method or window.

Table 4. GARCH(1,1) estimates for selected BSE and NSE indices (2015–2025).

Index	μ	$p(\mu)$	α_0	$p(\alpha_0)$	α_1	$p(\alpha_1)$	β_1	$p(\beta_1)$	$\alpha_1 + \beta_1$	ARCH p
BSE Sensex	0.148	0.000	0.000009	0.000	0.112	0.000	0.851	0.000	0.963	0.312
BSE Auto	0.131	0.000	0.000008	0.000	0.138	0.000	0.843	0.000	0.981	0.248
BSE Cap Goods	0.124	0.000	0.000011	0.000	0.152	0.000	0.809	0.000	0.961	0.031 *
BSE FMCG	0.038	0.061	0.000010	0.000	0.141	0.000	0.838	0.000	0.979	0.009 *
BSE Healthcare	0.076	0.000	0.000012	0.000	0.149	0.000	0.843	0.000	0.992	0.006 *
BSE IT	0.124	0.000	0.000016	0.000	0.129	0.000	0.844	0.000	0.973	0.418
BSE Bankex	0.128	0.000	0.000010	0.000	0.131	0.000	0.848	0.000	0.979	0.248
BSE Metal	0.001	0.011	0.000005	0.000	0.108	0.000	0.882	0.000	0.990	0.341
NSE Nifty	0.143	0.000	0.000009	0.000	0.118	0.000	0.852	0.000	0.970	0.338
NSE CNX Bank	0.127	0.000	0.000009	0.000	0.103	0.000	0.880	0.000	0.983	0.021 *
NSE CNX IT	0.259	0.000	0.000007	0.992	0.275	0.000	0.846	0.000	1.121	0.941
NSE CNX FMCG	0.065	0.000	0.000008	0.000	0.126	0.000	0.840	0.000	0.966	0.003 *
NSE CNX PSU Bk	0.145	0.000	0.000009	0.000	0.089	0.000	0.894	0.000	0.983	0.005 *

Notes: * indicates that the GARCH stability condition is not satisfied; the index is re-estimated under a higher-order or asymmetric specification. p = p -value; $\alpha_1 + \beta_1$ = persistence. The insignificant variance-equation intercept for the NSE CNX IT index ($\alpha_0, p = 0.992$) is not a reporting error: it accompanies a persistence sum ($\alpha_1 + \beta_1 = 1.121$) above unity and is the signature of an integrated-GARCH (IGARCH) process, in which the long-run variance is not finite and the intercept is consequently not separately identified. This index is re-estimated under GARCH(2,1).

Two specific findings warrant comment. First, the NSE CNX IT index exhibits a statistically insignificant intercept α_0 in the conditional-variance equation ($p = 0.992$) and a persistence measure exceeding unity ($\alpha_1 + \beta_1 = 1.121$), indicative of an integrated-GARCH process. Second, the ARCH test p -values flagged with an asterisk—BSE Capital Goods, BSE FMCG, BSE Healthcare, NSE CNX Bank, NSE CNX FMCG and NSE CNX PSU Bank—indicate residual ARCH effects after GARCH(1,1) and motivate the asymmetric and higher-order specifications reported next.

5.3. GJR-GARCH(1,1) Estimates

Table 5 reports the GJR-GARCH(1,1) estimates for the indices that failed the stability test under standard GARCH(1,1). The asymmetry coefficient γ is positive and statistically significant at the 1 per cent level for every index in the table, providing direct support for H3: leverage effects are a robust feature of Indian equity volatility. Compared with the

pre-2017 estimates of The benchmark framework, γ is materially larger in the 2015–2025 sample for most indices, most notably NSE CNX MNC ($\gamma = 0.156$), BSE FMCG ($\gamma = 0.136$), BSE TECK ($\gamma = 0.118$), and NSE CNX FMCG ($\gamma = 0.108$). This intensification of asymmetry is consistent with the heightened sensitivity of Indian equity markets to negative global shocks during the COVID-19 crash and the 2022 FPI sell-off; it is also consistent with the cross-country evidence that retail-heavy markets exhibit stronger leverage effects (Chiang & Doong, 2001; Bouri et al., 2021). Three indices—BSE FMCG, BSE Healthcare, and NSE CNX FMCG—retain residual ARCH effects under GJR-GARCH(1,1) and are therefore re-estimated under GARCH(2,1).

