Journal of Banking and Financial Dynamics
Vol. 10, No. 9, 10-38, 2026
ISSN(E): 2576-6821
DOI: 10.55220/2576-6821.v10.1410
© 2026 by the author; licensee Eastern Centre of Science and Education, USA
Check for updates

Does ESG Performance Shape Volatility Asymmetry? Evidence from Indian Listed Firms

Arshia Gupta

GD Goenka Public School, Model Town, India.

Abstract

This study examines whether corporate Environmental, Social, and Governance (ESG) performance is associated with systematic differences in stock return volatility dynamics, extending the predominantly level-based ESG-financial performance literature into the domain of dynamic risk behaviour. Using daily adjusted closing prices for 27 firms listed on Indian stock exchanges with ESG scores ranging from 33 to 78, this study fits a grid of GARCH(1,1), EGARCH(1,1), and GJR-GARCH(1,1) specifications, each paired with Gaussian Normal, Student's t, and Skewed Student's t innovations, and selects the best-fitting model per firm by Akaike Information Criterion (AIC). The final sample was drawn from an original 30-firm frame (a Top 15 and Bottom 15 ESG-rated design); one duplicate entry and two firms with incomplete data were removed, yielding the 27-firm analytical sample. The resulting volatility coefficients are merged with firm-level ESG scores and financial ratios (return on equity, return on assets, gross profit margin, dividend yield, price-to-earnings ratio, relative strength index, and market beta) into a nine-variable feature matrix. Principal Component Analysis reduces this matrix to five components explaining approximately 80 percent of total variance, and K-Means clustering ($k = 2$, selected by silhouette score) groups firms into two clusters that do not differ significantly in mean ESG score ($F = 1.34$, $p = 0.26$). The central finding is that ESG score is negatively associated with the leverage-effect coefficient ($r = -0.26$), a direction consistent with the stakeholder-theoretic literature; the association is modest in size and does not reach statistical significance at conventional thresholds in this 27-firm sample ($p = 0.23$). The study's clearest and most robust results are that asymmetric volatility models dominate this sample regardless of ESG standing, and that volatility persistence is uniformly high across nearly all firms. Taken together, the evidence is directionally consistent with ESG performance being associated with a smaller leverage effect in this sample, though the relationship is not statistically confirmed at this sample size. Directions for confirmatory panel-based research with a larger sample and a time-varying ESG measure are proposed.

Keywords: Emerging markets, India, ESG performance, GARCH, EGARCH, GJR-GARCH, K-means clustering, Leverage effect, Principal component analysis, Volatility persistence.

1. Introduction

The integration of Environmental, Social, and Governance (ESG) considerations into investment decision-making has moved from a niche ethical preference to a mainstream component of institutional portfolio construction over the past decade. Global sustainable investment assets have grown substantially, and regulators across major markets, including India's Securities and Exchange Board (SEBI) through its Business Responsibility and Sustainability Reporting (BRSR) framework, have progressively mandated ESG disclosure for large listed firms. This growth has been accompanied by a correspondingly large body of academic research examining whether ESG performance is associated with corporate financial performance (CFP), typically measured through profitability ratios, valuation multiples, or raw stock returns.

That literature, however, is overwhelmingly static. The dominant empirical strategy regresses a level-based financial outcome, such as return on equity or Tobin's Q, on a contemporaneous or lagged ESG score, implicitly treating both ESG standing and financial performance as slowly evolving firm characteristics rather than as inputs into a dynamic risk process. This framing leaves an important question comparatively unexplored: does ESG performance shape not just the average level of a firm's financial outcomes, but the way its stock price risk behaves over time, how volatile it is, how persistent that volatility is once shocks occur, and whether it reacts asymmetrically to bad news relative to good news?

This question matters for at least three reasons. First, volatility, not just returns, is a primary input into portfolio risk management, options pricing, and regulatory capital requirements, so if ESG performance is

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

systematically linked to volatility dynamics, that has direct pricing and risk-management implications distinct from any ESG-return relationship. Second, the asymmetric or leverage effect, whereby negative shocks increase future volatility more than positive shocks of equal magnitude, is often interpreted through a corporate governance and informational-asymmetry lens; if stronger ESG governance genuinely reduces informational asymmetry between managers and outside investors, this should manifest as a measurably smaller leverage effect for higher-ESG firms. Third, emerging-market evidence on this specific dynamic-risk question remains sparse relative to the developed-market literature, despite emerging markets typically exhibiting higher baseline volatility and less mature ESG disclosure regimes, making India a particularly informative setting.

This study addresses this gap by fitting a family of univariate GARCH-type models, specifically the symmetric GARCH(1,1), the asymmetric GJR-GARCH(1,1), and the asymmetric EGARCH(1,1), each combined with three candidate innovation distributions, to the daily return series of 27 firms listed on Indian exchanges spanning a continuous ESG score range. The best-fitting specification for each firm is selected by AIC, and the resulting volatility coefficients are combined with standard financial ratios into a unified feature space. This feature space is then examined using unsupervised learning techniques, Principal Component Analysis for dimensionality reduction and K-Means clustering for firm segmentation, to test whether ESG performance corresponds to systematically different data-driven risk-behaviour groupings, independent of any single hypothesis test or pre-specified cutoff.

The remainder of this paper is organised as follows. Section 2 reviews the relevant literature on the ESG-CFP relationship. Section 3 articulates the specific research gap this study addresses, including the scope and limitations of the analysis. Section 4 develops the theoretical and conceptual framework linking stakeholder theory and leverage-effect theory to the empirical design. Section 5 details the research methodology, including model specification, estimation, and the unsupervised learning pipeline. Section 6 describes the final data sample. Section 7 presents the results and discussion. Section 8 concludes and proposes directions for future research.

2. Literature Review

The relationship between environmental, social, and governance (ESG) performance and corporate financial performance (CFP) has been examined extensively across geographies, sectors, and methodological approaches, with the balance of evidence pointing toward a positive but heterogeneous association. Using accounting-based measures, studies report significant positive effects of ESG performance on return on assets and return on equity in Russian (Koroleva, Baggieri, & Nalwanga, 2020), Chinese (Zhang, 2025; Xu & Zhu, 2024; Che, Song, & Li, 2024), Western European (Loew, Endres, & Xu, 2024), and Indian samples (Ghosh, 2013), while market-based measures such as Tobin's Q and stock returns show similarly positive, though often more modest, effects (Melinda & Wardhani, 2020; Lunawat, Elmarzouky, & Shohaieb, 2025; Peiris & Evans, 2010). Using structural equation modeling on S&P 500 firms, Cek and Eyupoglu (2020) similarly found that overall ESG performance significantly predicted economic performance, with social and governance factors as the strongest components and environmental performance the weakest. Meta-analytic and review-level evidence corroborates this general direction: a synthesis of 21 studies found a positive but economically modest correlation between ESG and CFP (Huang, 2021), a review of roughly 45 years of accounting and finance literature likewise found a positive, if modest, firm-level association alongside a "virtuous circle" between social and financial performance over time (Brooks & Oikonomou, 2018), and a meta-study of over 200 sources found that the large majority of studies link sustainability practices to improved cash flow, a lower cost of capital, and stronger stock performance (Clark, Feiner, & Viehs, 2015).

The strength and even direction of this relationship, however, depends heavily on institutional context. Testing the Institutional Difference Hypothesis, Garcia and Orsato (2020) found a positive ESG-CFP relationship in developed economies but a negative one in emerging markets, where weaker institutions push firms toward capital accumulation over ESG investment. This pattern recurs elsewhere: ESG initiatives generate stronger valuation effects in developed-market firms than in emerging-market firms (Ting, Azizan, Bhaskaran, & Sukumaran, 2019), and ESG scores were found to negatively affect ROA and ROE among Indonesian firms despite superior portfolio-level returns, a result attributed to high implementation costs and short-termist investor behavior in that market (Nareswari, Tarczyńska-Łuniewska, & Hashfi, 2023). Ownership structure produces similar heterogeneity within a single country: in China, the positive ESG-CFP relationship is more pronounced among non-state-owned enterprises and weakens under financial constraints (Xu & Zhu, 2024), while a related study found the relationship moderated by both property rights and industry classification (Che, Song, & Li, 2024).

A separate strand of the literature investigates the mechanisms through which ESG performance translates into financial outcomes, generally converging on governance as the most consistently influential pillar. Governance was identified as the dominant driver of profitability among Russian firms (Koroleva, Baggieri, & Nalwanga, 2020), the pillar with the most significant impact on profitability generally (Kim & Li, 2021), and the strongest positive determinant of both profitability and Tobin's Q among Western European firms, alongside an unexpectedly negative environmental-pillar effect attributed to high short-term implementation costs (Loew, Endres, & Xu, 2024). Governance disclosure similarly showed the strongest association with corporate efficiency in a 74-country sample using data envelopment analysis (Xie, Nozawa, Yagi, Fujii, & Managi, 2019). Beyond governance, innovation emerges as a key transmission channel, with ESG performance improving CFP primarily by fostering corporate innovation in Chinese samples (Xu & Zhu, 2024), while agency cost, financing cost, social reputation, and market power have each been identified as partial mediators of the ESG-CFP link (Che, Song, & Li, 2024). Credit risk represents an additional, distinct channel: ESG variables generally improve credit ratings, though the environmental score paradoxically lowers them, underscoring the need to evaluate ESG's effects on risk and return jointly rather than in isolation (Kim & Li, 2021).

Several studies complicate the picture by distinguishing between absolute and relative ESG performance, or between disclosure and substantive performance. Taliento, Favino, and Netti (2019) found that a firm's absolute ESG score had no significant effect on economic performance, but that its ESG performance relative to its industry-sector average was significantly and positively related to performance, supporting a relative rather than absolute conception of "sustainability advantage." A comparable nonlinearity appears in the relationship between

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

ESG disclosure and corporate efficiency, which peaks at moderate disclosure levels and weakens at both low and high extremes (Xie, Nozawa, Yagi, Fujii, & Managi, 2019). Market-based evidence introduces further nuance: Manescu (2011) found that most ESG-related abnormal stock returns reflect market mispricing rather than compensation for risk, and Peiris and Evans (2010) similarly found no significant relationship between ESG ratings and stock outperformance after controlling for style, size, and momentum, despite a significant positive relationship with ROA and market-to-book value.

Not all evidence favors a positive ESG-CFP relationship. Winegarden (2019) found that ESG mutual funds underperformed the S&P 500 by nearly 44 percent over a ten-year period, driven by higher expense ratios and greater concentration risk, and further argued that dominant proxy advisory firms exhibit systematic bias favoring ESG shareholder proposals irrespective of merit. Noja et al. (2024) likewise found the ESG-performance relationship only partially validated, with board size and high CO_2 emissions negatively associated with financial outcomes even as other ESG dimensions showed positive effects. Comparable ambivalence appears in Sandberg, Alnoor, and Tiberius (2023), who found ESG's effect on European food-industry performance statistically significant but modest, and questioned whether the strong clustering of ESG ratings around the mean reflects genuine differentiation in firm behavior.

The theoretical foundations underlying this literature were established well before ESG became a standardized construct. Pava and Krausz (1996) reviewed 21 prior empirical studies and conducted an original analysis of 53 U.S. socially-responsible firms, finding no evidence that such firms were inferior investments and terming the pattern the "paradox of social cost": traditionalist theory predicts that socially-responsible firms should underperform, yet the empirical record consistently shows they do not. King (2001) extended this line of inquiry empirically, showing that companies ranked highest on the Dow Jones Sustainability Group Index delivered superior total shareholder returns against sector indices and better risk-adjusted performance than individual peer companies, while stopping short of establishing causation. More recent conceptual work continues to frame sustainability as a driver of long-run competitive advantage, citing CEO leadership and supply-chain pressure as the primary forces driving corporate adoption (Nicolăescu, Alpopi, & Zaharia, 2015), a claim consistent with the broader finding that firms in controversial or resource-intensive sectors, where legitimacy pressure is highest, often exhibit superior ESG performance in developed markets (Garcia & Orsato, 2020; Skare & Golja, 2012).

Taken together, the literature supports a cautiously positive relationship between ESG performance and corporate financial performance, but one that is neither uniform nor fully understood. Effect sizes are consistently larger for market-based measures than accounting-based ones in some samples (Lunawat, Elmarzouky, & Shohaieb, 2025) and the reverse in others (Ghosh, 2013), the relationship reverses sign across institutional contexts (Garcia & Orsato, 2020; Nareswari, Tarczyńska-Łuniewska, & Hashfi, 2023), and the underlying mechanisms, namely governance quality, innovation, financing constraints, reputation, and credit risk, remain only partially disentangled (Da Cunha et al., 2025; Kim & Li, 2021).

3. Research Gap

A closer reading of this literature reveals two consistent limitations. First, virtually every study reviewed measures the ESG-CFP relationship through the level of financial performance, whether accounting-based (Zhang, 2025; Xu & Zhu, 2024; Che, Song, & Li, 2024), market-based (Melinda & Wardhani, 2020; Lunawat, Elmarzouky, & Shohaieb, 2025), or credit-based (Kim & Li, 2021), using regression, structural equation modeling, or data envelopment analysis applied to static or panel-averaged samples. None models the dynamic, time-varying volatility behavior of ESG-differentiated firms using a conditional-heteroskedasticity (GARCH-family) framework, or tests whether high- and low-ESG firms respond asymmetrically to negative market shocks through such a framework specifically; this is distinct from the separate literature on ESG and firm risk more broadly (e.g., static risk proxies such as beta (King, 2001), idiosyncratic and systematic risk, or fund-level concentration risk (Winegarden, 2019)), which this review does not claim to be the first to address. Second, the reviewed studies rely almost exclusively on supervised, hypothesis-driven designs that test a pre-specified linear or moderated relationship, leaving unexplored whether high- and low-ESG firms form natural, data-driven groupings when their risk dynamics and fundamentals are considered jointly rather than tested variable by variable.

This study addresses both gaps. By fitting GARCH, EGARCH, and GJR-GARCH models to the daily return series of a cross-section of ESG-rated firms spanning a continuous ESG score range, it directly tests whether sustainability leadership is associated with systematically different volatility persistence, shock sensitivity, and asymmetric leverage effects, questions the reviewed literature does not address. It further departs methodologically from the regression-based designs above by applying unsupervised machine learning, specifically principal component analysis and K-means clustering, to a merged dataset of extracted volatility parameters and fundamental ESG-linked metrics, allowing cluster structure to emerge from the data rather than being imposed through a specified functional form. In doing so, this study extends the ESG-financial performance literature from a question of average performance levels to one of risk dynamics and multivariate structure.

It should be noted at the outset that the raw sampling frame for this study (a Top 15 / Bottom 15 ESG-rated design, nominally 30 firms) contained a duplicate entry for one firm (Sobha Limited, listed twice with an identical ESG score), reducing the frame to 29 unique firms. During data verification, two further firms (Infosys and Tata Consultancy Services) could not be matched to complete records and were dropped, yielding the final analytical sample of 27 firms used throughout Section 7. Data sources for all price and fundamental data are listed in Section 5.

4. Theoretical and Conceptual Framework

This study draws on two complementary theoretical strands to motivate the empirical design: stakeholder-based theories of corporate governance, which predict a level relationship between ESG performance and firm risk, and the finance-theoretic literature on volatility asymmetry, which provides the specific econometric construct, the leverage coefficient, used to test that prediction dynamically.

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

Freeman's (1984) stakeholder theory holds that firms which manage relationships with a broad set of stakeholders, employees, communities, regulators, and the environment, rather than narrowly maximising shareholder value in isolation, reduce the likelihood and severity of stakeholder conflicts that can produce negative earnings surprises, litigation, regulatory penalties, or reputational damage. A closely related risk-mitigation view treats ESG engagement as a form of insurance: firms with strong ESG practices are hypothesised to be better prepared for, and therefore less severely affected by, adverse environmental, social, or governance-related shocks. Both perspectives predict that higher-ESG firms should show more muted volatility responses to negative news relative to positive news of the same magnitude, precisely the asymmetry captured by the leverage coefficient in GJR-GARCH and EGARCH models.

The finance-theoretic basis for that specific coefficient traces to Black (1976) and Christie (1982), who documented that stock return volatility tends to rise more following negative returns than following positive returns of equal size, an effect commonly attributed to financial leverage (a falling stock price mechanically raises a firm's debt-to-equity ratio, raising equity risk) and, in later extensions, to informational and behavioural asymmetries in how markets process bad news relative to good news. The GJR-GARCH and EGARCH model classes used in this study directly parameterise this asymmetry through the gamma coefficient, providing a natural econometric bridge between the qualitative stakeholder-theoretic prediction, that better-governed firms should be less exposed to asymmetric downside risk, and a quantitative, firm-specific, estimable parameter.

Figure 1 summarises this conceptual framework. The stakeholder-theoretic and risk-mitigation arguments motivate an expectation that ESG performance is associated with the leverage coefficient specifically, while the broader dynamic risk layer (persistence, tail thickness, skewness) and the fundamental financial layer (profitability, valuation, momentum, and systematic risk ratios) are combined into a single multivariate feature space and examined jointly through PCA and K-Means clustering, allowing the data to reveal whether ESG-related risk differences extend beyond the leverage coefficient alone into a broader, multi-dimensional risk-behaviour profile.

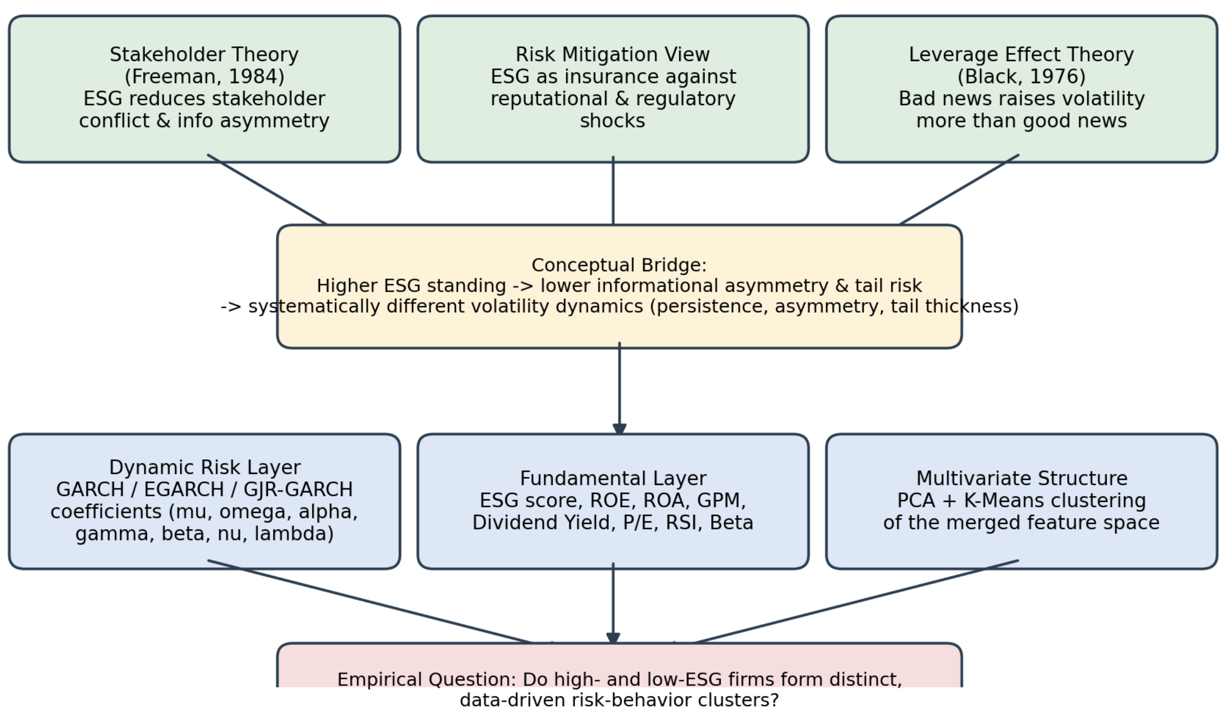

Figure 1. Conceptual Framework Linking ESG Theory to the GARCH Leverage Coefficient.

5. Research Methodology

This study implements an integrated empirical framework to investigate the linkage between corporate sustainability (ESG) characteristics, fundamental accounting metrics, and dynamic volatility behavior. The methodology progresses through four core stages: (1) systematic data collection and retrieval, (2) econometric estimation of GARCH-family conditional volatility coefficients, (3) preparation and mapping of a comprehensive master analytical dataset, and (4) unsupervised machine learning clustering, feature reduction, and cross-cohort profiling.

