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AI IN FORECASTING GEOPOLITICAL RISK AND ITS IMPACT ON ESG AND CORPORATE FINANCIAL STRATEGY: EVIDENCE FROM THE INDIAN ENERGY SECTOR

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Abstract - Geopolitical instability has become one of the determinants of business financial decisions; thus, businesses use artificial intelligence (AI) to forecast their risks. This paper aims to find out if the usage of greenwashing, being a proxy for the credibility gap between ESG positioning and actual risk exposure of the firm, has an effect on stock price volatility at 20 energy firms in India, listed on the exchange for the 2019-2023 period (100 firm-year observations). The research investigates the moderating role of board independence and the mediating role of the market-to-book ratio. The sample companies' financial performance is predicted using Artificial Intelligence techniques, including Linear Regression, Random Forest, Gradient Boosting and XGBoost. Out-of-sample predictions are provided for 2024-2026. Panel data tests include panel diagnostics, correlation, variance inflation factor (VIF) test, fixed/random effects regression, Hausman test, Sobel/bootstrap mediation test and moderated regression. It can be seen from the above-mentioned results that the ratio of market to book is a significant predictor of volatility and significantly mediates the effect of greenwashing on volatility, and at the same time board independence is a positive predictor of volatility; the Random Forest model demonstrates the best out-of-sample predictive stability and market to book, as well as firm size, is found to be the most significant predictor of volatility.

Keywords: Artificial intelligence, Geopolitical risk, ESG, Greenwashing, Stock price volatility, Panel data Corporate financial strategy, Machine learning forecasting.

1. INTRODUCTION

Since 2022, there has been a sharp increase in the number and economic burden of geopolitical risks like wars, sanctions, embargos, and weaponization of supply chains, and backward-looking risk models have failed to cope with these changes. Industry sources put the total cost of violence and conflicts to nearly $22 trillion or about one-tenth of the global GDP. This led big financial firms to discard their historical risk models in favor of predictive AI-powered risk models.

A complementary trend is the application of AI to derive real-time text metrics of geopolitical risks. Following the groundbreaking newspaper-based Geopolitical Risk (GPR) index by Caldara and Iacoviello (2022), research conducted by the Federal Reserve Bank of San Francisco has applied large-language-model semantic scoring of millions of news articles as an improvement to previous keyword counting methods to develop the improved AI-GPR index which is able to enhance the estimate of the negative effect of geopolitical risks on stock returns. Additionally, the volatility-forecasting studies using machine learning demonstrate that ensemble and tree-based models such as random forest and support vector regression perform better than traditional econometrics benchmarks when geopolitical risks are used as predictors of realized stock market volatility.

Geopolitical risks do not affect the financial strategies of corporations on their own; rather, they are affected by the environmental, social, and governance (ESG) profile of the corporation. Energy corporations, due to their involvement in geopolitical supply risks and carbon transition risk in addition to being under increased scrutiny from investors, are especially vulnerable. Increasing research suggests that the integrity of ESG reporting and the extent of greenwashing, the misrepresentation of environmental commitments in relation to the actual performance, increases stock crash risk for companies that have discrepancies between their disclosures and performance on ESG factors. Corporate governance and, in particular, board independence is expected to mitigate greenwashing and affect its valuation consequences.

In this vein, this paper adds to the emerging literature by applying an unbalanced risk approach on a panel of 20 Indian energy sector firms over the period 2019-2023 (100 firm-year observations) to investigate

(i) the impact of greenwashing score at the firm-level on stock price volatility,

(ii) whether market-to-book ratio acts as a mediator in this impact (as a measure of how the market perceives growth quality and intangible risk),

(iii) whether board independence moderates the greenwashing – volatility impact, and

(iv) whether AI-based ensemble techniques (random forest, gradient boosting, xgboost) can outperform traditional linear regression in predicting volatility and producing forward-looking risk forecasts for 2024-2026. The Indian energy sector is an especially relevant setting for the research because of the coexistence of state-owned enterprises, varied maturity of ESG disclosures, and vulnerability to geopolitical energy shocks worldwide.