Table 5. GJR-GARCH(1,1) estimates for selected sectoral indices (2015–2025).

Index	μ	$p(\mu)$	α_0	$p(\alpha_0)$	α_1	$p(\alpha_1)$	γ	$p(\gamma)$	β_1	ARCH p
BSE Cap Goods	0.136	0.000	0.0000103	0.000	0.090	0.000	0.093	0.000	0.839	0.214
BSE FMCG	0.040	0.000	0.0000114	0.000	0.081	0.000	0.136	0.000	0.806	0.012 *
BSE Healthcare	0.141	0.000	0.0000067	0.000	0.120	0.000	0.056	0.000	0.826	0.039 *
BSE TECK	0.062	0.002	0.0000052	0.000	0.089	0.000	0.118	0.000	0.855	0.621
NSE CNX MNC	0.000	0.000	0.0000083	0.000	0.089	0.000	0.156	0.000	0.796	0.074
NSE CNX FMCG	0.067	0.000	0.0000101	0.000	0.076	0.000	0.108	0.000	0.835	0.009 *
NSE CNX Bank	0.135	0.000	0.0000091	0.000	0.065	0.000	0.071	0.000	0.878	0.162
NSE CNX PSU Bk	0.149	0.000	0.0000134	0.000	0.051	0.000	0.077	0.000	0.886	0.049

Notes: * indicates that residual ARCH effects remain, motivating GARCH(2,1) estimation. γ = asymmetric (leverage) coefficient.

5.4. GARCH(2,1) Estimates

Table 6 reports GARCH(2,1) estimates for seven indices. For four of them—BSE FMCG, BSE Healthcare, and NSE CNX FMCG, which retain residual ARCH effects under both GARCH(1,1) and GJR-GARCH(1,1), together with NSE CNX IT, whose integrated-GARCH behaviour under GARCH(1,1) rules out that specification—the GARCH(2,1) model is the preferred specification. The remaining three indices in the table (BSE TECK, NSE CNX Bank, and NSE CNX PSU Bank) are already adequately described by the GJR-GARCH(1,1) of Section 5.3 and their GARCH(2,1) estimates are presented only for comparison. All mean- and variance-equation parameters are statistically significant. The ARCH test probabilities and the Ljung–Box statistics on squared residuals indicate that residual ARCH effects and squared-residual autocorrelation have been removed, confirming that the GARCH(2,1) specification adequately characterises the conditional-variance dynamics of these indices. The negative α_2 coefficient is a technically natural outcome under GARCH(2,1) and indicates an attenuating, rather than amplifying, role for the second-lag innovation in the variance process. The evidence supports H4: a non-trivial subset of Indian indices requires a higher-order specification, and the standard GARCH(1,1) is insufficient. Notably, the three indices most affected—BSE FMCG, BSE Healthcare, and NSE CNX FMCG—are precisely those most exposed to regulatory and policy-driven news cycles (input-cost notifications, pharma price controls, FMCG GST revisions), in which information arrives in discrete clusters with effects extending beyond a single trading day.

Table 6. GARCH(2,1) estimates for residual-problem indices (2015–2025).

Coefficient	BSE FMCG	BSE Healthcare	NSE CNX FMCG	NSE CNX IT +	BSE TECK	NSE CNX Bank	NSE CNX PSU Bk
μ	0.000843	0.000748	0.000724	0.000822	0.000758	0.000716	0.000849
α_0	0.0000068	0.0000047	0.0000051	0.0000048	0.0000058	0.0000061	0.0000092
α_1	0.2214	0.2198	0.2103	0.1986	0.1924	0.1876	0.1645
α_2 (ARCH-2)	−0.1158	−0.1438	−0.1192	−0.1064	−0.0982	−0.1043	−0.0883
β_1	0.871	0.919	0.891	0.904	0.883	0.896	0.906
ARCH test p	0.724	0.891	0.756	0.813	0.668	0.792	0.604
Q(sq.res.) p	0.718	0.886	0.749	0.809	0.662	0.788	0.598
Log-likelihood	9812.64	10124.37	12491.08	8874.22	7789.43	7742.19	4924.88

Notes: All parameters are significant at $p < 0.01$. + NSE CNX IT is modelled with GARCH(2,1) because of integrated-GARCH behaviour under GARCH(1,1). ARCH test = F-statistic probability; Q(sq.res.) = Ljung–Box statistic on squared residuals at lag 1.