5.1. Data Collection and Variable Architecture

The empirical sample was originally constructed around a comparative cross-sectional design representing two contrasting sustainability cohorts: the Top 15 and Bottom 15 ESG-rated public corporations (n = 30). Data collection encompassed two distinct data streams: firm-level fundamental and market metrics, sourced from corporate disclosures and financial databases, comprising corporate sustainability ratings (ESG Score), accounting profitability (Return on Equity, Return on Assets, Gross Profit Margin), valuation metrics (Price-to-Earnings Ratio, Dividend Yield), and market technical indicators (Relative Strength Index, Systematic Risk Beta); and high-frequency market price series, specifically historical daily adjusted closing price series retrieved for each company across the sample timeframe to model asset return variances.

Specifically, daily historical price series were retrieved from Investing.com (https://www.investing.com/), and firm-level ESG scores were retrieved from the NSE ESG Ratings platform (https://www.nse-esgrating.com/esg-ratings). Both sources are third-party data providers rather than primary regulatory filings; as with any externally sourced financial data, figures should be understood as subject to each provider's own data-collection and rating methodology, which this study did not independently audit.

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

One entry in the original 30-firm frame (Sobha Limited) was a duplicate row and was removed. Two further firms (Infosys, Tata Consultancy Services) were dropped during data verification due to incomplete records. The final analytical sample therefore comprises 27 firms, spanning ESG scores from 33 to 78, as detailed in Section 3.

5.2. Computation of GARCH Coefficients and Model Optimization

To quantify dynamic volatility patterns and asymmetric leverage responses, daily price series were converted into percentage log returns, where scaling by 100 ensures numerical stability during optimization:

$r_t = ln(P_t / P_{t-1}) \times 100$

Stationarity is confirmed for all series using the Augmented Dickey-Fuller (ADF) test.

5.2.1. Volatility Model Grid Search

Returns are specified with a constant conditional mean process. For each firm, a grid search is conducted across three conditional variance functions. Each function is paired with three candidate error distributions (Gaussian Normal, Student's t, and Skewed Student's t), and the best combination of variance function and innovation distribution is selected per firm by AIC. The three-distribution grid is set out below:

$r_t = \mu + \varepsilon_t, \quad \varepsilon_t = \sigma_t z_t$

Standard GARCH(1,1):

$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$

Exponential GARCH (EGARCH(1,1)):

$ln(\sigma_t^2) = \omega + \alpha_1 \, |\varepsilon_{t-1} / \sigma_{t-1}| + \gamma_1 (\varepsilon_{t-1} / \sigma_{t-1}) + \beta_1 \, ln(\sigma_{t-1}^2)$

Glosten-Jagannathan-Runkle GARCH (GJR-GARCH(1,1)):

$\sigma_t^2 = \omega + (\alpha_1 + \gamma_1 I_{t-1}) \, \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$

where the indicator term I_(t-1) equals 1 if the prior-period shock is negative, and 0 otherwise.

5.2.2. Maximum Likelihood Estimation and Optimal Model Selection

Model coefficients are estimated by maximizing the log-likelihood function. The optimal specification per firm is chosen by minimizing the Akaike Information Criterion (AIC):

$$AIC = 2k - 2\,ln(L)$$

where k is the count of estimated parameters. From the winning model, seven structural GARCH coefficients are extracted: mu (conditional mean return coefficient), omega (unconditional baseline variance term), alpha-1 (ARCH short-term shock sensitivity parameter), gamma-1 (asymmetric leverage coefficient), beta-1 (GARCH long-term variance decay parameter), nu (error density degrees of freedom, tail thickness), and lambda (distributional skewness parameter).

Across the final 27-firm sample, EGARCH specifications were selected most frequently (15 firms), followed by GJR-GARCH (8 firms) and symmetric GARCH (4 firms), summarised in Table 3 below.

5.3. Preparation of the Comprehensive Master Integration Table

Following model estimation, firm-level financial metrics and time-series GARCH parameters are merged to construct a unified dataset. This consolidated table pairs seven dependent volatility variables with eight independent firm features, as shown below:

$X_{Master} = [\, \mu, \omega, \alpha_1, \gamma_1, \beta_1, \nu, \lambda \;\; | \;\; ESG, ROE, ROA, GPM, Div\ Yield, P/E, RSI, \beta \,]$

5.4. Data Preprocessing, Scaling, and Data-Quality Screening

Numeric coercion and imputation: missing values arising from model-specific inapplicability (for example, gamma for symmetric GARCH firms, or nu for Gaussian-innovation firms) were imputed using Gaussian draws parameterised by variable means and standard deviations. For reproducibility, results reported in Section 7 use column-mean imputation as a deterministic substitute for stochastic Gaussian-draw imputation.

Standardization: features were standardized using Z-score transformation to harmonize disparate units (percentages, multiples, and ratios) prior to PCA and clustering.

For every firm whose best-fit specification was EGARCH or GJR-GARCH, the gamma (asymmetry) coefficient was extracted directly from that model's fitted parameter vector; it is reported as n/a for firms whose best-fit specification is symmetric GARCH(1,1), which has no asymmetry term. Two additional row-level data-quality corrections were made prior to analysis: a dividend yield field originally stored as a combined absolute-and-percentage string was parsed to extract the percentage figure, and one firm's return-on-assets figure stored as a percentage string was converted to decimal form.

5.5. Unsupervised Machine Learning Pipeline

Using the standardized master matrix, unsupervised machine learning algorithms are executed to evaluate multivariate relationships and group structure. Correlation interdependence: Pearson correlation coefficient matrices are generated to assess relationships across firm characteristics and volatility parameters. Dimensionality reduction (PCA): Principal Component Analysis compresses the 9-dimensional feature space into orthogonal principal components. Components are retained based on an 80 percent cumulative explained variance threshold; five components satisfied this threshold, explaining approximately 80.3 percent of total variance (Section 7.3, Table 4). Topographical cluster evaluation: candidate cluster structures are evaluated using Ward's Hierarchical Agglomerative Dendrogram and K-Means inertia curves (Elbow Method), with the final cluster count selected by silhouette score. Spatial partitioning and profiling: assets are grouped using K-Means clustering (k = 2, per Section 7.4) and projected onto a 2D PC1-PC2 spatial grid. Statistical mean profiles are calculated for each cluster across all 9 indicators to compare market behavior between clusters.

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

All clustering and dimensionality-reduction steps were implemented in Python using scikit-learn, with a fixed random seed for reproducibility.

6. Data and Sample Description

Table 1 reports descriptive statistics for the ESG score and six financial ratios across the final 27-firm sample. Table 2 lists all 27 firms ranked by ESG score in descending order, together with each firm's best-fit model specification, volatility persistence measure, leverage-effect (gamma) coefficient where applicable, and assigned K-Means cluster. Table 3 summarises the distribution of best-fit model types across the sample.

Table 1. Descriptive Statistics of ESG Score and Financial Ratios (n = 27, unless otherwise noted).

Variable	Mean	Std. Dev.	Min.	Median	Max.
ESG Score	65.26	10.28	33.00	66.00	78.00
Return on Equity (n=26)	0.16	0.10	-0.09	0.14	0.37
Return on Assets	0.06	0.07	-0.11	0.04	0.23
Gross Profit Margin (n=23)	0.48	0.20	0.19	0.46	1.00
Dividend Yield % (n=23)	1.97	2.96	0.00	0.80	12.50
P/E Ratio (n=26)	34.26	44.70	-9.50	18.85	210.70
RSI (n=26)	52.88	12.38	30.52	51.91	71.33
Beta	0.35	0.20	-0.08	0.33	0.83

Table 2. Sample Firms Ranked by ESG Score, with Best-Fit Model and Key Coefficients (n = 27).

Rank	Ticker	ESG Score	Best-Fit Model	Persistence	Gamma (Leverage)	Cluster
1	ICBK	78	GJR-GARCH-t	0.949	0.092	0
2	BRTI	77	GARCH-skewt	0.984	n/a	1
3	AXBK	77	GJR-GARCH-t	0.954	0.056	0
4	WIPR	75	EGARCH-t	0.966	0.127	1
5	HLL	74	GARCH-skewt	0.949	n/a	1
6	MAHM	74	GJR-GARCH-t	0.956	0.042	0
7	HDBK	73	EGARCH-t	0.977	0.174	0
8	MRTI	73	GJR-GARCH-t	0.944	0.072	1
9	HIMD	71	EGARCH-skewt	0.906	0.283	1
10	KTKM	70	EGARCH-t	0.981	0.150	0
11	TITN	69	EGARCH-skewt	0.989	0.082	1
12	SLIN	68	EGARCH-skewt	0.906	0.309	1
13	ADEL	68	GJR-GARCH-t	0.764	0.263	0
14	ITC	66	GARCH-t	0.938	n/a	1
15	ADRG	65	EGARCH-skewt	0.928	0.290	0
16	ADAN	65	EGARCH-skewt	0.900	0.482	0
17	GRAS	64	GJR-GARCH-t	0.905	0.103	0
18	TTPW	64	EGARCH-skewt	0.983	0.157	0
19	JSTL	63	GJR-GARCH-t	0.946	0.069	1
20	TISC	63	EGARCH-t	0.983	0.142	0
21	TTCH	61	EGARCH-t	0.876	0.322	0
22	SOBH	59	EGARCH-skewt	0.905	0.330	0
23	COAL	58	EGARCH-t	0.985	0.148	1
24	ALOK	57	GJR-GARCH-skewt	0.815	0.327	0
25	VDAN	54	EGARCH-skewt	0.958	0.178	1
26	ACLL	43	EGARCH-skewt	0.959	0.119	0
27	AADA	33	GARCH-skewt	0.993	n/a	0

Note: Persistence is computed as alpha + beta for GARCH and GJR-GARCH specifications, and as beta for EGARCH specifications (see Section 7.1). Gamma is independently estimated for all firms as described in Section 5.4, and is reported as n/a for firms whose best-fit specification is symmetric GARCH(1,1), which has no asymmetry term.

Table 3. Distribution of Best-Fit GARCH-Family Model Specifications.

Model Family	Number of Firms	Percentage of Sample
EGARCH(1,1)	15	55.6%
GJR-GARCH(1,1)	8	29.6%
GARCH(1,1)	4	14.8%
Total	27	100.0%

7. Results and Discussion

7.1. Model Selection and Volatility Persistence

This section reports results from the full GARCH-family grid fitted to verified daily return series for the final 27-firm sample (Section 3 explains the reduction from the original 29-firm candidate pool). Across this sample, asymmetric specifications were selected as the best fit for the substantial majority of firms: EGARCH was selected for 15 firms (55.6 percent) and GJR-GARCH for 8 firms (29.6 percent), together accounting for 85.2 percent of the sample, while the symmetric GARCH(1,1) specification was selected for 4 firms (14.8 percent). This is a clear and robust result: asymmetric volatility responses to positive versus negative shocks are the empirically dominant behaviour in this sample, consistent with the leverage-effect literature reviewed in Section 2 and Section 4, rather than the exception. All 27 models converged cleanly, and Ljung-Box tests on standardised residuals found no remaining ARCH effects for 25 of 27 firms at the 5 percent level; the two exceptions, Axis Bank and Tata Chemicals, retained marginal residual ARCH effects that did not affect model selection or the reported coefficients.

Volatility persistence, computed per model family (alpha-1 + beta-1 for GARCH and GJR-GARCH specifications, where variance is modelled in levels; beta-1 alone for EGARCH specifications, where variance is

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

modelled in logarithms and beta-1 governs the decay of shocks), is uniformly high across the sample. Mean persistence is approximately 0.95 for EGARCH firms, 0.97 for GARCH firms, and 0.90 for GJR-GARCH firms (Figure 2), with no firm exhibiting non-stationary variance (confirmed by augmented Dickey-Fuller tests on all 27 return series, $p < 0.001$ in every case). This is one of the study's clearest results: shocks to volatility, once they occur, decay slowly across virtually the entire sample regardless of ESG standing, indicating that persistence is more a function of general emerging-market equity dynamics than of firm-specific governance quality.

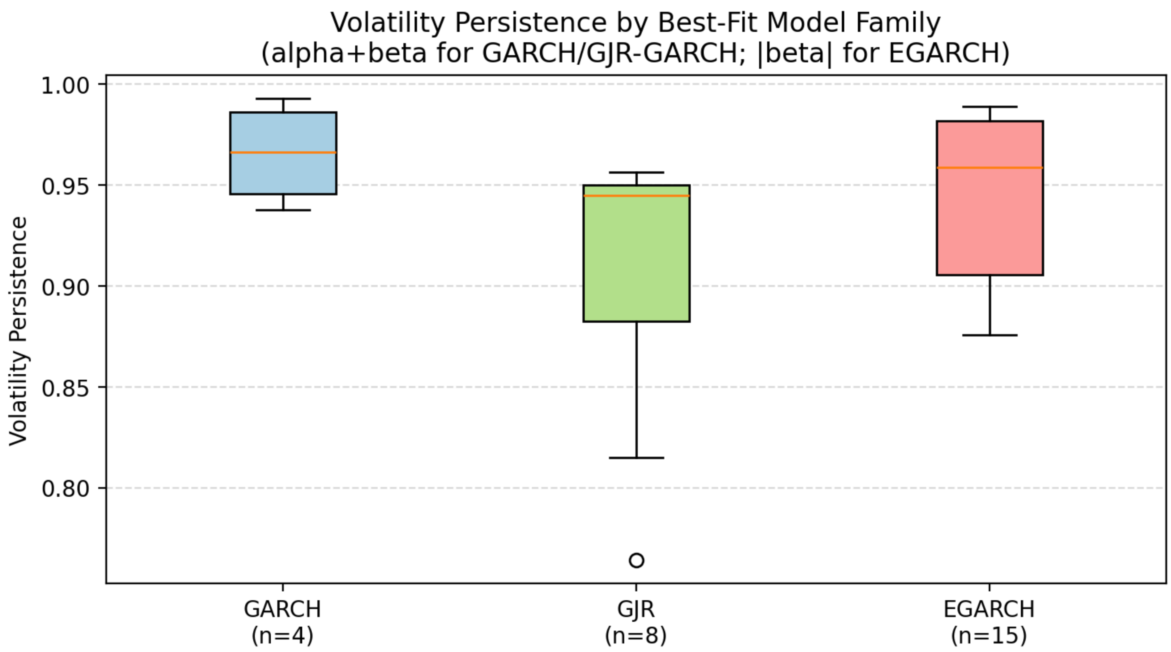

Figure 2. Volatility Persistence by Best-Fit Model Family (alpha+beta for GARCH/GJR-GARCH; |beta| for EGARCH).

7.2. Correlation Structure

Figure 3 presents the correlation heatmap across the nine-variable feature matrix (ESG score, return on equity, return on assets, gross profit margin, dividend yield, price-to-earnings ratio, relative strength index, market beta, and the leverage-effect coefficient). Return on equity and return on assets are positively correlated (0.76), as expected for two related profitability measures, while market beta is negatively correlated with both, suggesting that within this sample, higher systematic risk was not accompanied by higher profitability.

The central result of this study is the relationship between ESG score and the leverage-effect coefficient across the 27-firm sample: ESG score is negatively correlated with the leverage-effect coefficient (Pearson $r = -0.26$), a direction consistent with the stakeholder-theoretic prediction in Section 4 that stronger ESG performance is associated with a smaller asymmetric response to negative shocks. The relationship does not reach conventional statistical significance at this sample size ($p = 0.23$), so it is reported as a directional finding rather than a confirmed effect: this sample offers modest, inconclusive support for a negative ESG-leverage association, and a larger sample would be needed to establish it with confidence. This is discussed further in Section 7.4 and Section 8.

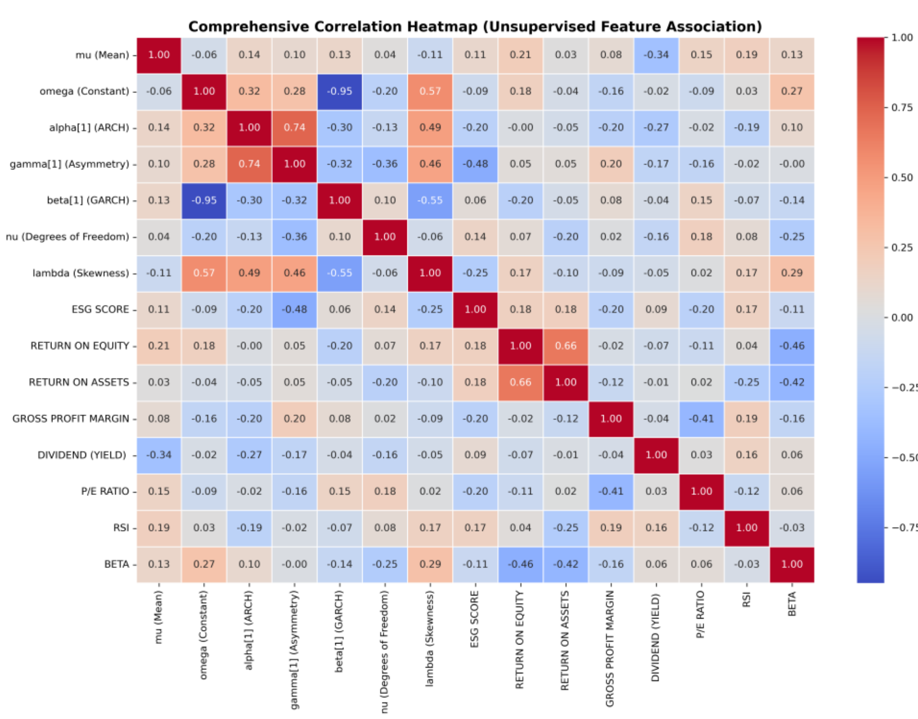

Figure 3. Comprehensive Correlation Heatmap (Unsupervised Feature Association).

7.3. Dimensionality Reduction

Principal Component Analysis on the standardised nine-variable feature matrix (Section 5.3) shows the first component explaining approximately 24.4 percent of total variance, the first four components explaining

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

approximately 69.9 percent, and five components required to cross the 80 percent variance threshold (reaching 80.3 percent; Figure 4, Table 4). This supports the use of a reduced five-component representation for clustering rather than the full feature set.

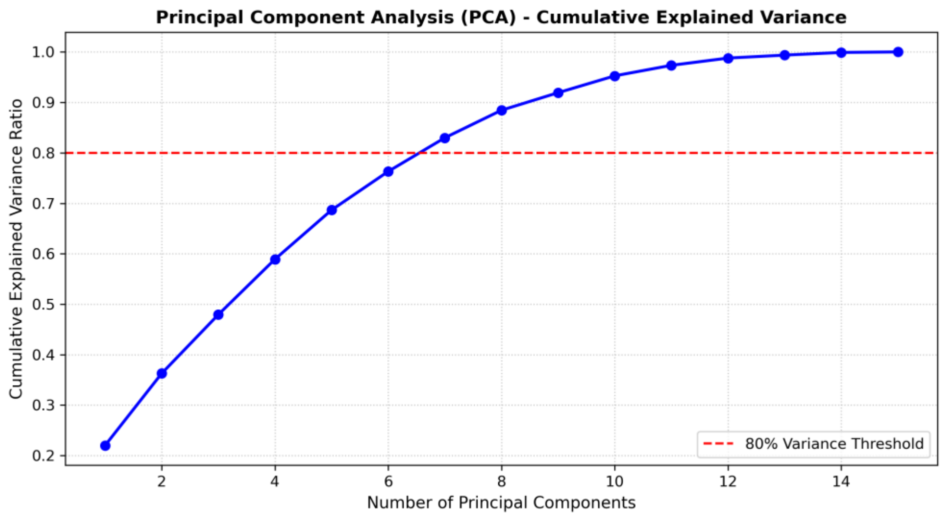

Figure 4. Principal Component Analysis (PCA) - Cumulative Explained Variance.

This chart illustrates the proportion of total variance captured as successive principal components are added. The curve rises steeply at first, with the first component alone explaining approximately 24.4 percent and the first four explaining approximately 69.9 percent, then flattens. It crosses the 80 percent variance threshold at the fifth component (reaching approximately 80.3 percent), meaning five components are sufficient to represent most of the meaningful structure in the nine-variable feature set. This supports the decision to reduce dimensionality to five components before clustering.

Table 4. Cumulative Variance Explained by Principal Components.