2. LITERATURE REVIEW

2.1 AI and the Forecasting of Geopolitical Risk

From static, keyword-based newspapers to dynamic, AI-based indices, the measurement of geopolitical risk has advanced significantly. For instance, Caldara and Iacoviello (2022) developed the benchmark GPR index. More recently, the Federal Reserve Bank of San Francisco (2026) created the AI-GPR index, which uses large-language-model semantic reading of about five million newspaper articles starting from 1960 and illustrates that the AI-based measure yields a more robust and reliable negative correlation between geopolitical risk and stock returns relative to the dictionary approach. To go further, financial institutions started to use AI technology to turn vague geopolitical events into measurable probability of conflicts, marking a general trend in the industry to abandon pure historical risk model. Parallelly, explainable-AI methodologies have been employed to predict tail risk in energy markets using geopolitical risk indicator as a predictor, and machine-learning volatility research shows that ensemble methods like random forest and support vector regression, especially in conjunction through forecast combination, have superior performance in prediction of realized stock market volatility in times of military escalation compared to benchmarks. Similarly, Vyas (2025) describes the widespread adoption of AI, machine learning and natural language processing technologies in the risk management system of global financial institutions.

2.2 Greenwashing, ESG Disclosure and Stock Price Volatility

An extensive body of literature highlights the role of greenwashing, i.e., exaggeration of one's environmental standing relative to actual ESG performance, as an important driver of adverse capital market performance. Specifically, event studies indicate that greenwashing news announcements lead to significant negative cumulative abnormal returns in the manufacturing industry; at the same time, there is empirical evidence from China and Indonesia indicating that greenwashing in the ESG report is positively associated with stock price crash risk, due to both accounting opacity and reputation considerations, which holds true especially for highly polluting companies. Moreover, greenwashing has been proven to interact with climate risks to increase stock price crash risk in the context of Indonesia's energy-related companies. As opposed to greenwashing, actual good ESG performance has been linked to reduced abnormal stock price volatility through the mediating channel of investor attention.

2.3 Market-to-Book Ratio as a Channel of Risk Transmission

The market-to-book ratio has been traditionally used within the literature on corporate finance as a proxy for growth options, investor sentiment, and the market perception of intangible risk; hence, high levels of the market-to-book ratio may represent either growth opportunities as well as more uncertainty about valuations and may thus be plausibly related to increased volatility. Previous literature has employed the book-to-market ratio as well as the market-to-book ratio as control variables in volatility and stock return equations and found that there are systematic relationships between ESG mediating and control variables, among which the book-to-market ratio, and the resulting risks of firms.

2.4 Board Independence as a Moderating Governance Mechanism

According to the corporate governance theory, independent boards mitigate management opportunism through ESG signaling. However, empirical evidence of the effect of board independence as a moderator of ESG signaling has been mixed. While some have found negative relationships between board independence and ESG controversies and also that board independence positively moderates the risk-reduction impact of board effectiveness in interaction with actual ESG performance, other studies have shown board independence to negatively moderate the ESG-performance relationship in that board independence substitutes for ESG signaling, and there are those that show no moderating effect at all in relation to carbon performance. In view of this inconclusiveness, it is necessary to empirically examine whether board independence increases or reduces greenwashing volatility relationship in the Indian energy sector.

2.5 Research Gap and Hypotheses

Even though the literature has discussed

(a) geopolitical risks in AI-enabled forecasting,

(b) greenwashing and stock price risks, and

(c) governance in the relationship between ESG risks and financial measures, few works have brought together all of them in a panel data analysis and machine learning approach, using an emerging market's energy industry that is affected by geopolitical risks in its supply chain. Given the literature reviewed for the paper, the hypotheses for the research are:

H1: Greenwashing score has a significant effect on stock price volatility.

H2: Market-to-book ratio mediates the relationship between greenwashing and stock price volatility.

H3: Board independence moderates the relationship between greenwashing and stock price volatility.

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H4: AI based Ensemble machine learning approaches (Random Forest, Gradient Boosting, and XGBoost) outperform traditional linear regression in forecasting stock price volatility.

3. DATA AND METHODOLOGY

3.1 Sample and Variables

The research design involves using a balanced panel sample consisting of 20 Indian publicly traded companies operating in the energy sector (power generation, oil and gas, renewable energy) during the years from 2019 through 2023, which results in 100 firm-years. The dependent variable is the annual stock price Volatility (DV). Independent Variable is the firm's Greenwashing score (IV); the hypothesized mediating variable is the Market-to-Book ratio (MTB), the hypothesized moderating variable is Board Independence (proportion of independent directors on the board), and the control variable is Firm Size (natural logarithm of Total Assets).