5.5. Discussion in Light of the EMH and International Comparators

The combined results have a clear interpretation under the Efficient Market Hypothesis. The pervasive presence of ARCH effects, the high and persistent values of $\alpha_1 + \beta_1$, and the statistical significance of the leverage coefficient γ together imply that Indian equity returns are inconsistent with strong-form efficiency: conditional variance is forecastable, and the forecast carries economic value for risk management. This is consistent with the broader emerging-market evidence (Karmakar, 2007; Bouri et al., 2021), but is rendered more striking by the magnitudes documented here. The $\alpha_1 + \beta_1$ values for the Indian sectoral indices in 2015–2025 are comparable to those reported for the Brazilian Bovespa and Turkish BIST 100 in the COVID-19 episode (Salisu et al., 2020), and exceed those typically reported for mature markets such as the S&P 500 over comparable windows.

The intensification of leverage effects in FMCG, banking, and consumer-durables indices is also instructive. The pattern is consistent with the behavioural-finance view (Shiller, 2003) that retail-heavy markets process negative information more asymmetrically than positive information, particularly in sectors covered intensively by financial media. The fact that internationally integrated sectors (IT, Metal) show weaker autocorrelation but stronger persistence indicates that the channels through which negative news affects volatility differ across sectors—a finding that aligns with the index-construction sensitivity documented by Doğan and Ugurlu (2025). H5 is therefore supported: documented persistence and asymmetry are inconsistent with strong-form efficiency, and the preferred GARCH-family specifications retain economic value for short-horizon variance forecasting.

6. Conclusions

This paper re-estimates the volatility-modelling framework of The benchmark framework on an updated 2015–2025 sample covering some of the most unusual macro-financial episodes in the recent history of Indian equity markets—demonetisation, the IL&FS crisis, the COVID-19 crash and recovery, the 2022 commodity shock, and the 2022–2024 monetary-tightening cycle—and integrates the findings with the EMH and behavioural-finance literature. Four substantive conclusions emerge.

First, the GARCH(1,1) specification adequately characterises the conditional variance of BSE Sensex, BSE Auto, BSE Consumer Durables, BSE IT, BSE Metal, BSE PSU, BSE Oil & Gas, BSE Bankex, BSE Power, BSE Realty, NSE CNX Nifty, NSE CNX Service, NSE CNX Energy, NSE CNX Pharma, raNSE CNX Auto, NSE CNX Finance, and NSE CNX Media. Volatility is persistent for all these indices, with the sum of ARCH and GARCH coefficients

$(\alpha_1 + \beta_1)$ typically exceeding 0.96 and lying above the corresponding 2017 benchmark. Volatility shocks—including those associated with the COVID-19 episode and the 2022 commodity spike—exhibit long memory in the Indian market, supporting H2.

Second, the NSE CNX IT index is best characterised by the GARCH(2,1) specification. The GARCH(1,1) specification is inadequate for this index because of its near-integrated-GARCH behaviour, plausibly explained by the unusually large and slowly decaying shocks experienced by IT stocks during the post-COVID global technology boom and the subsequent correction. The GARCH(2,1) specification produces a stable and statistically adequate description, supporting H4 for this index.

Third, asymmetric volatility—the leverage effect—is a pervasive and intensifying characteristic of Indian markets in the post-2015 decade. The GJR-GARCH(1,1) specification is sufficient for BSE Capital Goods, BSE TECK, NSE CNX MNC, NSE CNX Bank, and NSE CNX PSU Bank. The positive and statistically significant γ coefficient in all these indices indicates that negative price shocks produce disproportionately larger volatility responses than equivalently large positive shocks; the magnitude of γ has increased relative to the 2017 estimates, plausibly reflecting the amplifying effect of adverse global news flows in a market environment of higher retail participation and real-time news dissemination. H3 is therefore supported.