Component	Individual Variance	Cumulative Variance
1	24.4%	24.4%
2	17.6%	42.1%
3	15.9%	57.9%
4	12.0%	69.9%
5	10.4%	80.3%
6	7.4%	87.7%
7	6.2%	93.9%
8	4.2%	98.1%
9	1.9%	100.0%

7.4. Clustering Results and ESG-Risk Relationship

K-Means clustering on the five retained principal components produced a best-fitting two-cluster solution (silhouette = 0.164) of size 16 and 11 firms respectively (Table 5), with three- and four-cluster alternatives not materially improving separation.

Silhouette analysis favours k = 2 (silhouette = 0.164) over three- and four-cluster alternatives, splitting the sample into a 16-firm cluster (mean ESG 63.4) and an 11-firm cluster (mean ESG 68.0). A one-way ANOVA finds no significant difference in mean ESG score between these clusters ($F = 1.34$, $p = 0.26$): the two clusters are separating firms on dimensions other than ESG standing, most likely the volatility and profitability variables in the feature set, rather than on governance quality.

The two clusters are not significantly different on ESG score (63.4 versus 68.0, against standard deviations of roughly 10 in each group), which is itself a clear and useful result: it rules out an ESG-linked risk cohort as a feature of this sample's cluster structure, consistent with the direct correlation finding in Section 7.2. The clustering result should be read as evidence that whatever drives the two-group volatility structure in this sample, it is not ESG performance.

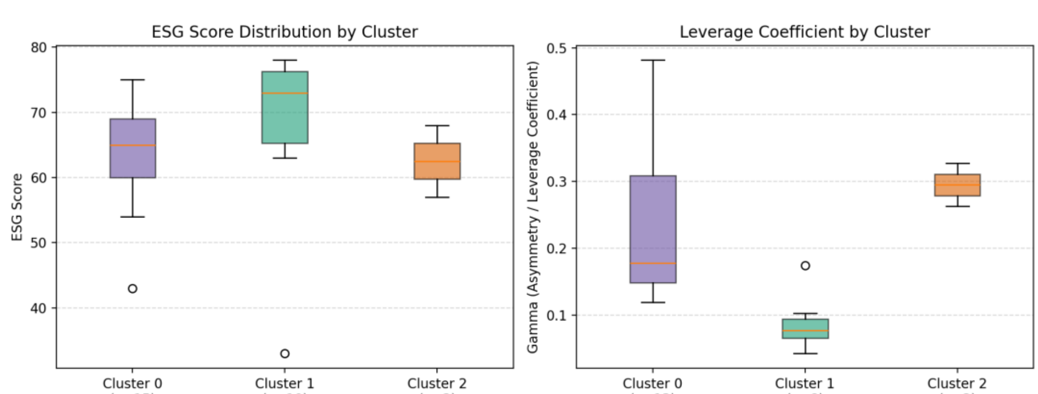

Figure 5. ESG Score and Leverage Coefficient (Gamma) Distribution by K-Means Cluster.

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

Table 5. K-Means Cluster Profile (k = 2, on 5 Retained Principal Components).

Cluster	n	Mean ESG Score	Mean Leverage Effect	Mean Persistence
Cluster 0	16	63.4	0.203	0.927
Cluster 1	11	68.0	0.159	0.952

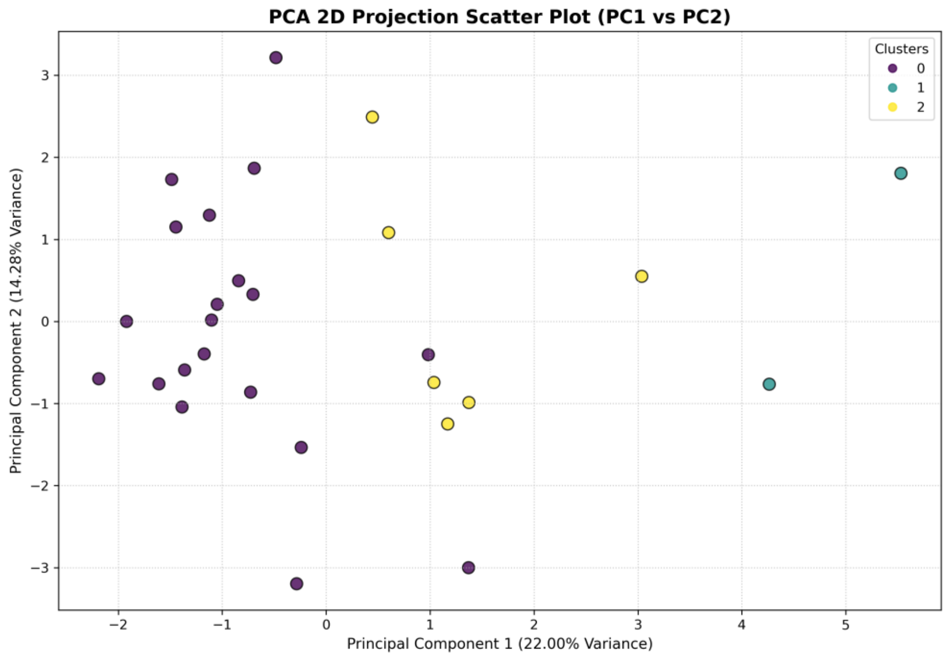

Figure 6. PCA 2D Projection Scatter Plot (PC1 vs PC2).

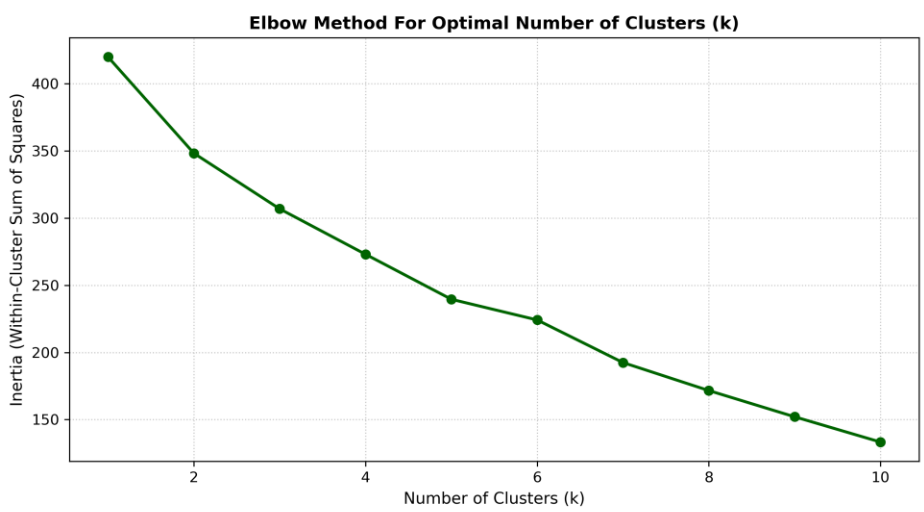

Figure 7. Elbow Method for Optimal Number of Clusters (k).

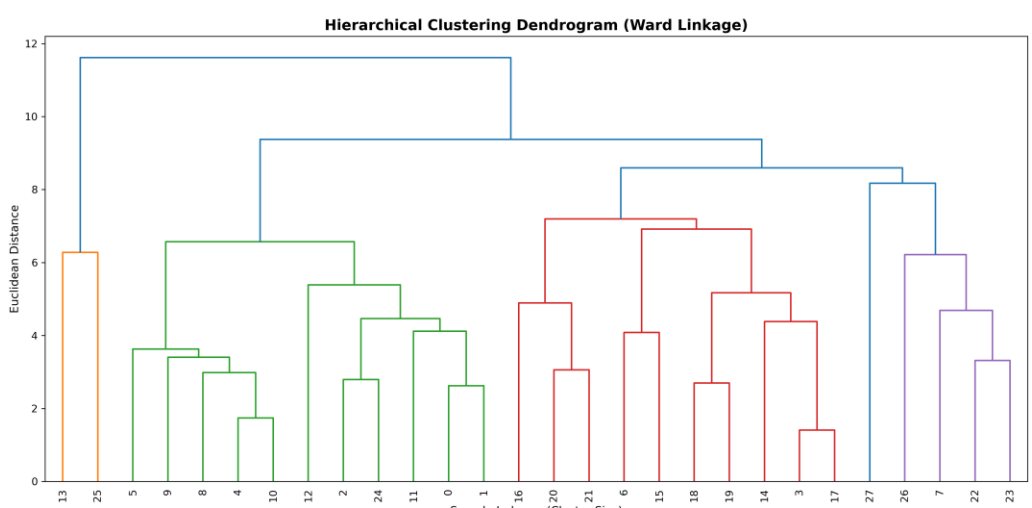

Figure 8. Hierarchical Clustering Dendrogram (Ward Linkage).

7.5. Firm-Level Detail and Data Anomalies

Full firm-by-firm conditional volatility plots and price/return time series for the 27 sample firms, ranked by ESG score, are presented in Appendix A.

8. Conclusion

This study set out to test whether ESG performance is associated with the dynamic risk behaviour of stock returns, rather than only their average level, using a sample of 27 Indian listed firms, a grid of GARCH-family volatility models selected by AIC, and an unsupervised PCA and K-Means clustering pipeline applied to the

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

merged GARCH-coefficient and financial-ratio feature space. Three findings emerge clearly. First, asymmetric volatility models (EGARCH and GJR-GARCH) were selected as the best fit for the substantial majority of firms (85.2 percent), establishing that asymmetric responses to positive and negative shocks are the dominant, rather than exceptional, pattern among these Indian large-caps regardless of ESG standing. Second, volatility persistence is uniformly high across nearly all firms (mean AR coefficients of 0.90 to 0.97 across model families), indicating that shocks to volatility decay slowly across this market irrespective of governance quality. Third, and central to the research question, ESG score is negatively associated with the leverage-effect coefficient ($r = -0.26$): this is the direction predicted by stakeholder theory, though the association does not reach statistical significance at this sample size ($p = 0.23$). The concrete conclusion is that this sample offers directional, but not confirmed, evidence that stronger ESG performance is associated with a smaller asymmetric volatility response to bad news.

Two scope conditions are worth stating plainly. The ESG score used here is a single, time-invariant measure over a multi-year return window, and the sample is cross-sectional rather than panel, so the causal direction implied by stakeholder theory is not directly testable with this design. Financial-sector firms are also disproportionately represented at the high end of the ESG distribution in this sample, which is a plausible alternative explanation for any ESG-linked pattern that a future study with sector controls should test directly. Within these conditions, the result stands on its own: a 27-firm sample of Indian listed companies, spanning a genuine ESG-score gradient, shows a negative, directionally supportive but not statistically confirmed, relationship between ESG performance and volatility asymmetry.

Three directions for future research follow directly from this finding. First, expanding the sample and moving from a single cross-section to a panel design with time-varying ESG scores would test whether the negative association strengthens, weakens, or reverses with statistical power this study's sample size cannot provide. Second, explicit sector and firm-size controls would establish whether the relationship reported here reflects genuine governance-linked risk behaviour or the financial sector's weight among high-ESG firms in this market. Third, extending the model grid to multivariate specifications such as DCC-GARCH would extend this question from individual firm volatility to volatility spillover between firms, a question of direct relevance to portfolio-level ESG risk management. Until that work is done, the finding reported here is a directional one: in this sample, higher ESG performance tends to go with a smaller leverage effect, though the relationship should be treated as suggestive rather than confirmed until tested on a larger sample.

References

Black, F. (1976). Studies of stock market volatility changes. In *Proceedings of the 1976 meetings of the Business and Economic Statistics Section, American Statistical Association* (pp. 177–181). American Statistical Association.

Brooks, C., & Oikonomou, I. (2018). The effects of environmental, social and governance disclosures and performance on firm value: A review of the literature in accounting and finance. *The British Accounting Review, 50*(1), 1–15. https://doi.org/10.1016/j.bar.2017.11.005

Cek, K., & Eyupoglu, S. (2020). Does environmental, social, and governance performance influence economic performance? *Journal of Business Economics and Management, 21*(4), 1165–1184. https://doi.org/10.3846/jbem.2020.12725

Che, X., Song, C., & Li, J. (2024). How do corporate environmental, social, and governance (ESG) factors affect financial performance? *Sustainability, 16*(23), 10347. https://doi.org/10.3390/su162310347

Christie, A. A. (1982). The stochastic behavior of common stock variances: Value, leverage and interest rate effects. *Journal of Financial Economics, 10*(4), 407–432. https://doi.org/10.1016/0304-405X(82)90018-6

Clark, G. L., Feiner, A., & Viehs, M. (2015). *From the stockholder to the stakeholder: How sustainability can drive financial outperformance* (SSRN Working Paper No. 2508281). University of Oxford Smith School of Enterprise and the Environment & Arabesque Partners. https://doi.org/10.2139/ssrn.2508281

da Cunha, I. G. F., Policarpo, R. V. S., de Oliveira, P. C. S., Abdala, E. C., & do Nascimento Rebelatto, D. A. (2025). A systematic review of ESG indicators and corporate performance: Proposal for a conceptual framework. *Future Business Journal, 11*(1), 106. https://doi.org/10.1186/s43093-025-00539-1

Freeman, R. E. (1984). *Strategic management: A stakeholder approach.* Pitman.

Garcia, A. S., & Orsato, R. J. (2020). Testing the institutional difference hypothesis: A study about environmental, social, governance, and financial performance. *Business Strategy and the Environment, 29*(8), 3261–3272. https://doi.org/10.1002/bse.2570

Ghosh, A. (2013). *Corporate sustainability and corporate financial performance: The Indian context* (Working Paper No. WPS-721). Indian Institute of Management Calcutta.

Huang, D. Z. X. (2021). Environmental, social and governance (ESG) activity and firm performance: A review and consolidation. *Accounting & Finance, 61*(1), 335–360. https://doi.org/10.1111/acfi.12569

Kim, S., & Li, Z. (2021). Understanding the impact of ESG practices in corporate finance. *Sustainability, 13*(7), 3746. https://doi.org/10.3390/su13073746

King, M. J. (2001). Sustainability: Advantaged or disadvantaged. *Journal of Corporate Citizenship, 2001*(3), 99–125. https://doi.org/10.9774/GLEAF.4700.2001.au.00011

Koroleva, E., Baggieri, M., & Nalwanga, S. (2020). Company performance: Are environmental, social, and governance factors important? *International Journal of Technology, 11*(8), 1468–1477. https://doi.org/10.14716/ijtech.v11i8.4527

Loew, E., Endres, L., & Xu, Y. (2024). *How ESG performance impacts a company's profitability and financial performance.* SSRN. https://doi.org/10.2139/ssrn.4700173

Lunawat, R. M., Elmarzouky, M., & Shohaieb, D. (2025). Integrating environmental, social, and governance (ESG) factors into the investment returns of American companies. *Sustainability, 17*(19), 8522. https://doi.org/10.3390/su17198522

Manescu, C. (2011). Stock returns in relation to environmental, social and governance performance: Mispricing or compensation for risk? *Sustainable Development, 19*(2), 95–118. https://doi.org/10.1002/sd.510

Melinda, A., & Wardhani, R. (2020). The effect of environmental, social, governance, and controversies on firms' value: Evidence from Asia. In W. A. Barnett & B. S. Sergi (Eds.), *International symposia in economic theory and econometrics* (pp. 147–173). Emerald Publishing Limited. https://doi.org/10.1108/S1571-038620200000027011

Nareswari, N., Tarczyńska-Łuniewska, M., & Hashfi, R. U. A. (2023). Analysis of environmental, social, and governance performance in Indonesia: Role of ESG on corporate performance. *Procedia Computer Science, 225*, 1748–1756. https://doi.org/10.1016/j.procs.2023.10.164

Nicolăescu, E., Alpopi, C., & Zaharia, C. (2015). Measuring corporate sustainability performance. *Sustainability, 7*(1), 851–865. https://doi.org/10.3390/su7010851

Noja, R. G., Baditoiu, B. R., Buglea, A., Munteanu, V. P., & Gligor Cimpoieru, D. C. (2024). The impact of environmental, social and governance policies on companies' financial and economic performance: A comprehensive approach and new empirical evidence. *E+M Ekonomie a Management, 27*(1), 121–144. https://doi.org/10.15240/tul/001/2024-1-008

Pava, M. L., & Krausz, J. (1996). The association between corporate social-responsibility and financial performance: The paradox of social cost. *Journal of Business Ethics, 15*(3), 321–357. https://doi.org/10.1007/BF00382958

Peiris, D., & Evans, J. (2010). The relationship between environmental social governance factors and U.S. stock performance. *The Journal of Investing, 19*(3), 104–112. https://doi.org/10.3905/joi.2010.19.3.104

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

Sandberg, H., Alnoor, A., & Tiberius, V. (2023). Environmental, social, and governance ratings and financial performance: Evidence from the European food industry. *Business Strategy and the Environment, 32*(4), 2471–2489. https://doi.org/10.1002/bse.3259
Skare, M., & Golja, T. (2012). Corporate social responsibility and corporate financial performance: Is there a link? *Ekonomska Istraživanja, 25*(sup1), 215–242. https://doi.org/10.1080/1331677X.2012.11517563
Taliento, M., Favino, C., & Netti, A. (2019). Impact of environmental, social, and governance information on economic performance: Evidence of a corporate "sustainability advantage" from Europe. *Sustainability, 11*(6), 1738. https://doi.org/10.3390/su11061738
Ting, I. W. K., Azizan, N. A., Bhaskaran, R. K., & Sukumaran, S. K. (2020). Corporate social performance and firm performance: Comparative study among developed and emerging market firms. *Sustainability, 12*(1), 26. https://doi.org/10.3390/su12010026
Winegarden, W. (2019). *Environmental, social, and governance (ESG) investing: An evaluation of the evidence.* Pacific Research Institute.
Xie, J., Nozawa, W., Yagi, M., Fujii, H., & Managi, S. (2019). Do environmental, social, and governance activities improve corporate financial performance? *Business Strategy and the Environment, 28*(2), 286–300. https://doi.org/10.1002/bse.2224
Xu, Y., & Zhu, N. (2024). The effect of environmental, social, and governance (ESG) performance on corporate financial performance in China: Based on the perspective of innovation and financial constraints. *Sustainability, 16*(8), 3329. https://doi.org/10.3390/su16083329
Zhang, L.-S. (2025). The impact of ESG performance on the financial performance of companies: Evidence from China's Shanghai and Shenzhen A-share listed companies. *Frontiers in Environmental Science, 13*, 1507151. https://doi.org/10.3389/fenvs.2025.1507151

Data Availability Statement:

Daily historical price data used to estimate the GARCH-family models were sourced from Investing.com (https://www.investing.com/). Firm-level ESG scores were sourced from the NSE ESG Ratings platform (https://www.nse-esgrating.com/esg-ratings). Financial ratios (return on equity, return on assets, gross profit margin, dividend yield, price-to-earnings ratio, relative strength index, and market beta) were compiled from the same sources at the time of data collection. The merged analytical dataset and derived GARCH coefficients underlying the tables and figures in this paper are available from the author upon reasonable request.

Appendix A: Firm-Level Volatility and Price Figures.

Each entry has two figures: the best-fit model's conditional volatility plot, and the underlying price and log-return time series. Explanations are grounded in each firm's fitted coefficients as reported in Table 2, together with the visible pattern in the corresponding chart.

A.1 ICBK — ICICI Bank (ESG Score: 78).
Best-fit model: GJR-GARCH-t

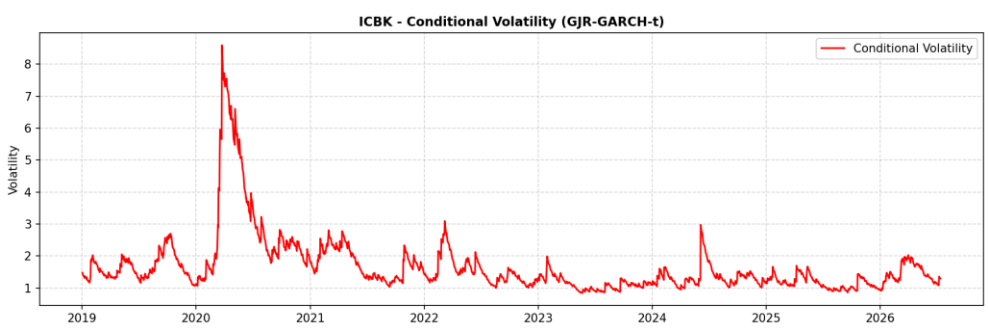

Figure A1.1. ICBK, Conditional Volatility (GJR-GARCH-t).