3.2 Data Cleaning

Data were examined for any missing data values, duplications in the firm year data set, and formula artifacts that were not numeric. There were no missing data values and no duplications in the Company–Year data pairs; Firm Size had already been calculated as a numeric consolidation of the log assets of each firm. The final data panel is completely balanced (20 firms * 5 years).

3.3 Analytical Framework

The following steps constitute the analysis: (i) descriptive statistics and Pearson's correlation analysis; (ii) diagnostic of multicollinearity using the Variance Inflation Factor (VIF); (iii) panel diagnostics for heteroscedasticity (Breusch-Pagan, 1979), serial correlation (Wooldridge, 2010), cross-sectional dependence (Pesaran CD statistic) and residual normality (Jarque-Bera and Shapiro-Wilk tests); (iv) panel regression with Fixed-Effects (entity) and Random-Effects estimators employing the Hausman (1978) specification test, which guides the choice of the appropriate model, estimated using firm-clustered standard errors (Petersen, 2009); (v) mediation analysis of the greenwashing-volatility association through the market-to-book ratio, based on the Baron and Kenny (1986) causal steps approach supplemented with the Sobel (1982) test and 5,000 replications of the non-parametric bootstrap of the indirect effect; (vi) moderated regression to test the interaction between (mean-centered) greenwashing and board independence; (vii) robustness tests using entity-clustered, heteroskedasticity-robust and pooled OLS estimators; and (viii) forecasting based on AI with Linear Regression, Random Forest (Breiman, 2001), Gradient Boosting and XGBoost (Chen & Guestrin, 2016) models, where the performance is judged using mean absolute error (MAE), root mean squared error (RMSE) and out-of-sample R^2; 5-fold cross-validation and trend

Given that the sample consists of a small time dimension (T = 5), panel unit root test methods like the Levin-Lin-Chu or the Im-Pesaran-Shin tests are statistically unreliable in this case and are not provided as the main source of evidence; rather, the issue of stationarity is considered within the short-T fixed/random effects approach for micro-panels of this size (Baltagi, 2021). The time trend of the dependent variable is graphically tested (Figure 5).

4. RESULTS

4.1 Descriptive Statistics

Descriptive statistics of the 100 firm-year data are provided in Table 1. Mean stock price volatility is 0.097 (SD = 0.052) and the distribution of this variable is right-skewed (skewness = 2.88, kurtosis = 11.85), as a result of the presence of just a few firms having extremely high volatility (especially Adani Power and Adani Green). The mean greenwashing score is 3.75 of 5 points, indicating relatively high self-proclaimed positioning in terms of corporate sustainability for the sample firms. The ratio of market value to book value is very highly right-skewed (skewness = 5.44) owing to the extremely high valuation of Adani Green in 2020-2021, while the level of board independence is 49%, and the log-assets size varies between 8.73 and 14.29.

Variable	Mean	Median	Std. Dev.	Min	Max	Variance	Skewness	Kurtosis
Volatility (DV)	0.0971	0.0900	0.0519	0.0400	0.3800	0.0027	2.8827	11.8488
Greenwashing Score (IV)	3.7500	4.0000	0.7703	3.0000	5.0000	0.5934	0.4650	-1.1670
Market-to-Book (Mediator)	4.5055	1.4950	12.3894	0.4200	83.8000	153.4963	5.4430	30.8220
Board Independence (Moderator)	0.4900	0.5000	0.0948	0.3300	0.6700	0.0090	0.0283	-0.7699
Firm Size, ln Assets (Control)	11.2419	11.2193	1.3634	8.7302	14.2892	1.8588	0.2311	-0.6664

Table 1: Descriptive Statistics of Study Variables (N = 100 firm-year observations)