Fourth, the GARCH(2,1) specification is the preferred model for the BSE FMCG, BSE Healthcare, and NSE CNX FMCG indices, for which neither GARCH(1,1) nor GJR-GARCH(1,1) removes the residual ARCH effects, together with the NSE CNX IT index, whose integrated-GARCH behaviour under GARCH(1,1) (Table 4) likewise requires the higher-order specification. For these indices, the lag-2 innovation continues to exert a statistically significant and economically distinct effect on current conditional variance, consistent with the slower price-adjustment patterns of sectors subject to regulatory and policy-driven news cycles. The remaining indices appearing in Table 6—BSE TECK, NSE CNX Bank, and NSE CNX PSU Bank—are reported there for comparison only; their preferred specification is the GJR-GARCH(1,1) of the previous paragraph, under which they satisfy the residual-whitening criterion (Table 5), and are not classified as GARCH(2,1) indices. This higher-order requirement for a genuine subset of indices constitutes one of the principal contributions of the paper relative to the 2017 framework, in which lag-2 ARCH effects were not material. H4 is supported.

Taken together, the findings provide direct empirical evidence against strong-form efficiency for Indian equity markets in the post-2015 decade and quantify the channels—persistence, asymmetry, and ARCH order—through which the structural changes in the past decade have altered the conditional-variance dynamics of the market. The contribution of the paper, accordingly, is not a mechanical extension of the sample window of an earlier study, but an empirical re-mapping of the volatility-modelling architecture onto a structurally different market regime, with explicit hypothesis tests, international comparators, and a theoretical interpretation rooted in the EMH and behavioural-finance literature.

7. Policy and Practical Implications

The empirical findings carry direct implications for three groups of decision-makers.

For portfolio managers, the upward shift in volatility persistence and the strengthening of the leverage effect have material consequences for hedging design. Hedge ratios calibrated on pre-2017 GARCH parameters will systematically understate required protection during episodes of negative shocks, particularly in FMCG, banking, and consumer-durables exposures. The use of GJR-GARCH or GARCH(2,1) parameter estimates produced on a rolling post-2015 window is therefore advisable for these segments.

For options traders and structured-product desks, the implied-volatility surfaces calibrated on the post-2015 GARCH parameters reported here will produce more accurate short-horizon variance forecasts than surfaces calibrated on pre-2015 estimates. The higher persistence implies slower mean-reversion of implied volatility aftershocks, with direct implications for the pricing of variance swaps and volatility-targeted strategies.

For regulators—in particular the Securities and Exchange Board of India (SEBI) and the Reserve Bank of India—the rise in persistence may be interpreted as an indicator of latent systemic risk in a market characterised by a rapidly expanding retail investor base and an increasingly leveraged derivatives segment. The combination of high persistence and strong asymmetry implies that adverse shocks have prolonged volatility consequences, which strengthens the prudential case for circuit-breaker calibration, margining rules, and disclosure standards that internalise the post-2015 risk profile rather than the materially different pre-2015 profile.

8. Limitations and Avenues for Future Research

The paper has three principal limitations that suggest specific extensions for future research. First, the analysis is univariate: cross-sector spillovers are not modelled, although the cross-country literature (Bouri et al., 2021) suggests that they are material. A multi-variate DCC-GARCH or BEKK-GARCH extension on the present cross-section is a natural next step. Second, with respect to the role of macroeconomic variables in the present study, it is essentially interpretative rather than structural. Some of the earlier GARCH-MIDAS studies have demonstrated that low-frequency macroeconomic data, interest rates, inflation-related data, foreign institutional investment flows, etc., can be directly included in the long-run variance component, which introduces a more explicit macro-financial linkage in volatility modelling can be extended. Third, future work is left with the comparison to other machine-learning volatility forecasting models. The results indicate that in the Indian context of the stock market, recurrent neural network (RNN) architectures can make more competitive forecasts than the traditional GARCH specifications are doing (Mahajan et al., 2022). Future research could also extend the analysis to higher-frequency intra-day data and to the inclusion of intra-day jump-detection diagnostics, which fall outside the scope of the daily frequency framework adopted here.

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