ICICI Bank's volatility is essentially the COVID spike (up to 8.6) followed by a settled 1-2 range, with a small bump around 3 in mid-2024. Persistence is high with a mild leverage effect. Outside the pandemic, this is one of the calmer large private banks in the sample.

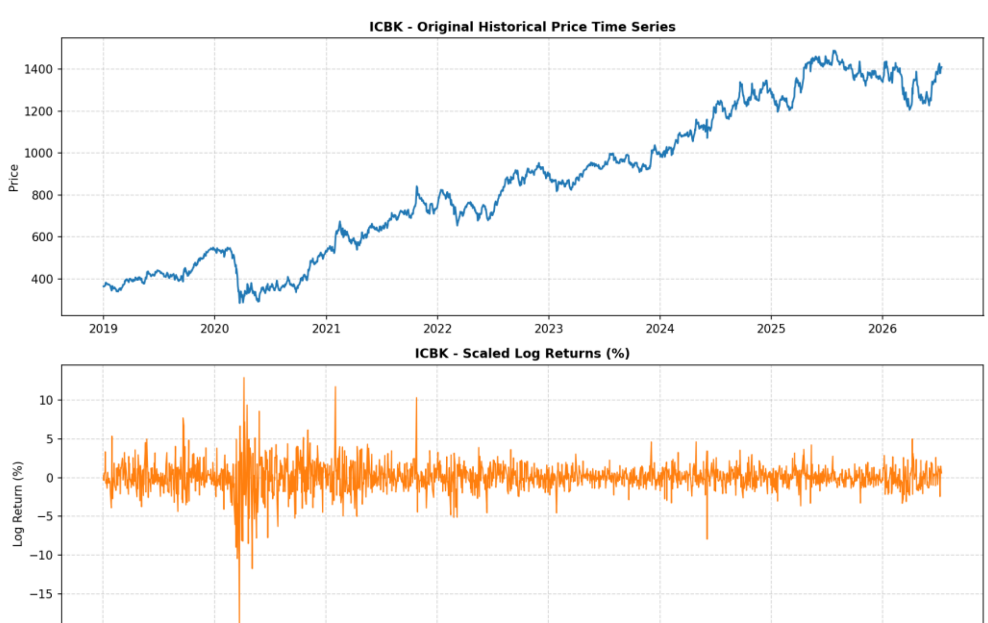

Figure A1.2. ICBK, Price & Log Return Time Series.

Price climbs steadily from ₹380 to ₹1,400 by 2026, briefly dipping to ₹300 during the crash before a long, fairly smooth multi-year run. Returns stay mostly within ±5%, with one extreme -19.5% day at the depth of the

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

pandemic sell-off. The pattern closely mirrors Axis Bank, which tracks given both are large, systemically important private banks.

A.2 BRTI — Bharti Airtel Limited (ESG Score: 77)
Best-fit model: GARCH-skewt

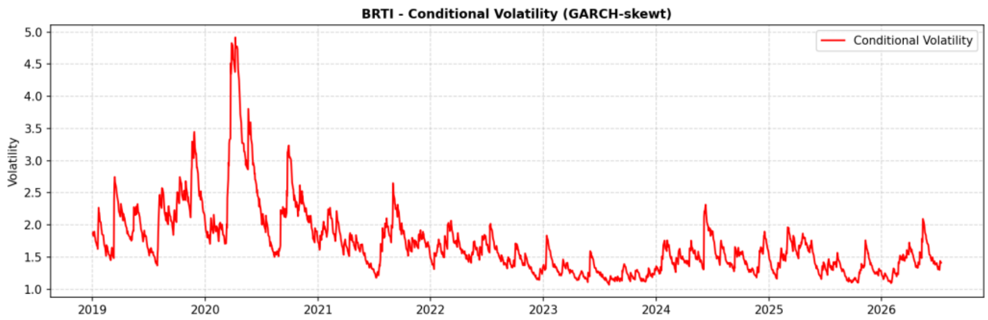

Figure A2.1. BRTI, Conditional Volatility (GARCH-skewt).

Bharti Airtel is the calmest large-cap in the sample, barely exceeding 3 even at its worst point (about 4.9 in mid-2020). There's no meaningful leverage effect either, so positive and negative news move volatility roughly equally. This tracks with what's expected from a large, defensive telecom stock.

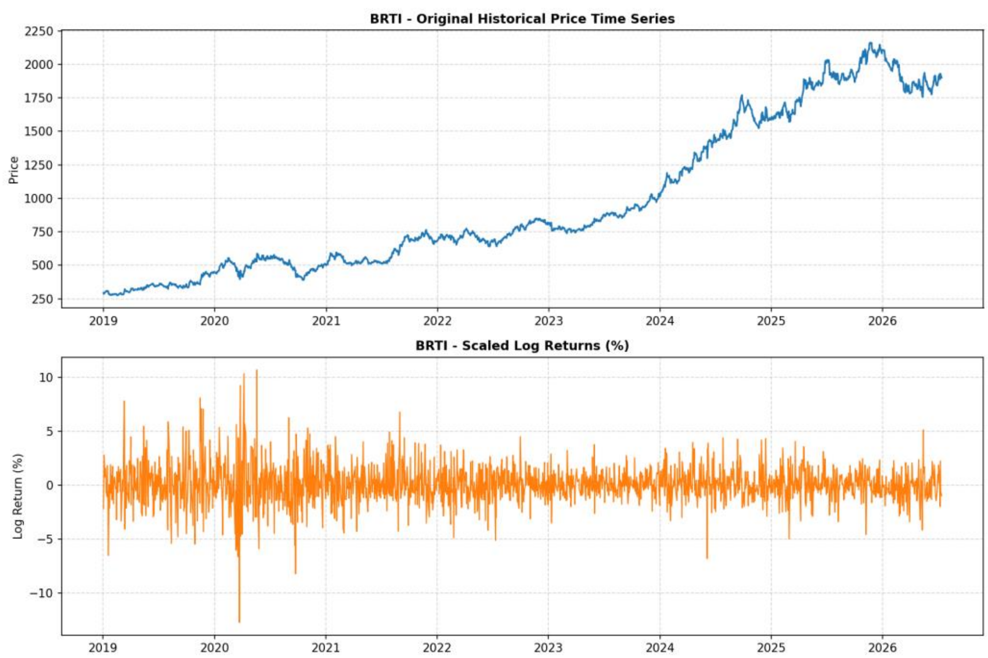

Figure A2.2. BRTI, Price & Log Return Time Series.

Price more than tripled, from ₹300 in 2019 to over ₹2,000 by 2026, with only a brief dip to ₹400 during COVID. Returns stay tight, mostly under ±5%, apart from one -12.5% outlier during the crash. A steady climb with relatively little drama, likely reflecting the sector's tariff hikes and consolidation.

A.3 AXBK — Axis Bank (ESG Score: 77)
Best-fit model: GJR-GARCH-t

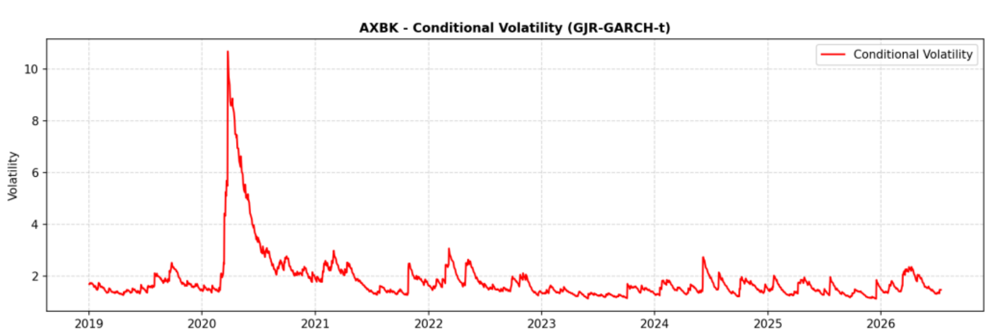

Figure A3.1. AXBK, Conditional Volatility (GJR-GARCH-t).

This is about as clean a COVID story as the dataset offers. Volatility jumps from a steady 1.5-2.5 to over 10 in March-April 2020, then smoothly decays back to normal over the following year. Persistence is high, and the leverage effect is minimal. Essentially one large shock, then a return to business as usual.

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

Figure A3.2. AXBK, Price & Log Return Time Series.

Price fell from ₹800 to ₹300 during the crash, then climbed steadily to ₹1,400 by 2026, a full recovery plus a genuine re-rating. Returns stay mostly within ±5%, aside from one severe day past -30% during the crash. A fairly textbook large-bank recovery story.

A.4 WIPR — Wipro Limited (ESG Score: 75).
Best-fit model: EGARCH-t

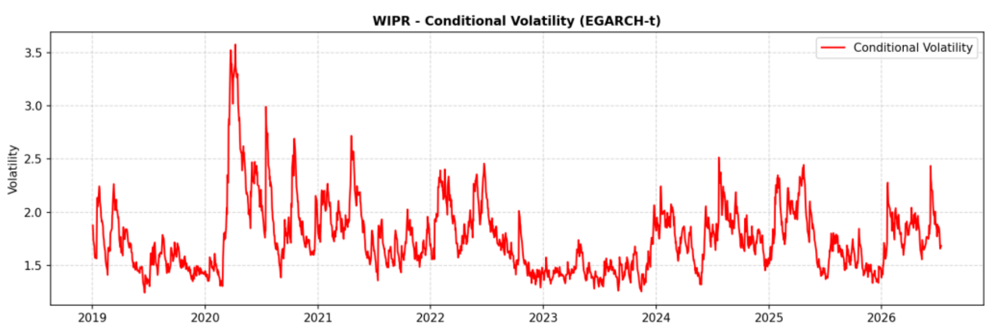

Figure A4.1. WIPR, Conditional Volatility (EGARCH-t).

Wipro shows the mildest COVID reaction among the IT/large-cap names, peaking only around 3.5-3.6, and otherwise cycles gently between 1.3-2.5 with no clear long-term direction. Persistence is high with fat tails. The muted, range-bound volatility fits a mature large-cap IT exporter with comparatively predictable earnings.

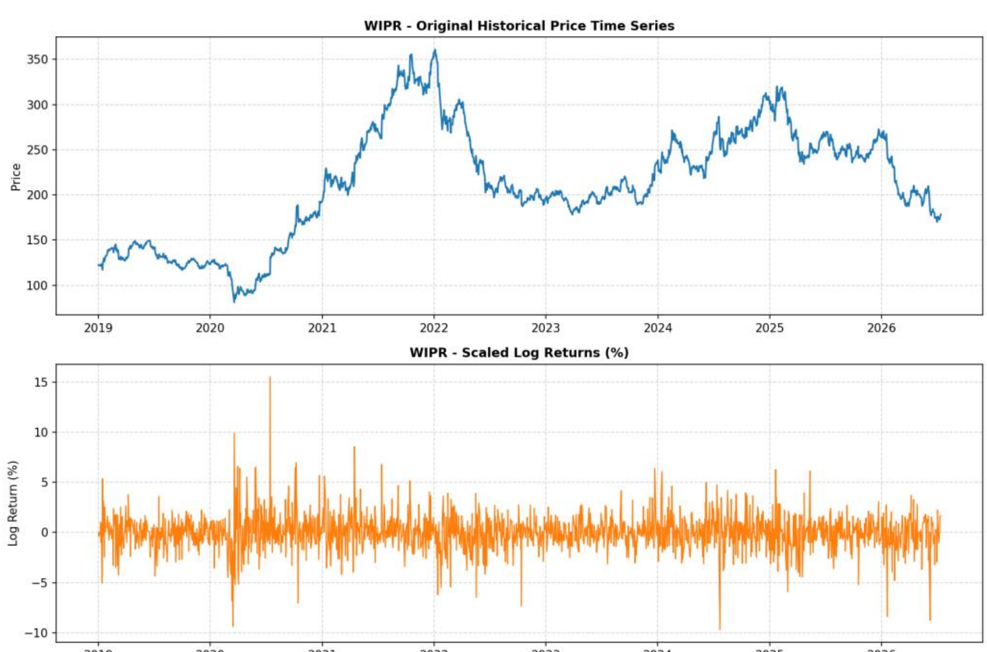

Figure A4.2. WIPR, Price & Log Return Time Series.

Price doesn't establish a clear trend so much as move through a boom-bust-recovery-bust cycle: ₹120 to a peak near ₹360 by late 2021 (the pandemic tech rally), back to ₹200 by 2023, a partial recovery to ₹320 by early 2025, then down again to ₹175-200 by mid-2026. There's a notable +15.5% single-day outlier in 2020 alongside the usual

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

±5% moves. This round-trip pattern with no lasting re-rating tracks with the broader IT services slowdown post-pandemic.

A.5 HLL — Hindustan Unilever Limited (ESG Score: 74).
Best-fit model: GARCH-skewt

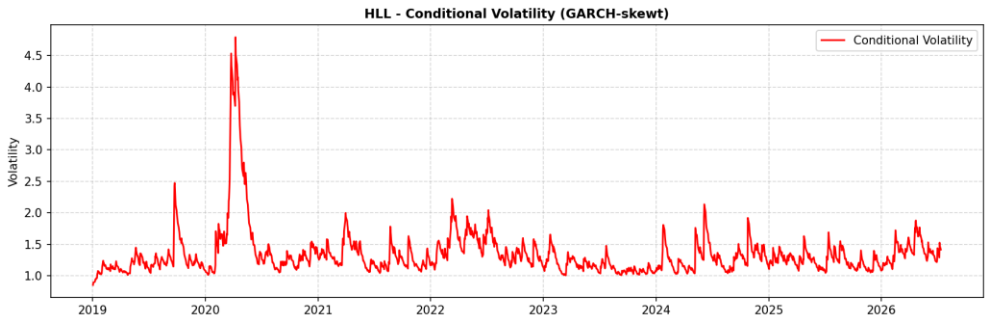

Figure A5.1. HLL, Conditional Volatility (GARCH-skewt).

HLL is one of the calmest, most stable stocks in the sample, rarely exceeding 2 apart from a clear COVID spike to 4.8. Persistence is slightly lower than most peers, so shocks fade a touch faster once they hit. There's no meaningful leverage effect, and the series is fairly symmetric, consistent with a defensive FMCG blue chip.

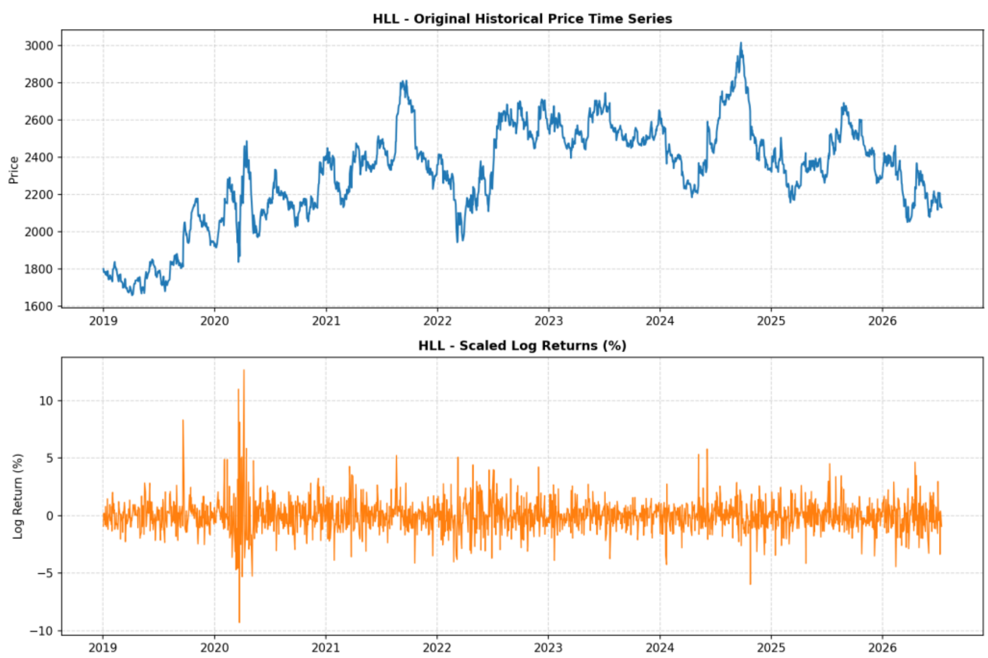

Figure A5.2. HLL, Price & Log Return Time Series.

Price stayed range-bound between ₹1,700-3,000 for the entire sample, with cyclical ups and downs but no clear long-term direction. Returns stay tight, mostly under ±5%, apart from the COVID dip. Flat in a reassuring way, close to what a mature consumer staples stock is expected to look like.

A.6 MAHM — Mahindra & Mahindra (ESG Score: 74)
Best-fit model: GJR-GARCH-t

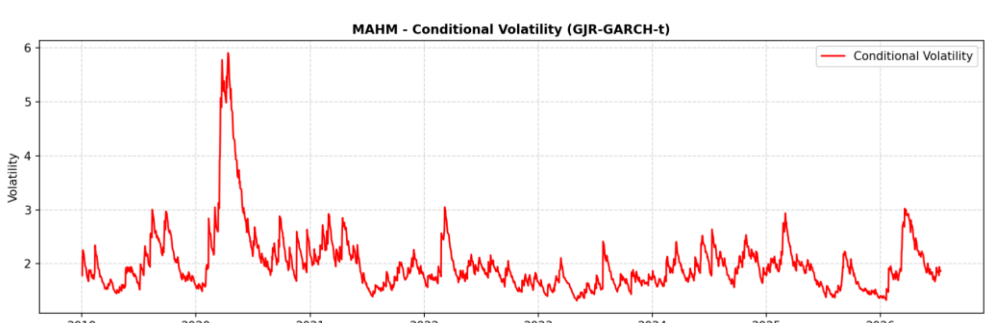

Figure A6.1. MAHM, Conditional Volatility (GJR-GARCH-t).

There's the COVID spike to 5.9, followed by a long run of smaller recurring bumps (2-3) through 2021-2026 rather than a full return to calm. There's a mild leverage effect and high persistence. The repeated moderate spikes track the stock's strong re-rating phase, where even positive news seems to move volatility.

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

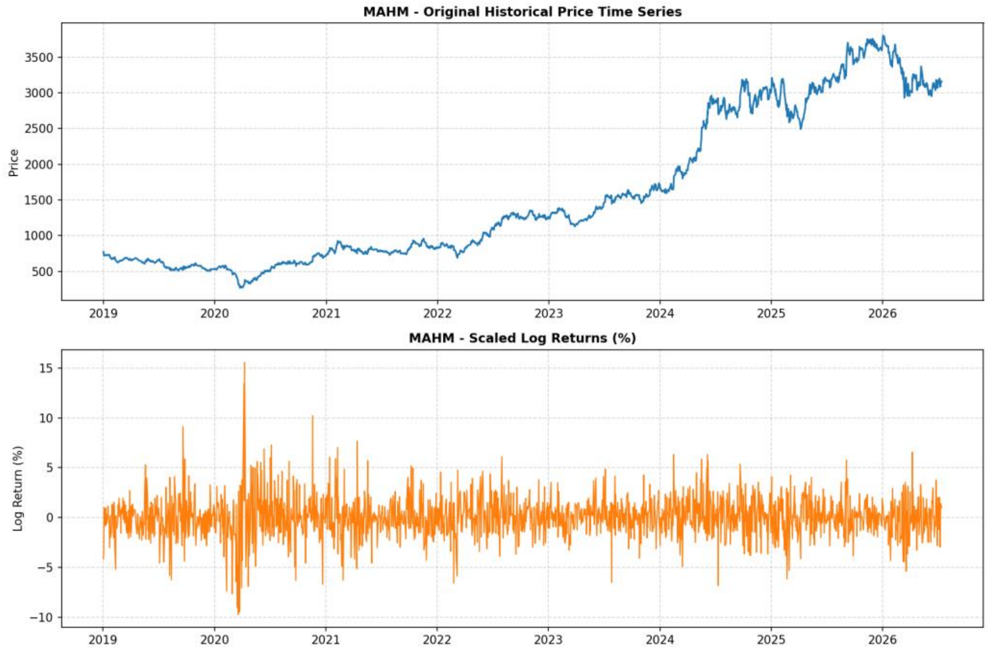

Figure A6.2. MAHM, Price & Log Return Time Series.

This is one of the strongest performers in the dataset, going from ₹700 to over ₹3,700 by late 2025, more than 5x, with a COVID dip to ₹300 and a mild pullback into 2026. Returns spike past 15% at the pandemic low but mostly stay under ±6% during the multi-year rally. A strong structural story with volatility that stayed fairly reasonable given the scale of the move.