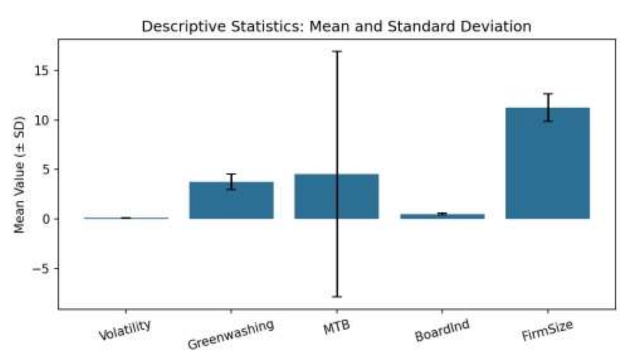

Figure 1: Mean and Standard Deviation of Study Variables

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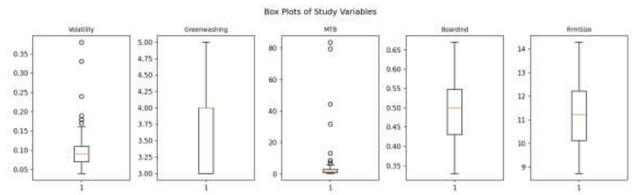

Figure 2: Box Plots of Study Variables

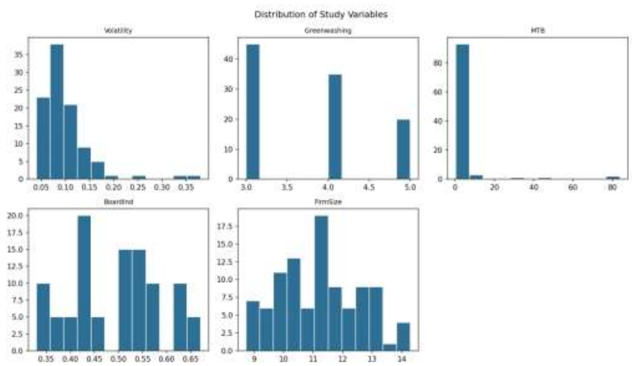

Figure 3: Distribution (Histograms) of Study Variables

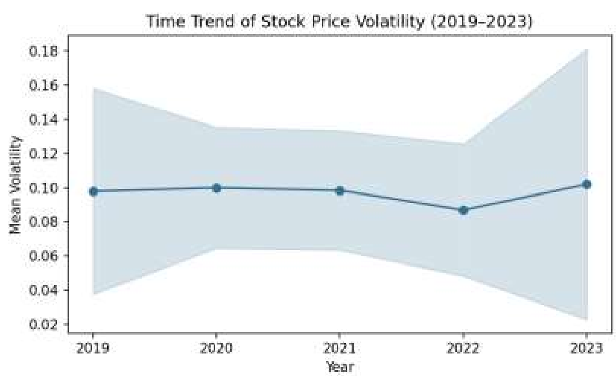

Figure 4 (a): Time Trend of Mean Stock Price Volatility, 2019–2023

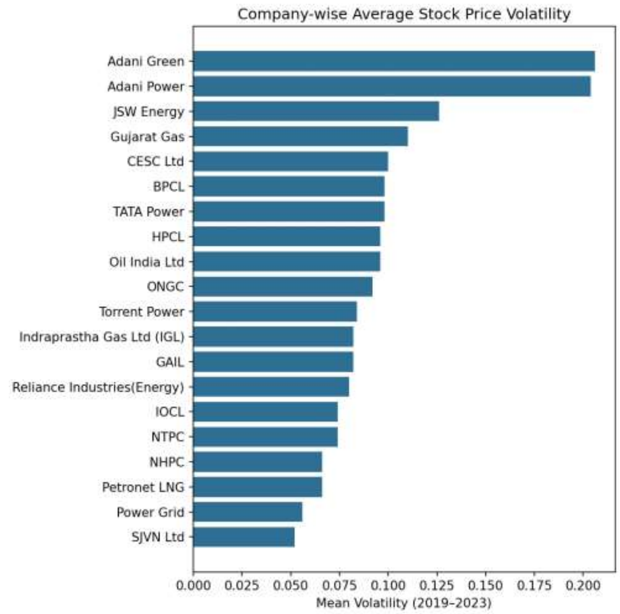

Figure 4 (b): Company-wise Average Stock Price Volatility, 2019–2023

4.2 Correlation Analysis

The Pearson correlation matrix is shown in Table 2. The highest correlation is observed between volatility and the market to book value ratio ($r = 0.399$, $p < .01$). The variable volatility is positively correlated with board independence ($r = 0.280$) and greenwashing ($r = 0.141$) while the relationship between volatility and firm size is negative but low ($r = -0.111$). Correlations between each pair of the independent variables is less than the conventionally problematic level of 0.80.