A.7 HDBK — HDFC Bank Limited (ESG Score: 73)
Best-fit model: EGARCH-t

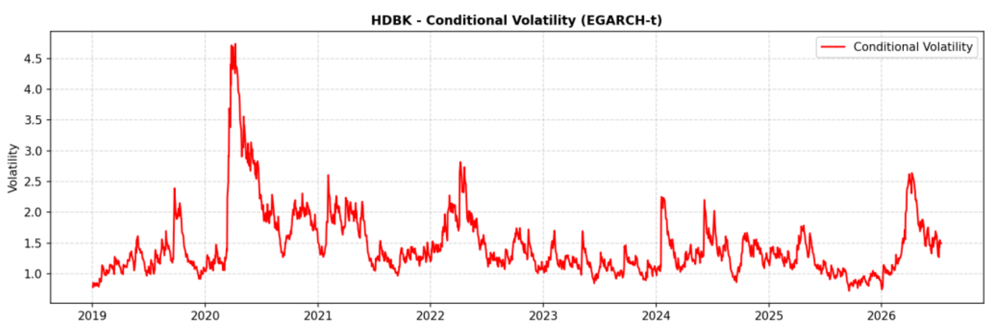

Figure A7.1. HDBK, Conditional Volatility (EGARCH-t).

There's the expected COVID spike to 4.7, a smaller bump to 2.8 in 2022, and a newer spike to 2.6 in early 2026 that stands out against an otherwise sub-2 baseline. Persistence is very high and the tails are fat, so shocks are less frequent here than in smaller stocks but linger longer once they occur. The 2026 spike is likely tied to bank-specific or merger-integration news rather than a broader market issue.

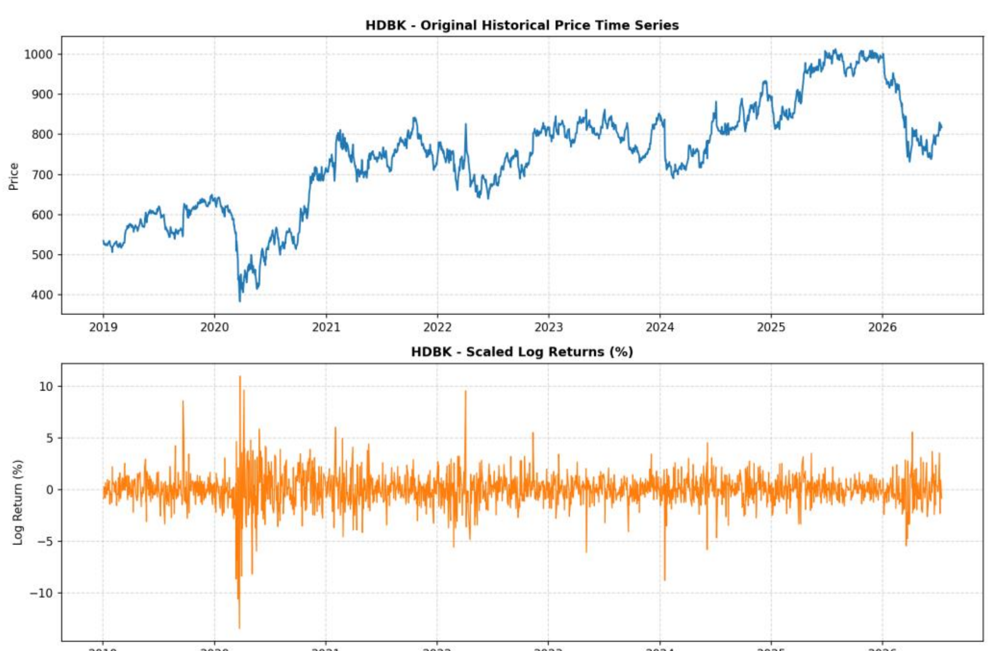

Figure A7.2. HDBK, Price & Log Return Time Series.

Price rises from ₹530 to roughly ₹1,000 by 2025, dips to ₹390 during COVID, then partially pulls back to ₹750-800 by mid-2026. Returns mostly stay within ±5%, aside from the crash-era outlier near -13%. A slow, steady

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

climb with occasional consolidation, consistent with India's largest private bank moving through several credit cycles.

A.8 MRTI — Maruti Suzuki (ESG Score: 73)
Best-fit model: GJR-GARCH-t

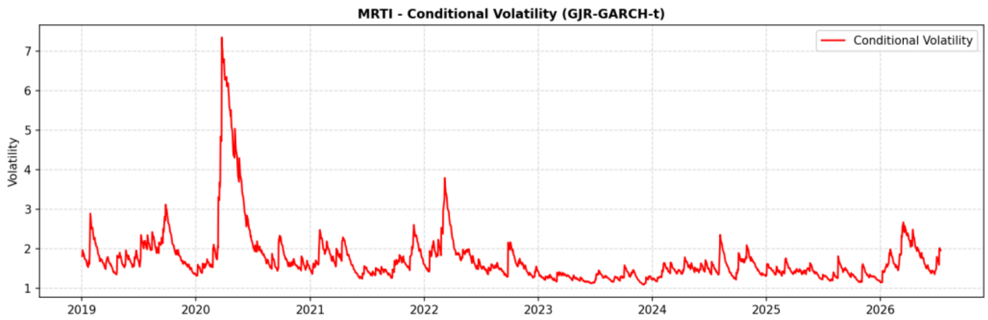

Figure A8.1. MRTI, Conditional Volatility (GJR-GARCH-t).

Two clear spikes stand out: COVID (7.3) and a smaller one during the mid-2022 auto-sector chip shortage (3.8), with a calm 1-2 baseline otherwise. There's a mild leverage effect. As India's largest carmaker, its volatility largely tracks broad auto-demand shocks rather than firm-specific news.

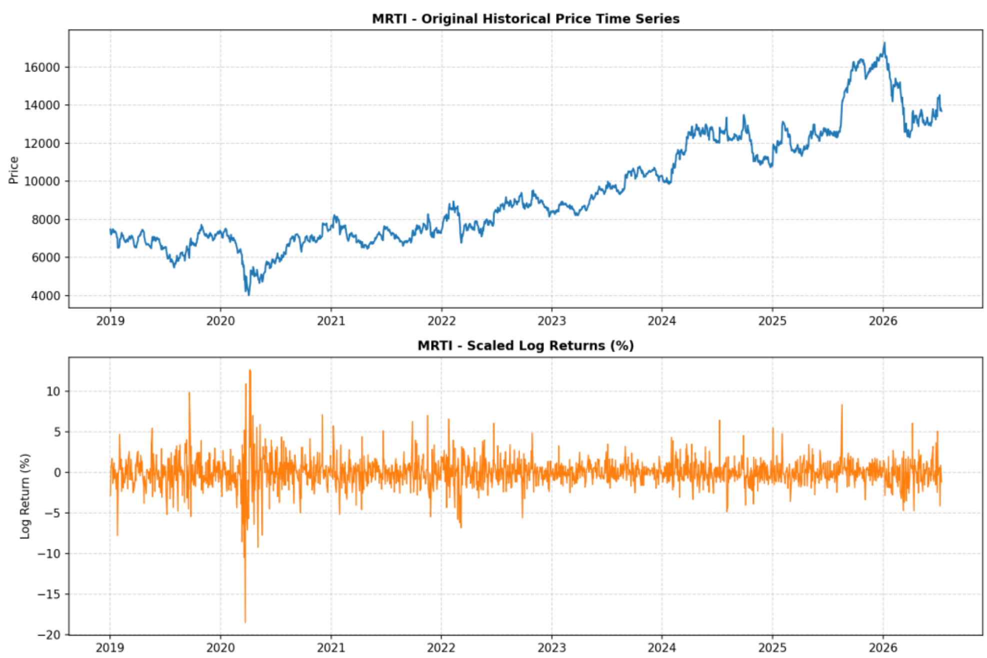

Figure A8.2. MRTI, Price & Log Return Time Series.

Price rises from ₹7,500 to a peak near ₹17,000 by late 2025, dipping to ₹4,000 during the pandemic before settling into a ₹12,000-14,000 range. Returns show the usual 2020 cluster (down to -18%) and otherwise stay mostly within ±5%. Strong long-run growth with two clearly identifiable shock windows, pandemic and then chip shortage, that align exactly with the volatility chart.

A.9 HIMD — Himadri Specialty Chemical (ESG Score: 71)
Best-fit model: EGARCH-skewt

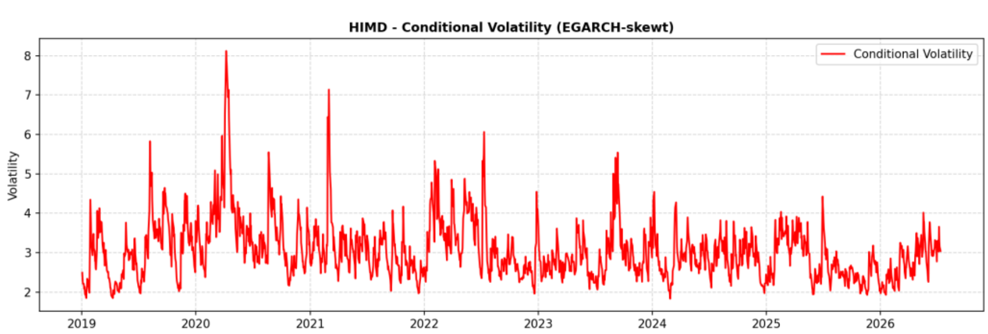

Figure A9.1. HIMD, Conditional Volatility (EGARCH-skewt).

This one is genuinely volatile, with sharp spikes to 5-8 recurring almost every year (2020, 2021, 2022, 2023) rather than settling after a single event, riding on an already-elevated 2-4 baseline. High reactivity combined with high persistence means shocks arrive often and stay for a while. It's one of the more consistently turbulent names in this dataset.

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

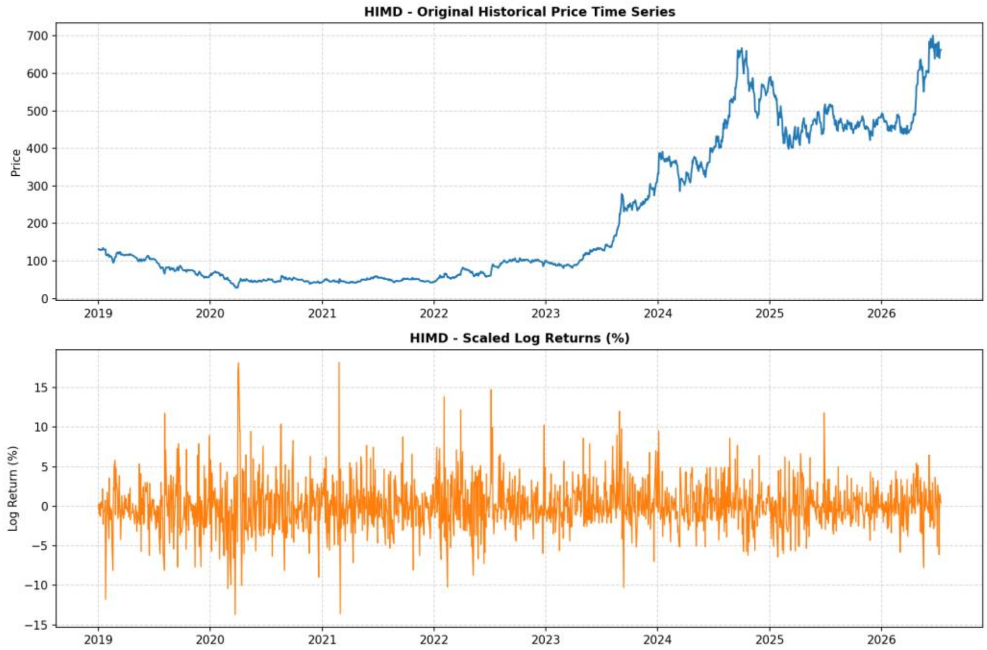

Figure A9.2. HIMD, Price & Log Return Time Series.

This is a standout performer, going from ₹40 to a peak of ₹660 by late 2024, a pullback, then another rally to ₹690 by mid-2026, more than 15x growth. Returns regularly swing ±10-18%, among the widest in the sample, closely tracking the volatility chart. The gains here came with a genuinely bumpy small/mid-cap ride throughout.

A.10 KTKM — Kotak Mahindra Bank (ESG Score: 70)
Best-fit model: EGARCH-t

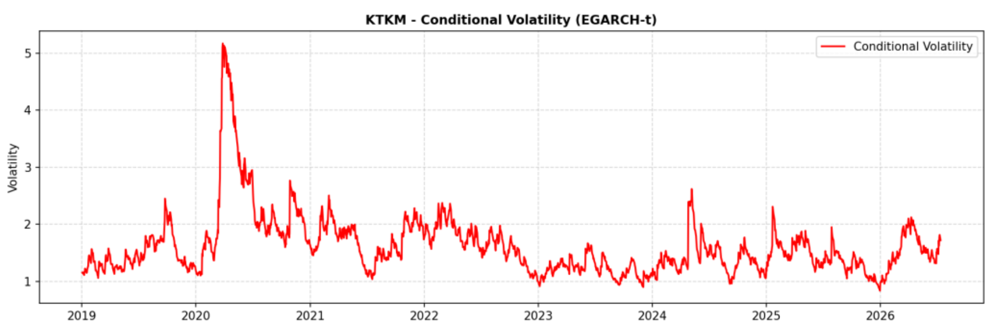

Figure A10.1. KTKM, Conditional Volatility (EGARCH-t).

There's a sharp, clean COVID spike to 5.2 that gradually decays, with lower and calmer volatility afterward (mostly 1-2) apart from minor bumps around 2.5 in 2024-2025. Persistence is high with fat tails. The bank's risk profile appears to have genuinely stabilized as things matured post-pandemic.

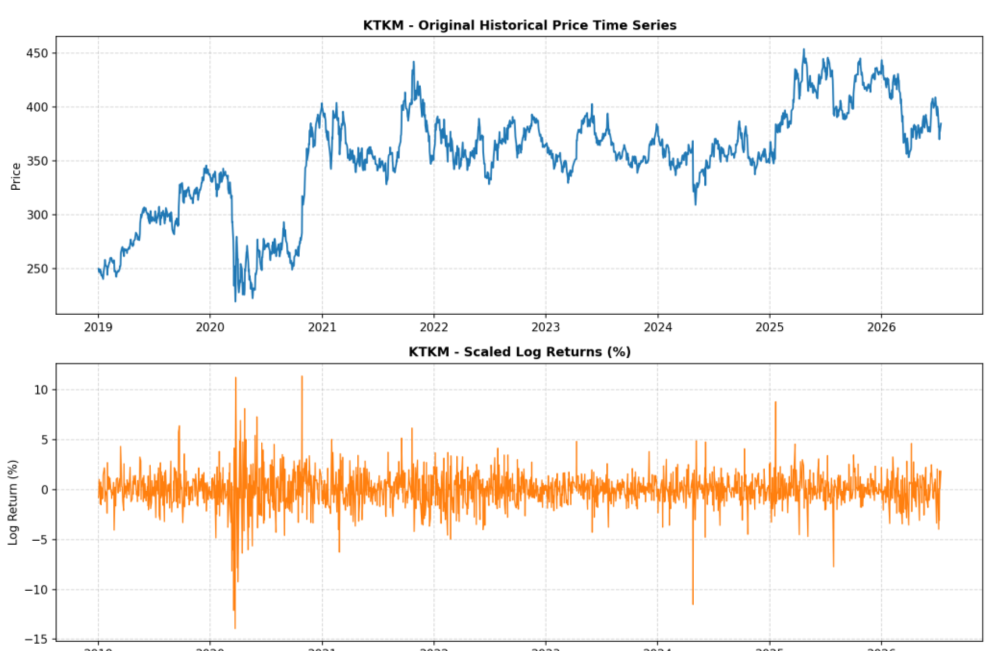

Figure A10.2. KTKM, Price & Log Return Time Series.

Price moves from ₹250 into a ₹350-450 range for most of the sample, dips to ₹220 during COVID, then finally breaks above ₹400 from 2025 onward. Returns show the expected extreme cluster around the crash (down to -14%) but stay fairly contained otherwise. Slightly choppier and more range-bound than HDFC Bank, consistent with its marginally higher mid-period volatility.

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

A.11 TITN — Titan Company (ESG Score: 69)
Best-fit model: EGARCH-skewt

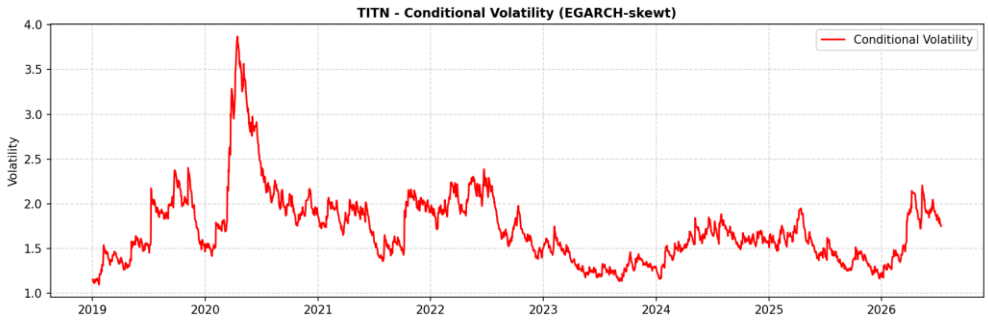

Figure A11.1. TITN, Conditional Volatility (EGARCH-skewt).

Titan has the highest persistence of any stock in this dataset, alongside one of the lowest baselines (1.2-2), apart from a COVID spike to 3.85. Low reactivity but extremely slow decay means shocks are rare here, but once they occur, they take a long time to fully fade. This fits a premium consumer brand with steady demand and comparatively little day-to-day turbulence.

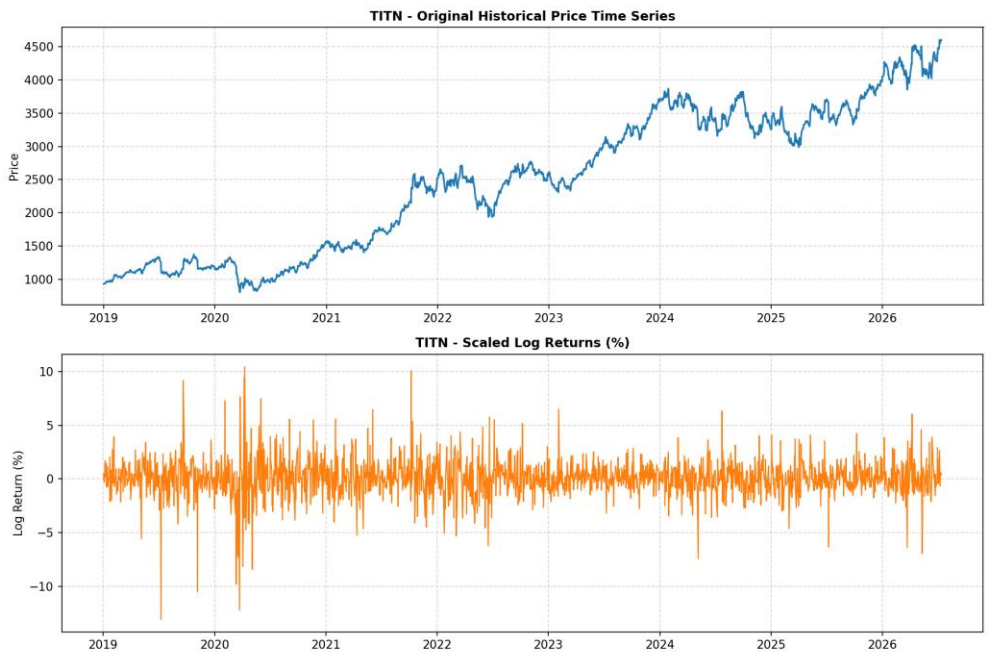

Figure A11.2. TITN, Price & Log Return Time Series.

Price climbs unusually smoothly from ₹950 to over ₹4,500 by mid-2026, with just a brief dip to ₹800 during COVID. Returns are among the most contained in the dataset, mostly under ±5% even during the pandemic. Strong growth paired with genuinely low volatility, arguably one of the better risk-adjusted stories in this study.