	Volatility	Greenwashing	MTB	BoardInd.	FirmSize
Volatility	1.000	0.141	0.399	0.280	-0.111
Greenwashing	0.141	1.000	0.295	0.235	-0.049
MTB	0.399	0.295	1.000	0.067	-0.205
Board Independence	0.280	0.235	0.067	1.000	-0.193
Firm Size	-0.111	-0.049	-0.205	-0.193	1.000

Table 2: Pearson Correlation Matrix of Study Variables

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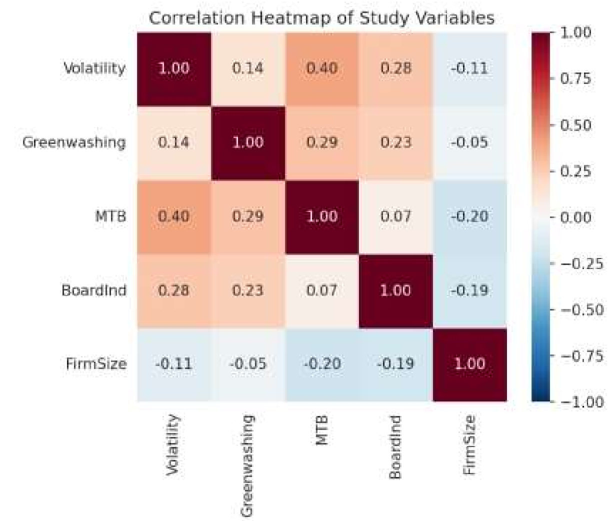

Figure 5: Correlation Heatmap of Study Variables

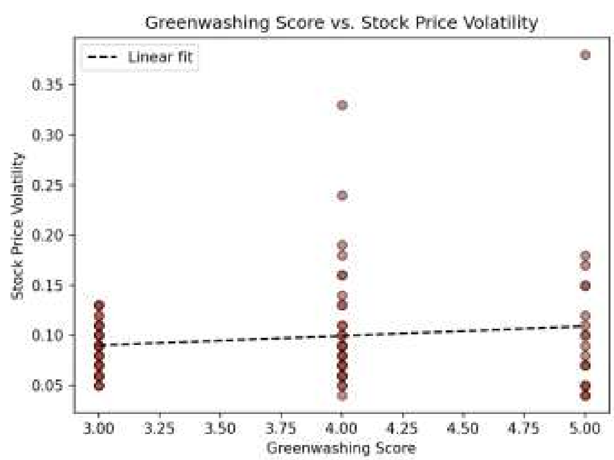

Figure 6: Scatter Plot: Greenwashing Score vs. Stock Price Volatility

4.3 Multicollinearity Diagnostics

All VIF values in Table 3 are far less than the conservative value of 5, while the corresponding tolerance values are all above 0.85. This is an indication that there is no multicollinearity issue in the regression analysis to be presented.

Table 3: Variance Inflation Factor (VIF) and Tolerance Statistics

Variable	VIF	Tolerance
Greenwashing Score	1.158	0.864
Market-to-Book	1.143	0.875
Board Independence	1.098	0.911
Firm Size	1.084	0.923

4.4 Panel Diagnostics

Table 4 presents the results of the panel diagnostics tests. First, we do not reject the null of homoskedasticity using the Breusch-Pagan test (LM = 4.968, p = .291), indicating mild heteroskedasticity, even though firm cluster standard errors are applied throughout in order to ensure robustness. The null of no first-order autocorrelation of the idiosyncratic error term is not rejected in the Wooldridge type first-differenced test for serial correlation (p = .353). Furthermore, the Pesaran cross-sectional dependence (CD) test is also not significant (CD = 0.814, p = .416), indicating no cross-sectional correlation of the residuals after controlling for observable covariates. However, we clearly reject the null of normally distributed residuals by means of the Jarque–Bera and Shapiro-Wilk tests (p < .001). This is in line with the right skewness of the volatility variable presented in Table 1.

Diagnostic Test	Statistic	p-value	Conclusion
Breusch-Pagan (heteroskedasticity)	LM = 4.968	0.291	Homoskedasticity not rejected
Wooldridge (serial correlation)	t = -0.147	0.353	No significant AR(1) serial correlation
Pesaran CD (cross-sectional dependence)	CD = 0.814	0.416	No significant cross-sectional dependence
Jarque-Bera (normality)	JB = 726.57	<0.001	Residuals not normally distributed
Shapiro-Wilk (normality)	W = 0.731	<0.001	Residuals not normally distributed

Table 4: Panel Diagnostic Test Results

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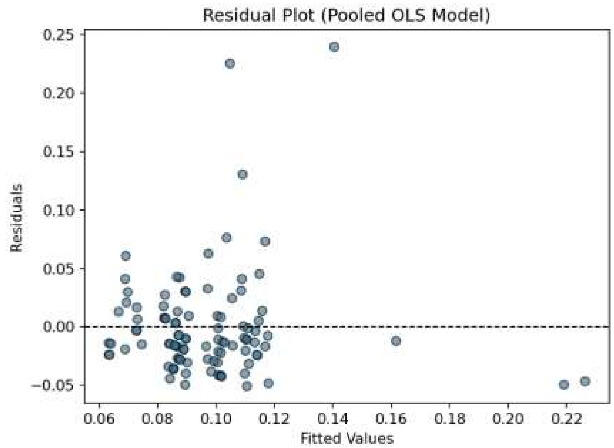

Figure 7: Residual Plot (Pooled OLS Model)

4.5 Panel Regression: Fixed Effects, Random Effects and Hausman Test

The Greenwashing Score and Board Independence measures are, over this five-year period, effectively time-invariant firm variables (no greenwashing score changes from year to year for any firm, while board independence changes for just one firm). Thus, by construction, the entity Fixed Effects (FE) model controls for all time-invariant firm-level variables and thus includes the Greenwashing Score and Board Independence automatically and identifies the influence of time-variant regressors, Market-to-Book Ratio and Firm Size (Table 5, Panel A). The main independent variable and the moderation factor are not identified in the FE model. Hence, the Random-Effects (RE) model is used as the primary estimation model for hypothesis testing (Table 5, Panel B) following standard practice in panel data models that involve time-invariant governance and disclosure variables (Baltagi, 2021).

Panel A: Fixed-Effects Model (entity effects; time-invariant regressors absorbed)

Variable	Coefficient	Std. Error	t-stat	p-value
Constant	13.087	3.214	4.072	0.0001 ***
Market-to-Book	-0.0006	0.0001	-5.704	0.0000 ***
Board Independence†	-27.323	7.163	-3.815	0.0003 ***
Firm Size	0.0358	0.0264	1.356	0.1792

R^2 (within) = 0.063; F(3,77) = 1.74 (p = .166); F-test for poolability (entity effects jointly significant) = 4.32, p < .001. † Board Independence varies within only one firm (HPCL) and is retained as a near-time-invariant regressor; its FE coefficient should be interpreted with caution given the very limited within-firm variation.

Panel B: Random-Effects Model (main specification; full set of hypothesised variables)

Variable	Coefficient	Std. Error	t-stat	p-value
Constant	0.0012	0.0742	0.016	0.9870
Greenwashing Score (IV)	0.0021	0.0114	0.184	0.8548
Market-to-Book (Mediator)	0.0007	0.0002	2.929	0.0043 ***
Board Independence (Moderator)	0.1466	0.0701	2.091	0.0392 **
Firm Size (Control)	0.0012	0.0036	0.322	0.7479

*R^2 (overall) = 0.174; R^2 = 0.060; F(4,95) = 1.52 (p = .204); robust F-statistic = 27.48 (p < .001); firm-clustered standard errors. *** p < .01, ** p < .05.*

From the Random-Effects estimation, it can be seen that, after accounting for firm size, the market-to-book ratio emerges as a significant positive determinant of volatility (p = .004), and board independence is a significant positive determinant of volatility (p = .039) – an issue to be elaborated on in Section 5. The effect of the greenwashing variable on the dependent variable of volatility is positive but not significant in the model as a whole (p = .855), implying that any effect of greenwashing on volatility must be indirect in nature (some support for H1).