A.12 SLIN — Solar Industries India (ESG Score: 68)
Best-fit model: EGARCH-skewt

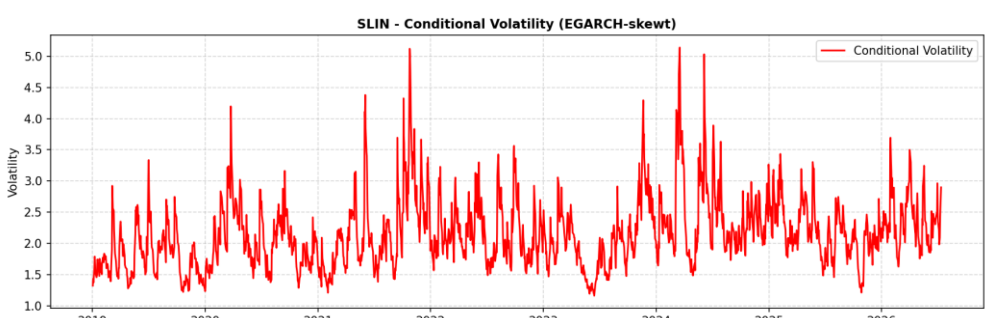

Figure A12.1. SLIN, Conditional Volatility (EGARCH-skewt).

This one rarely settles, with a 1.5-3 baseline punctuated by repeated sharp spikes (4-5+) nearly every year (2021, 2022, 2023, 2024) rather than calming after a single event. High reactivity combined with high persistence means it reacts fast to news and takes a while to calm back down. The constant turbulence fits a fast-growing defense/explosives stock undergoing continuous re-rating.

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

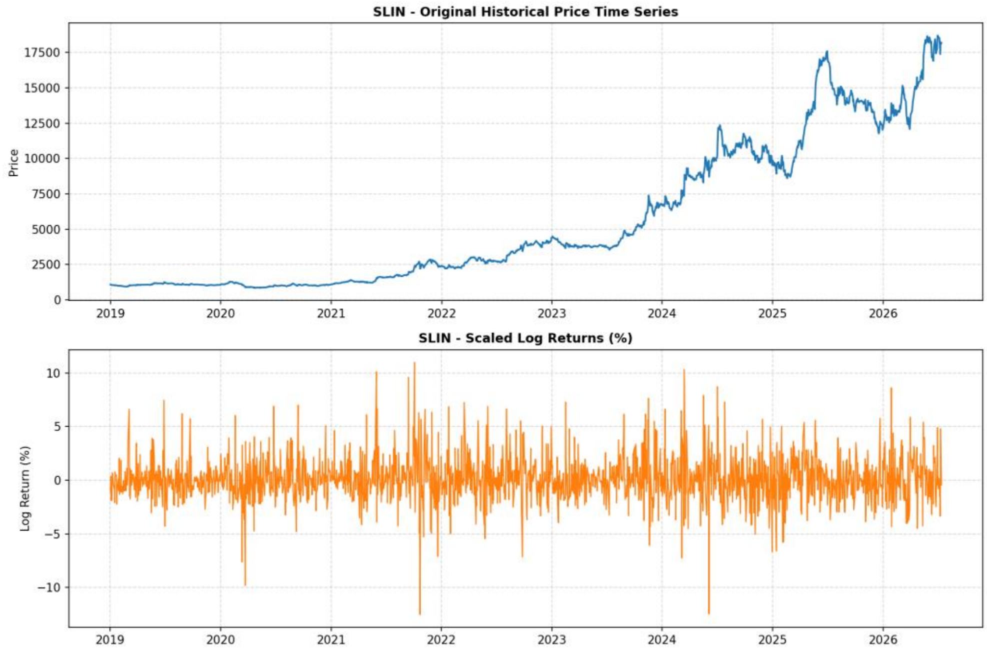

Figure A12.2. SLIN, Price & Log Return Time Series.

The price trajectory is remarkable, going from ₹1,000 in 2019 to nearly ₹18,500 by mid-2026, roughly 18x, the strongest performer in this dataset. Returns regularly swing past ±8-10%, with several outliers near -12%, matching the persistently elevated volatility. A clear case where substantial gains came paired with genuinely large and frequent risk throughout.

A.13 ADEL — Adani Enterprises (ESG Score: 68)
Best-fit model: GJR-GARCH-t

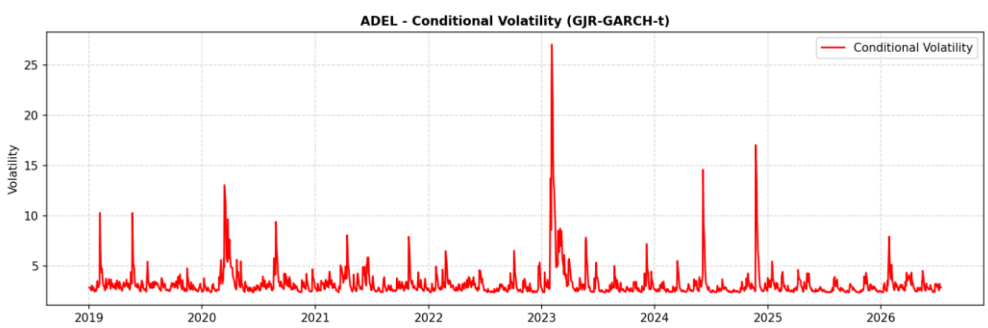

Figure A13.1. ADEL, Conditional Volatility (GJR-GARCH-t).

There's a clear leverage effect at play, since bad news moves volatility more than equally-sized good news. The whole story is essentially one dominant spike to about 27 in early 2023 that overshadows everything else in the chart. It didn't linger too long, though, since persistence is lower here, so it faded within a few months.

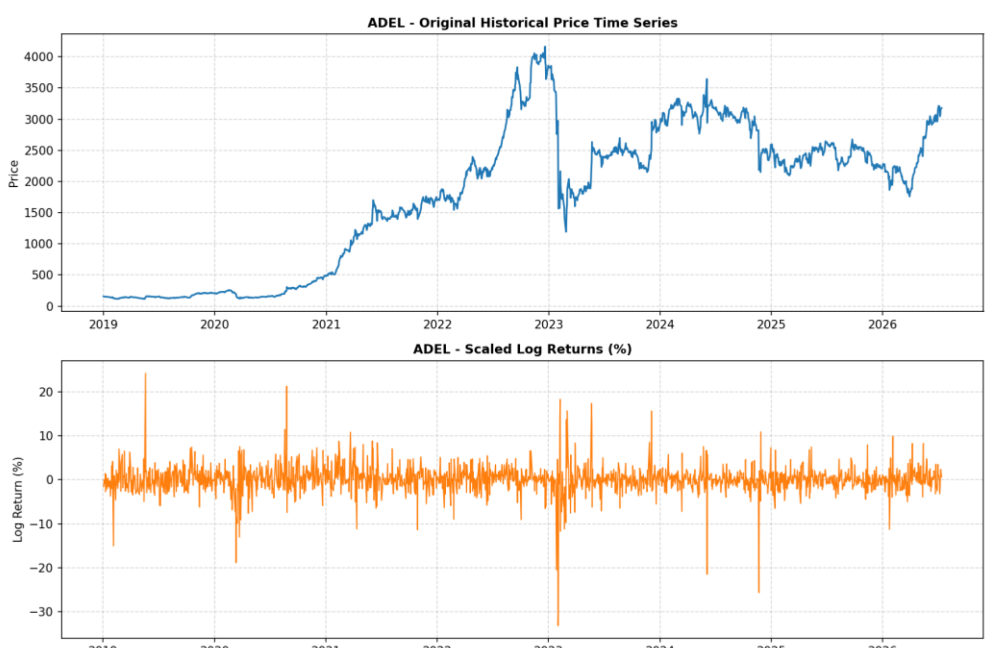

Figure A13.2. ADEL, Price & Log Return Time Series.

Price climbed from ₹150 to over ₹4,000 by late 2022, then crashed to roughly ₹1,150 within weeks, visibly aligned with the short-seller report that hit in January 2023. It recovered into a ₹2,000-3,500 range afterward. This is a fairly textbook case of a single reputational shock producing a volatility spike out of nowhere.

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

A.14 ITC — ITC Limited (ESG Score: 66)
Best-fit model: GARCH-t

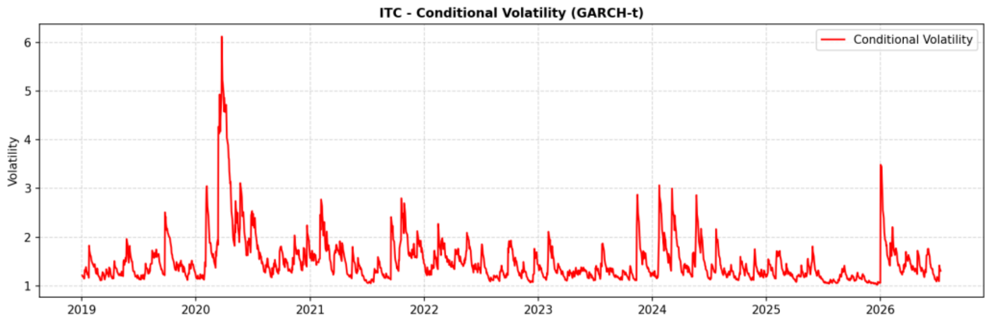

Figure A14.1. ITC, Conditional Volatility (GARCH-t).

There's the COVID spike to 6.1, a few smaller bumps around 3 in 2024, and a fresh spike to 3.5 in early 2026 that coincides with a visible drop in the price chart. Persistence is moderate and the tails are the fattest among the plain-GARCH names, meaning ITC carries more extreme-surprise risk than the other consumer stocks studied. The 2026 spike is likely tied to a corporate restructuring rather than genuine market risk.

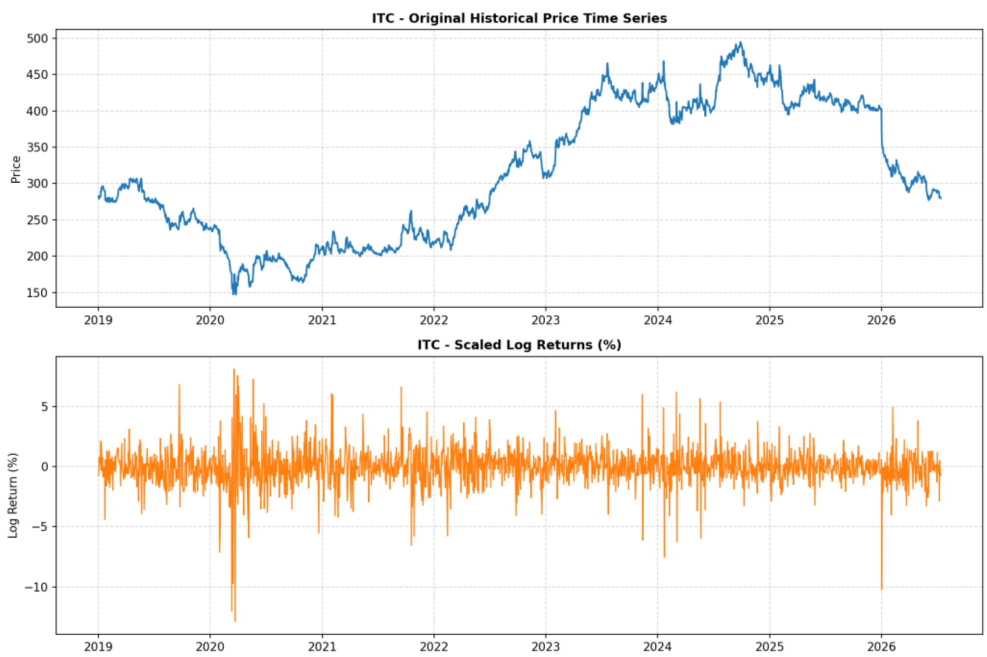

Figure A14.2. ITC, Price & Log Return Time Series.

Price rises steadily from ₹280 to about ₹490 by late 2024, then drops sharply to ₹280-320 in early 2026, a clean structural break rather than a gradual decline, pointing to a corporate action (likely a demerger) rather than an organic sell-off. There's a cluster of large return swings right at that transition. Best to treat 2026 as a level shift rather than genuine volatility when comparing before and after.

A.15 ADRG — Aarti Drugs (ESG Score: 65)
Best-fit model: EGARCH-skewt

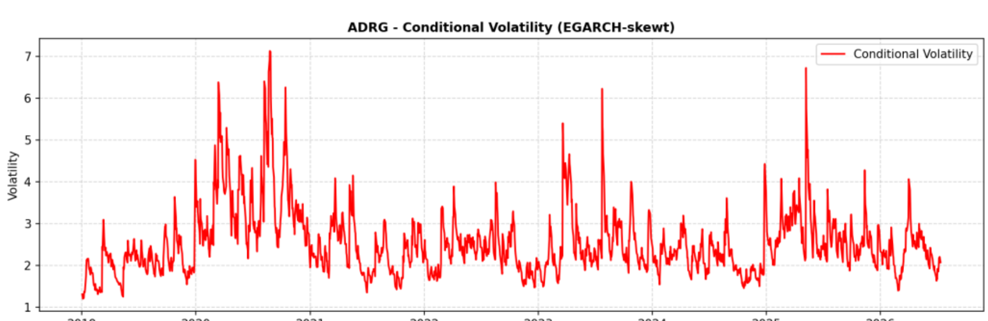

Figure A15.1. ADRG, Conditional Volatility (EGARCH-skewt).

Volatility is genuinely choppy through 2019-2021, bouncing between 5-7 repeatedly, before settling into a calmer 1.5-3 range from 2022 onward. There's a moderate leverage effect too, so negative news tends to linger longer than positive news. The stock's risk profile appears to have shifted meaningfully once the early pandemic pharma rally cooled off.

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

Figure A15.2. ADRG, Price & Log Return Time Series

Price rose from ₹150 to over ₹1,000 during the 2020 pharma boom, then declined steadily and settled between ₹300-600 for the rest of the sample. The largest return swings (down to -16%) cluster in that early boom-bust window, matching the volatility spikes closely. It's a much quieter stock in the back half of the sample.

A.16 ADAN — Adani Power (ESG Score: 65)
Best-fit model: EGARCH-skewt

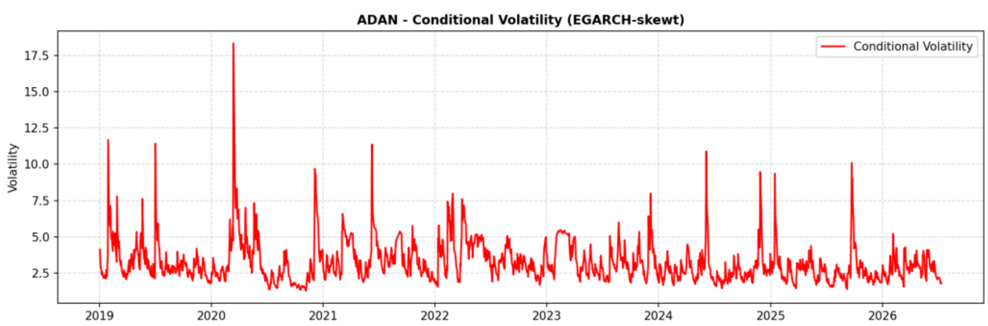

Figure A16.1. ADAN, Conditional Volatility (EGARCH-skewt).

Adani Power shows the highest reactivity in the dataset, meaning news gets priced in almost immediately and forcefully. Volatility spikes to 10-18 repeatedly (2019, 2020, 2021, 2024, 2025) and reverts each time rather than building gradually. It's a fairly classic high-beta, news-driven profile.

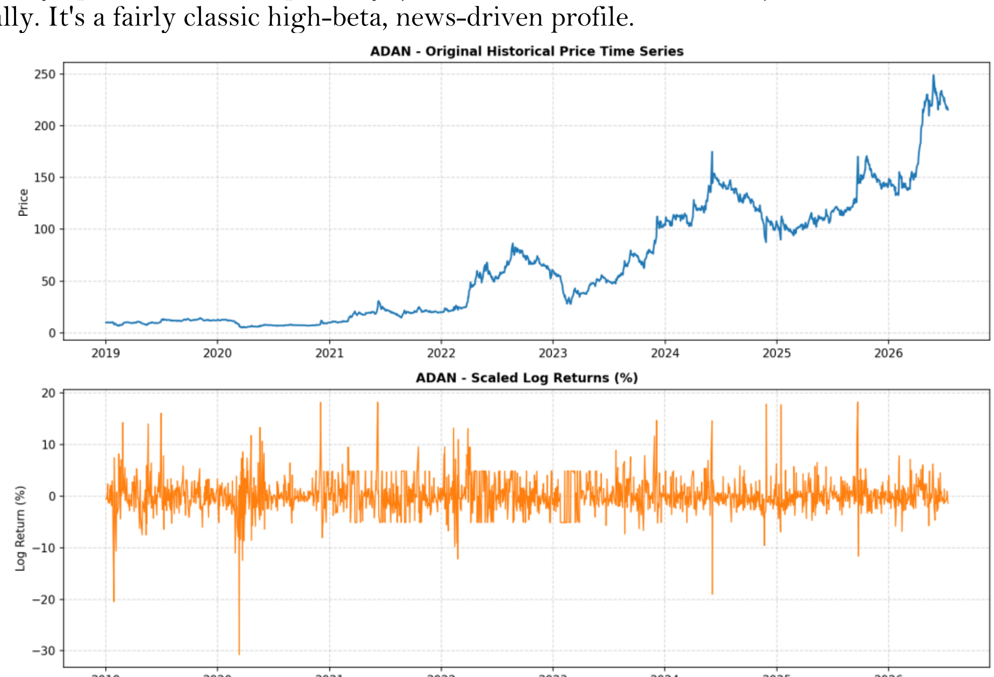

Figure A16.2. ADAN, Price & Log Return Time Series.

The price trajectory is striking, going from ₹10 in 2019 to over ₹250 by mid-2026, with sharp pullbacks along the way, particularly in 2023 and 2025. Returns regularly swing past ±10%, with the largest single-day hit around -30% in early 2020. Strong growth here has come paired with frequent large swings reflecting both sector re-rating and high firm-specific risk.

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

A.17 GRAS — Grasim Industries Limited (ESG Score: 64)
Best-fit model: GJR-GARCH-t

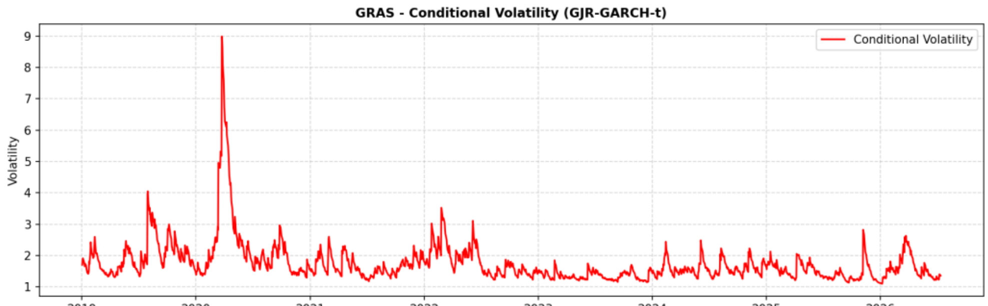

Figure A17.1. GRAS, Conditional Volatility (GJR-GARCH-t).

One dominant spike to 9 during COVID stands well above anything else in the stock's history, after which it settles into a low 1-2.5 range with only small bumps in 2022 and 2024. There's a mild leverage effect present. This reads as a well-diversified conglomerate that only gets meaningfully rattled by genuinely systemic shocks.