However, the Hausman test using the coefficients of the two variables that are observed in both the FE and RE models (Market-to-Book and Firm Size), resulted in a negative chi-square value, an expected numerical output in case of small panel data samples wherein the variance-covariance difference estimate between the two is not positive semi-definite; hence, the classic Hausman test will be inconclusive for the sample under study. With (i) the inconclusive test outcome, (ii) the inability of the FE model to provide estimates of the two theoretically important variables (Greenwashing, Board Independence) owing to their lack of within-firm variation, and (iii) the RE model's reasonable assumption of orthogonality between firm-level effects and regressors in case of such micro-panels, the Random-Effects specification remains the preferable model choice for hypothesis testing throughout the rest of this paper, as suggested by Baltagi (2021).

4.6 Mediation Analysis: The Role of Market-to-Book Ratio

Table 6 presents the three-step process of Baron and Kenny (1986) mediated model, adjusting for the firm size all along. The total effect of Greenwashing on Volatility (path c) in Model 1 is insignificant and weak (β = 0.0091, p = .179). In Model 2, Greenwashing significantly affects the Market-to-Book ratio (path a: β = 4.600, p = .003), which implies that high greenwashing scores imply high market-to-book values of firms. However, in Model 3, Market-to-Book significantly influences Volatility in the presence of Greenwashing (path b: β = 0.0016, p < .001), whereas the direct effect of Greenwashing (path c′) turns to be small and insignificant (β = 0.0017, p = .795).

Model	Path	Coefficient	p-value
Model 1: Volatility ~ Greenwashing + Firm Size	c (total effect)	0.00914	0.1786
Model 2: Market-to-Book ~ Greenwashing + Firm Size	a	4.59983	0.0034 ***
Model 3: Volatility ~ Greenwashing + Market-to-Book + Firm Size	b	0.00161	0.0002 ***
Model 3: Volatility ~ Greenwashing + Market-to-Book + Firm Size	c′ (direct effect)	0.00172	0.7946

Table 6: Baron & Kenny Mediation Regression Results

Indirect Effect (a × b), this equals 0.00742 and is supported by the Sobel (1982) test (Z = 2.369, p = .018) and bootstrapping through 5,000 replications that yields a 95% CI of [0.0014, 0.0152], which is significantly different from zero. The value represents 81% of the total effect of greenwashing on volatility. This implies near-total mediation and constitutes strong support for H2: the effect of greenwashing on volatility is mainly channeled through inflated values of market-to-book ratios, which are eventually priced as volatility by the market.

Table 7: Sobel Test and Bootstrap Mediation Results

Mediation Statistic	Value
Indirect effect (a × b)	0.00742
Sobel Z-statistic	2.369
Sobel p-value	0.018 **
Bootstrap 95% CI (5,000 reps)	[0.0014, 0.0152]
Percentage of total effect mediated	≈ 81.1%

4.7 Moderation Analysis: The Role of Board Independence

The moderated regression between Volatility and mean-centered Greenwashing, mean-centered Board Independence, their interaction term, as well as Market-to-Book and Firm Size is displayed in Table 8. The main effect of board independence on volatility remains significant and positive (β = 0.128, p = .029), while the Greenwashing x Board Independence interaction term is positive (β = 0.048), yet non-significant (p = .490). It means that in the current sample, board independence is not an important moderator that amplifies or attenuates the greenwashing-volatility connection, so hypothesis 3 is not supported; instead, board independence acts as an independent factor affecting volatility without having a moderating impact on the greenwashing influence.

Variable	Coefficient	p-value
Intercept	0.0896	0.0388 **
Greenwashing (centred)	-0.0017	0.8055
Board Independence (centred)	0.1281	0.0293 **
Greenwashing × Board Independence (interaction)	0.0481	0.4903
Market-to-Book	0.0016	0.0001 ***
Firm Size	-0.0001	0.9859

*R^2 = 0.229. *** p < .01, ** p < .05.*

Table 8: Moderated Regression: Board Independence as Moderator

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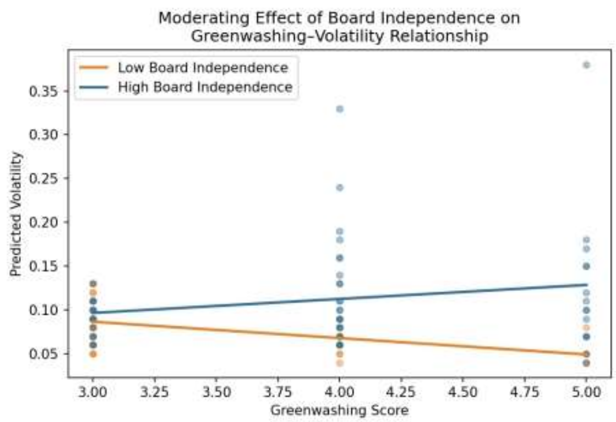