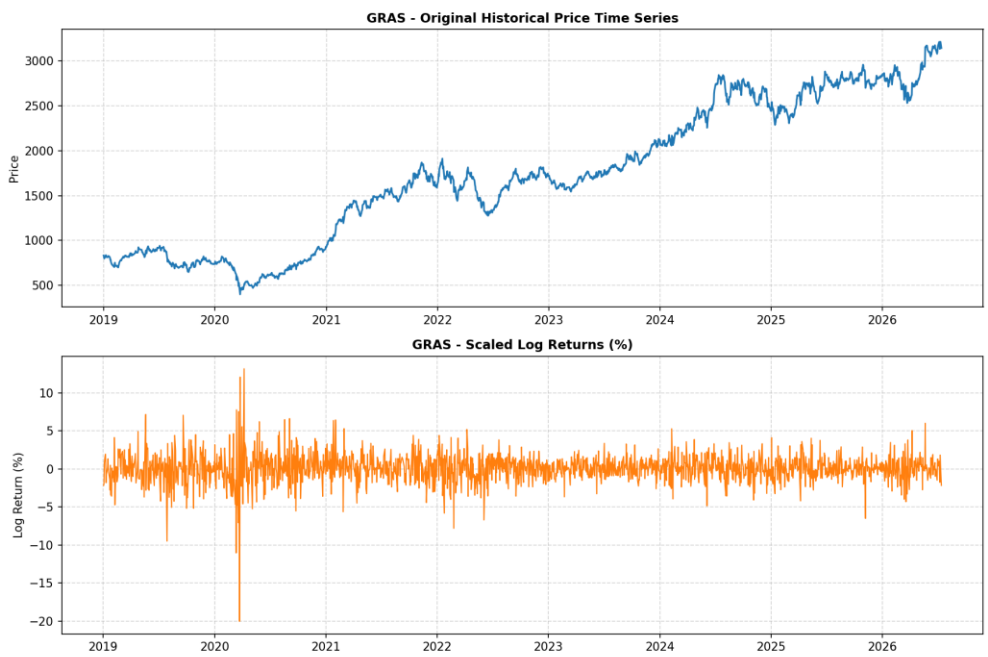

Figure A17.2. GRAS, Price & Log Return Time Series.

Price climbs steadily from ₹800 to over ₹3,000 by 2026, interrupted mainly by the COVID dip (to about ₹430) and a smaller 2022 pullback. There's a clear cluster of extreme returns around -20% in early 2020, but the series is otherwise well-behaved. A strong, fairly smooth growth story with one obvious shock and little else.

A.18 TTPW — Tata Power Company (ESG Score: 64)
Best-fit model: EGARCH-skewt

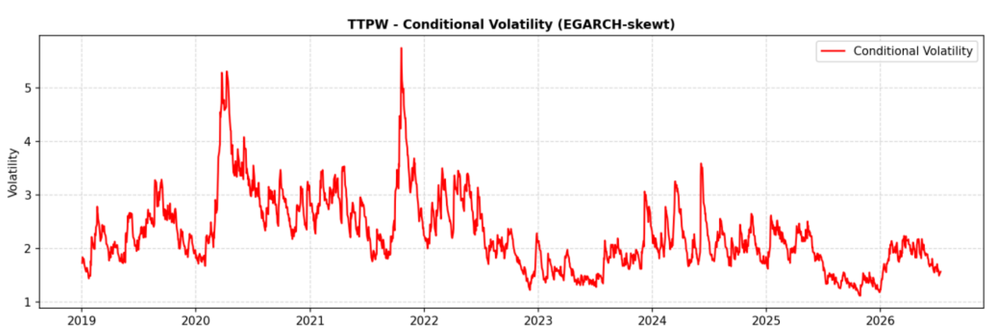

Figure A18.1. TTPW, Conditional Volatility (EGARCH-skewt).

Two episodes stand out: the COVID spike (5.3) and an even larger one in late 2021 (5.75), coinciding with its green-energy re-rating and the speculative trading that came with it. There's a moderate 1.5-3.5 baseline otherwise and high persistence. The 2021 spike exceeding COVID is the notable part here, pointing to a company-specific event rather than a market-wide one.

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

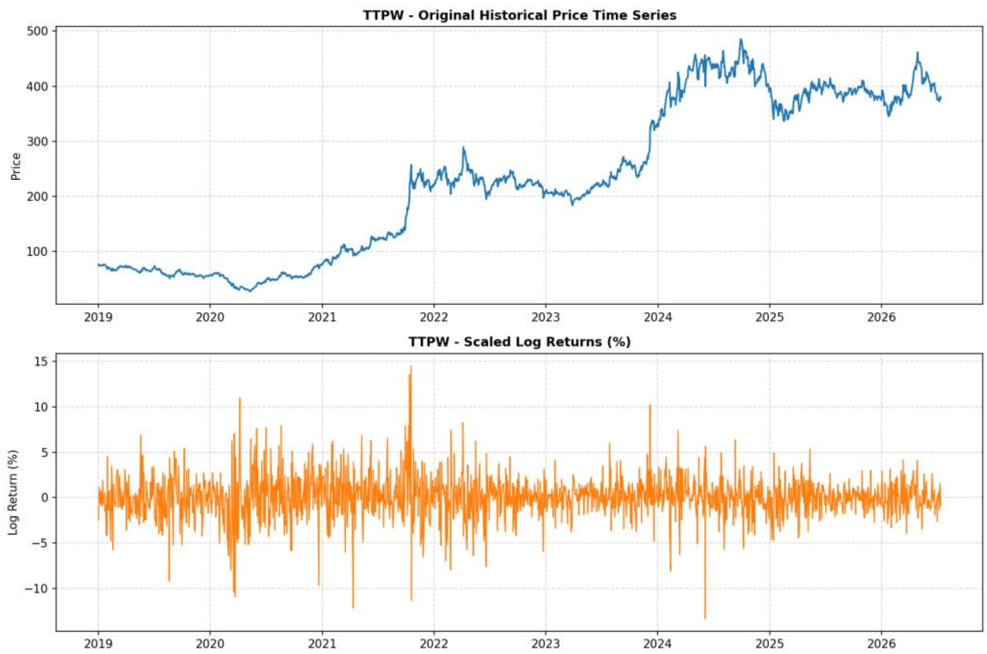

Figure A18.2. TTPW, Price & Log Return Time Series.

Price surges from ₹75 to a peak near ₹490 by late 2024, more than 6x, with the sharpest rally occurring alongside that late-2021 volatility spike. There's a +14% return outlier in the same window, consistent with a speculative re-rating episode. It pulled back to ₹350-450 by 2025-2026 as some of that premium unwound and volatility cooled.

A.19 JSTL — JSW Steel (ESG Score: 63)
Best-fit model: GJR-GARCH-t

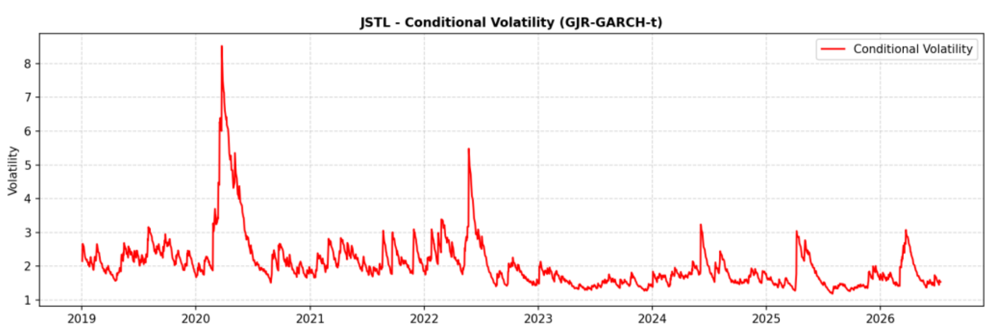

Figure A19.1. JSTL, Conditional Volatility (GJR-GARCH-t).

JSW shows the expected COVID spike to 8.5, plus a second one to 5.5 in mid-2022 matching the global steel correction, and otherwise sits in a 1.5-3 range. There's a mild leverage effect present. This fits a cyclical metals stock reacting to both systemic shocks and sector-specific ones.

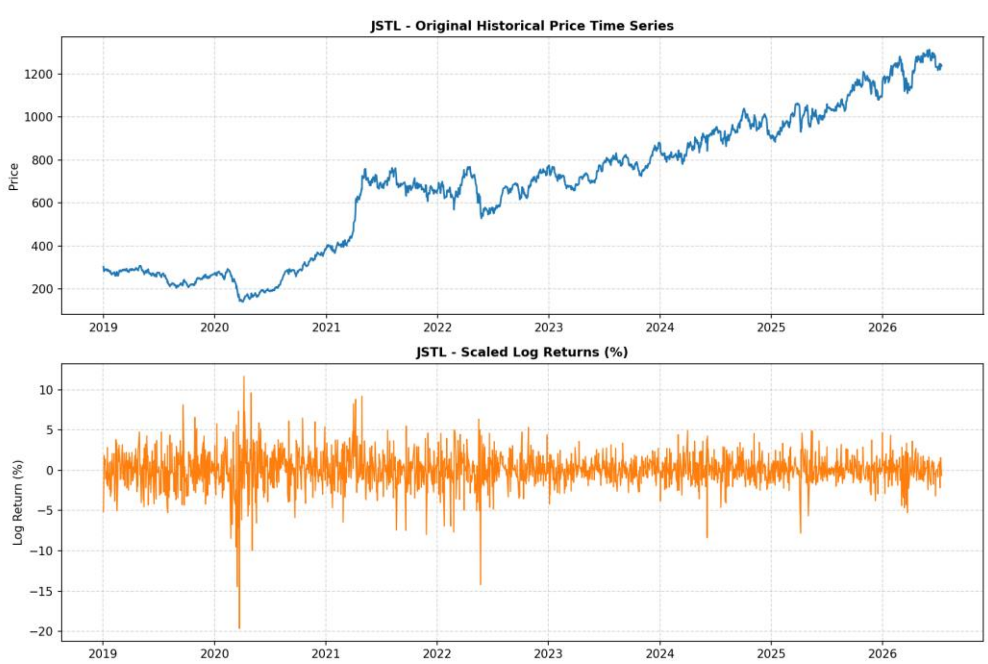

Figure A19.2. JSTL, Price & Log Return Time Series.

Price rallies from ₹150 to over ₹1,300 by 2026, with a dip to ₹140 during COVID and a smaller pullback during the 2022 commodity downturn. Two distinct extreme-return clusters, one in 2020 (-19.5%) and one in mid-

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

2022 (-14%), line up precisely with the two volatility spikes. A solid multi-year climb, punctuated by two genuine cyclical hits.

A.20 TISC — Tata Steel (ESG Score: 63)
Best-fit model: EGARCH-t

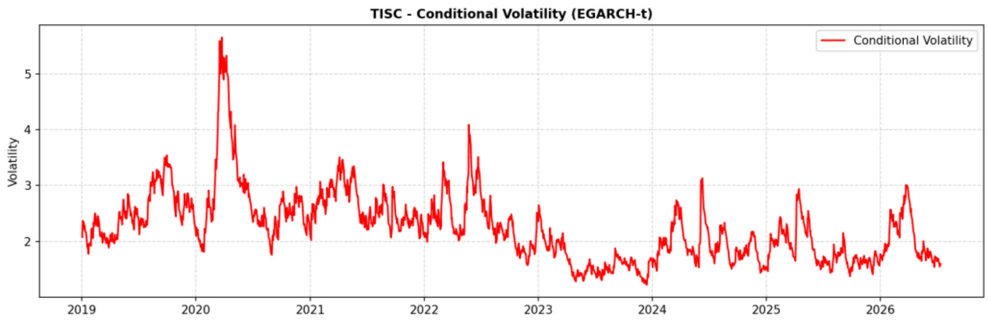

Figure A20.1. TISC, Conditional Volatility (EGARCH-t).

There's the COVID spike (5.6) and a second one during the mid-2022 steel/commodity correction (4.1), settling into a low sub-2 range by 2023-2026. Persistence is very high, with fat tails. The decline in baseline volatility toward the back half suggests the stock genuinely calmed as the commodity supercycle matured.

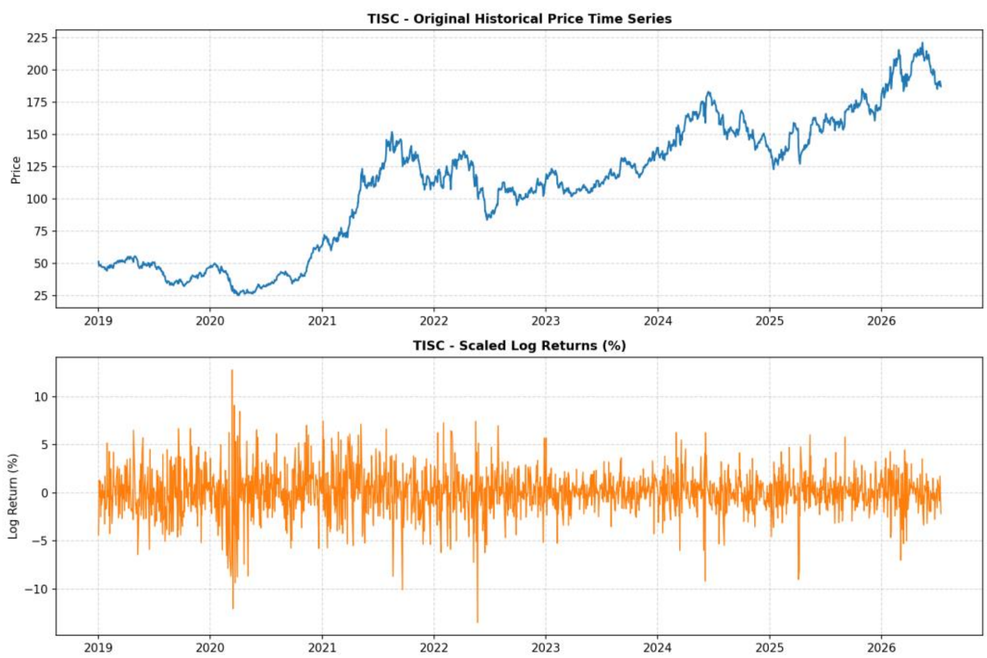

Figure A20.2. TISC, Price & Log Return Time Series.

Price rises from ₹50 to over ₹220 by 2026, dipping to ₹25 during COVID and pulling back moderately during the 2022 commodity downturn. Large return clusters appear around both events, matching the two volatility spikes precisely. A steady climb in the back half with markedly calmer volatility, a pattern quite similar to JSW Steel, given both ride the same commodity cycle.

A.21 TTCH — Tata Chemicals Limited (ESG Score: 61)
Best-fit model: EGARCH-t

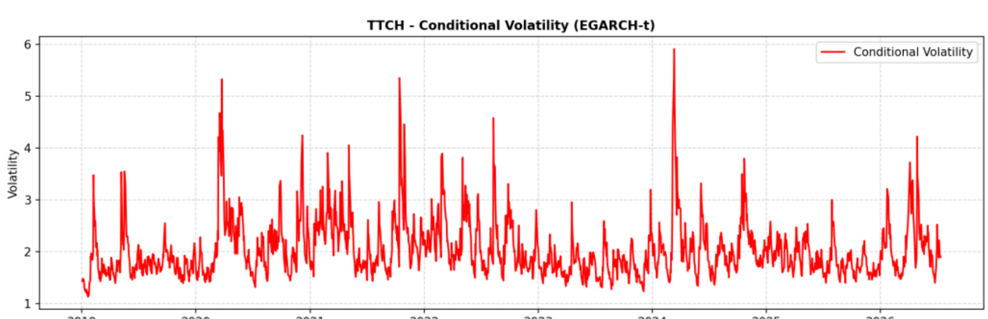

Figure A21.1. TTCH, Conditional Volatility (EGARCH-t).

This stock stays persistently choppy, with frequent moderate-to-large spikes (3-6) showing up nearly every year rather than one crisis and done, alongside high reactivity and the fattest tails in the dataset. Even after the initial COVID spike fades, it keeps generating fresh shocks through 2021-2026. One of the more consistently unpredictable large-caps in the sample.

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

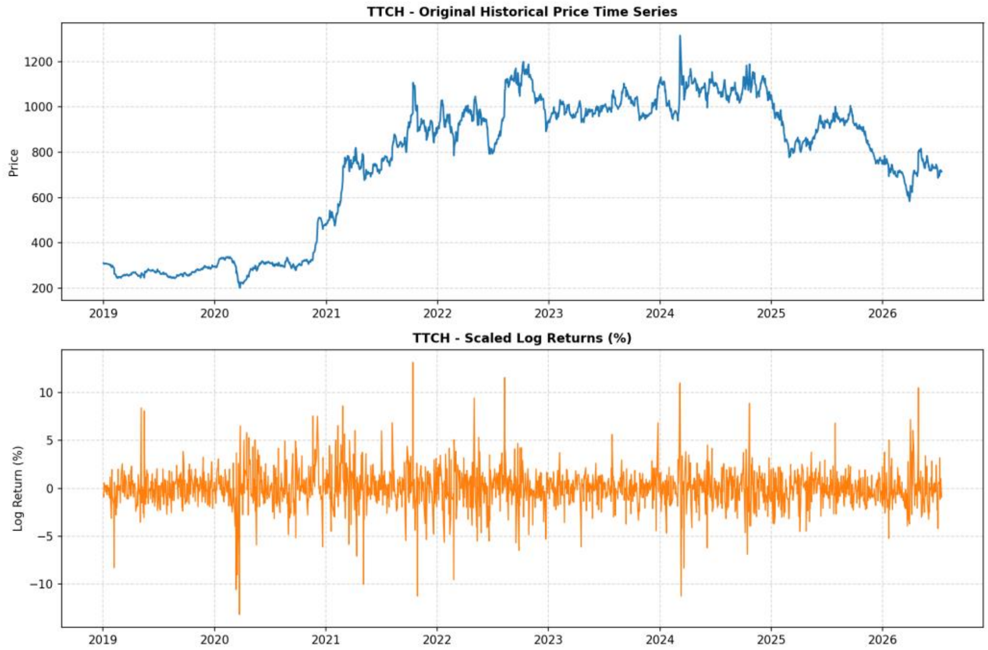

Figure A21.2. TTCH, Price & Log Return Time Series.

Price rallies from ₹300 to over ₹1,200 by late 2022, then falls back to ₹700-900 for most of 2023-2026, a partial round trip rather than holding onto new highs. Returns swing past ±8% fairly often, with outlier clusters spread across multiple years rather than concentrated in 2020 alone. This matches the chronically choppy volatility pattern closely.

A.22 SOBH — Sobha Limited (ESG Score: 59)
Best-fit model: EGARCH-skewt

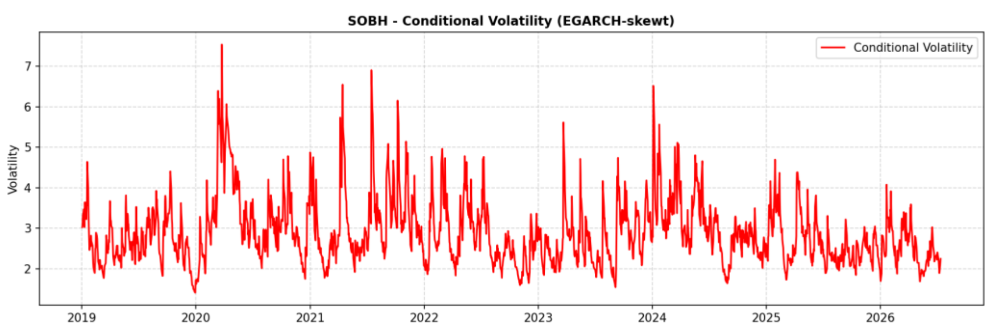

Figure A22.1. SOBH, Conditional Volatility (EGARCH-skewt).

Sobha carries one of the highest baseline volatilities in the sample, typically 2-4 and rarely dropping below 2, with large spikes throughout: COVID (7.5), 2021 (6.5-6.9), 2024 (6.5). There's no single dominant event, just consistently elevated risk. High reactivity and persistence together mean shocks are frequent, large, and slow to fade, which fits a real-estate developer where sentiment and project news keep repricing the stock.

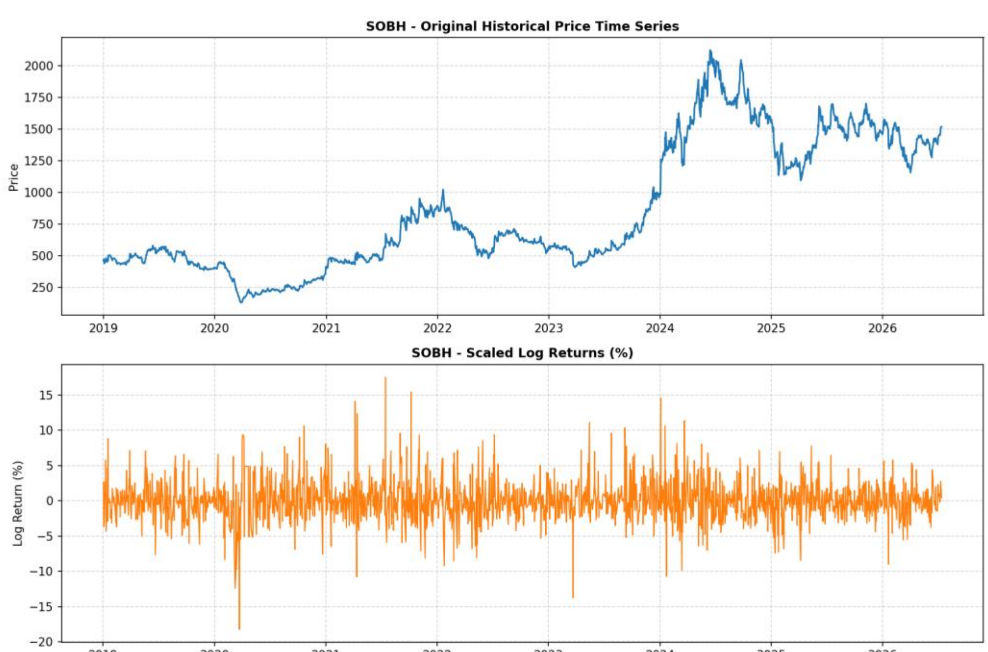

Figure A22.2. SOBH, Price & Log Return Time Series.

Price rises from ₹470 to a peak above ₹2,000 by mid-2024, then pulls back to ₹1,300-1,500, a fairly classic boom-and-partial-correction, matching the broader 2021-2024 Indian real estate cycle. Returns swing widely and

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

often, regularly ±10-15%, consistent with the persistently high volatility baseline. This stock reads as structurally riskier throughout rather than only during major market events.

A.23 COAL — Coal India Limited (ESG Score: 58)
Best-fit model: EGARCH-t

Figure A23.1. COAL, Conditional Volatility (EGARCH-t).

Coal India barely crosses 5 even during COVID and mostly sits in a 1-3 range otherwise, making it one of the lower-volatility names in the sample. Persistence is high, though, so even modest shocks take a while to fully decay. The fat tails suggest more extreme-event risk lurking beneath the surface than the day-to-day pattern implies.

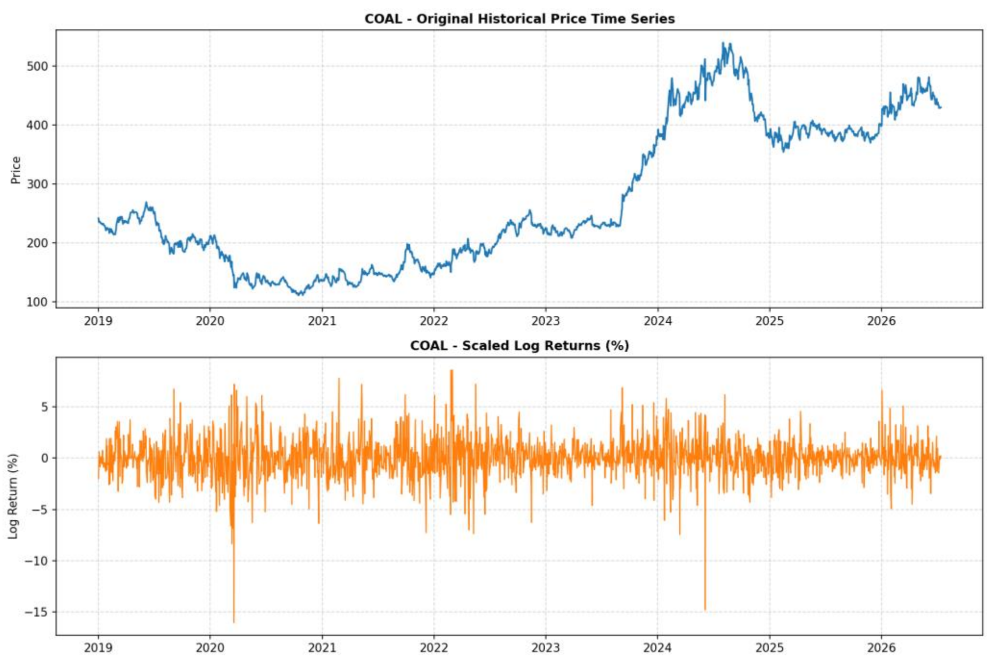

Figure A23.2. COAL, Price & Log Return Time Series.

Price was range-bound between ₹100-250 for four years, then broke out sharply to ₹540 in 2024 on the back of the energy cycle, before settling back to ₹400-480. Returns are mostly contained aside from a sharp -16% during the 2020 crash and a smaller move in 2024. The stock appears to shift from a range-bound PSU pattern to a trending commodity play in its later stretch.

A.24 ALOK — Alok Industries (ESG Score: 57)
Best-fit model: GJR-GARCH-skewt

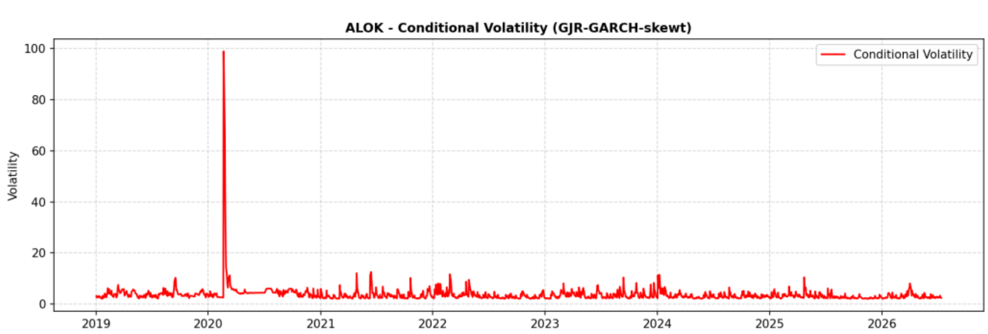

Figure A24.1. ALOK, Conditional Volatility (GJR-GARCH-skewt).

One extreme spike to nearly 99 in early 2020 dominates the chart, roughly 15-20x the stock's usual 3-8 range. Persistence is low here, though, so even something this extreme faded fast rather than becoming a new normal. This reads as a one-off event rather than a genuine shift in the stock's risk profile.

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

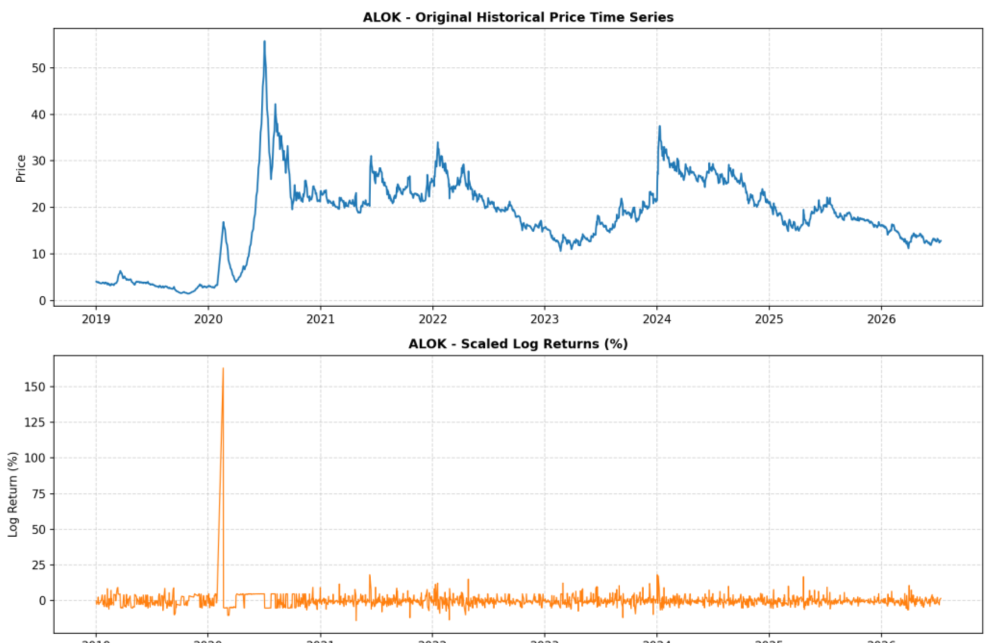

Figure A24.2. ALOK, Price & Log Return Time Series.

There's a single-day return of around +160% here, which isn't a plausible market move and is consistent with a corporate restructuring or share reorganisation rather than a data error. The firm is retained in the analytical sample on that basis (see Section 3). Excluding that single day, it's a volatile small-cap textile stock moving between ₹2 and ₹55, with a long decline after 2024.

A.25 VDAN — Vedanta Limited (ESG Score: 54)
Best-fit model: EGARCH-skewt

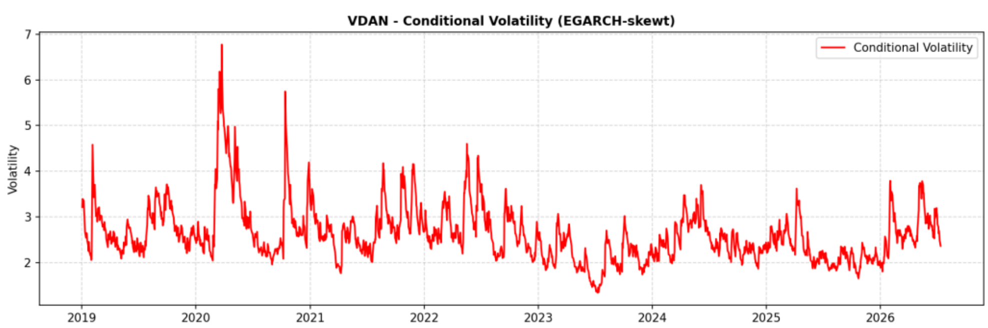

Figure A25.1. VDAN, Conditional Volatility (EGARCH-skewt).

Vedanta stays choppy throughout, with an elevated 2-4 baseline, and a dominant COVID spike to 6.75 plus a second one to 5.75 in late 2020. Moderate persistence combined with genuinely high reactivity means it reacts quickly to commodity and governance news and stays elevated for a while afterward. This fits a leveraged, diversified metals and mining conglomerate reasonably well.

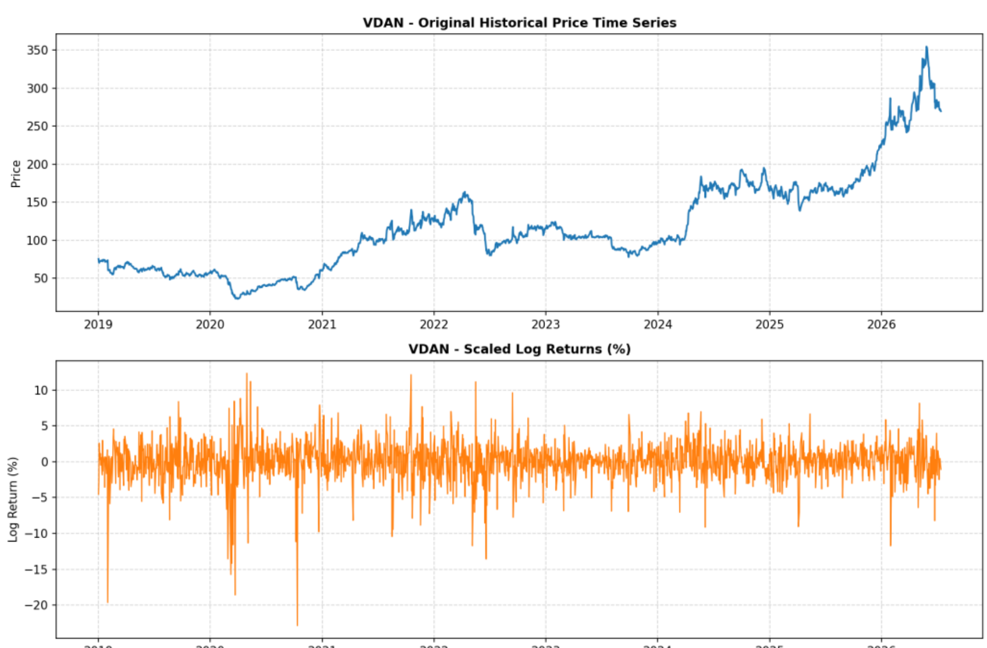

Figure A25.2. VDAN, Price & Log Return Time Series.

Price falls to around ₹20 during COVID, then climbs, at times unevenly, to over ₹350 by mid-2026, more than 15x off the bottom. Returns swing sharply throughout, with multiple moves past ±15% including a -22% outlier in

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

late 2020, consistent with the persistently elevated baseline rather than one settled crisis. Strong long-term growth here came with genuinely wide swings, from both the commodity cycle and firm-specific risk.

A.26 ACLL — Allcargo Logistics (ESG Score: 43)
Best-fit model: EGARCH-skewt

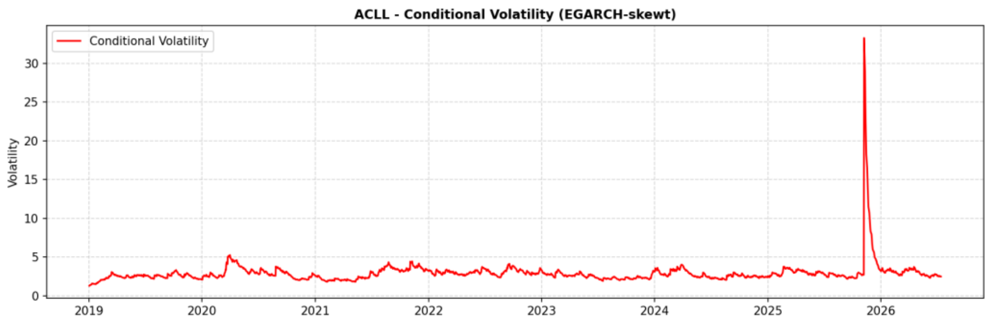

Figure A26.1. ACLL, Conditional Volatility (EGARCH-skewt).

Volatility stays calm through most of the sample (2-5 range) until late 2025, when it shoots up past 33, roughly 10x its normal level. EGARCH's asymmetry term confirms negative shocks hit harder than positive ones of the same size here. Persistence is high as well, so once the spike hit, it stuck around for a while before settling.

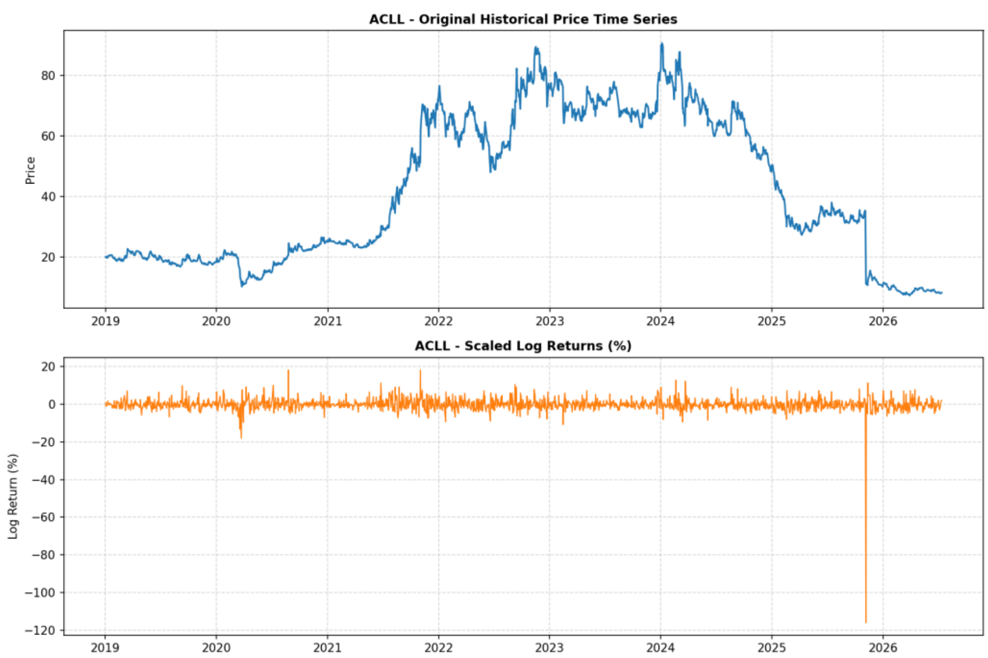

Figure A26.2. ACLL, Price & Log Return Time Series.

Price went from ₹20 up to nearly ₹90 by 2024, then dropped sharply to single digits in late 2025, matching a single-day return of around -115%, which isn't a genuine trading move. It's consistent with a stock split or corporate restructuring rather than a data error, and the firm is retained in the analytical sample on that basis (see Section 3).

A.27 AADA — Aadhar Housing Finance (ESG Score: 33)
Best-fit model: GARCH-skewt

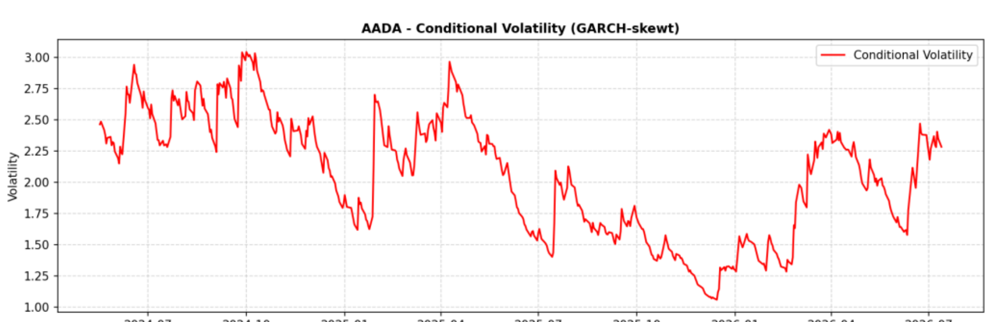

Figure A27.1. AADA, Conditional Volatility (GARCH-skewt).

The alpha+beta here is 0.99, which means once volatility goes up, it takes a long time to come back down, exhibiting high persistence. It can also be seen in the chart that volatility moves in slow multi-month waves (roughly between 1 and 3) instead of sharp one-day spikes.

© 2026 by the author; licensee Eastern Centre of Science and Education, USA

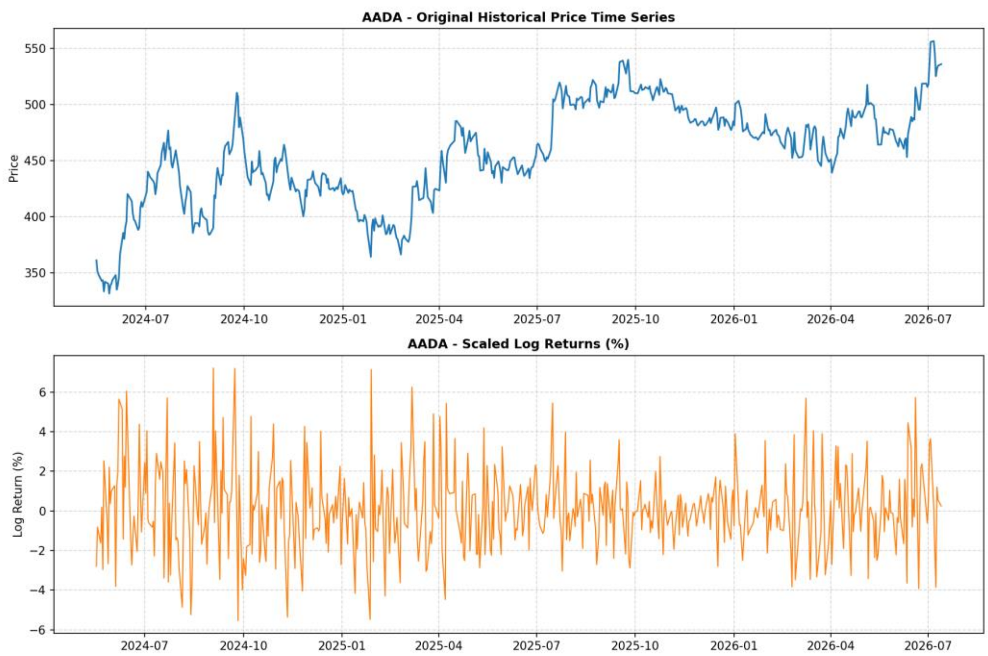

Figure A27.2. AADA, Price & Log Return Time Series.

Price went from around ₹340 to ₹550 in three separate rally-and-correction cycles stacked on each other rather than a smooth uptrend. Returns mostly stay under ±4%, with only a few outliers exceeding 6%. No single crisis moment stands out here, so the volatility seems more like rolling business-cycle sentiment than event shocks.

© 2026 by the author; licensee Eastern Centre of Science and Education, USA