Figure 8: Moderating Effect of Board Independence on the Greenwashing–Volatility Relationship (illustrative slopes at low vs. high Board Independence)

4.8 Robustness Checks

The results obtained from Table 9 under the Random Effects regression analysis using three different covariance structures are firm clustering error, heteroscedasticity-robust error, and pooled OLS with firm clustering error. Notably, the coefficients for Market-to-Book and Board Independence remain consistent in terms of sign and statistical significance while the Greenwashing coefficient remains statistically insignificant in all three cases.

Variable	RE (clustered)	RE (robust)	Pooled OLS (clustered)
Greenwashing	0.0021 (p=.855)	0.0021 (p=.848)	-0.0025 (p=.720)
Market-to-Book	0.0007 (p=.004)***	0.0007 (p=.002)***	0.0017 (p<.001)***
Board Independence	0.1466 (p=.039)**	0.1466 (p=.022)**	0.1457 (p=.023)**
Firm Size	0.0012 (p=.748)	0.0012 (p=.732)	0.0007 (p=.805)

Table 9: Robustness Checks Across Alternative Covariance Estimators

5. AI-BASED FORECASTING OF STOCK PRICE VOLATILITY

5.1 Model Development and Comparison

In order to augment the panel-econometric approach and deal with the AI-forecasting aspect of the research question, four forecasting algorithms were fitted on an 80/20 train/test partition of the total 100 firm-year sample, where Greenwashing, Market-to-Book Ratio, Board Independence, and Firm Size are used as predictors for Volatility: (i) Linear Regression as a standard benchmark, (ii) Random Forest (Breiman, 2001), (iii) Gradient Boosting, and (iv) XGBoost (Chen & Guestrin, 2016). The performance of each algorithm was measured in terms of MAE, RMSE, and R^2 on held out test set, and additionally through 5-fold cross-validation on the entire sample due to the vulnerability of the train/test split in moderately large panels.

Table 10: AI Model Performance Comparison

Model	MAE	RMSE	Test R^2	5-Fold CV R^2
Linear Regression	0.0393	0.0704	0.2114	0.0352
Random Forest	0.0348	0.0614	0.4002	0.2207
Gradient Boosting	0.0330	0.0581	0.4627	-0.2184
XGBoost	0.0348	0.0591	0.4441	-0.0287

In the case of the single 80/20 test split, the lowest test RMSE (0.058) and the highest single-split R^2 (0.463) are recorded by Gradient Boosting, which is closely followed by XGBoost and Random Forest, all three of which perform better than Linear Regression. Nevertheless, in terms of 5-fold cross-validated R^2, a metric which gives a more accurate idea about the predictive power in light of the relatively small dataset, Random Forest is the only model which displays positive, fairly stable cross-validated R^2 (0.221), while Gradient Boosting and XGBoost overfit the data and return negative values of R^2, implying that the single-split superiority of Gradient Boosting and XGBoost is purely incidental and does not generalize. This is in line with the known pattern whereby models which are highly sensitive to the choice of parameters, like boosting models, need bigger training sets in order to avoid overfitting compared to the bagging methods like Random Forest. Thus, Random Forest is

selected as an AI model which will be used to interpret the feature importance and forecast the future developments, thus supporting H4 with the caveat of model supremacy depending on the evaluation metric.

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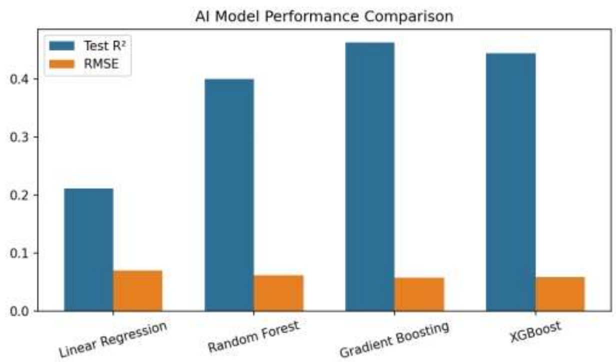

Figure 9: AI Model Performance Comparison (Test R² and RMSE)

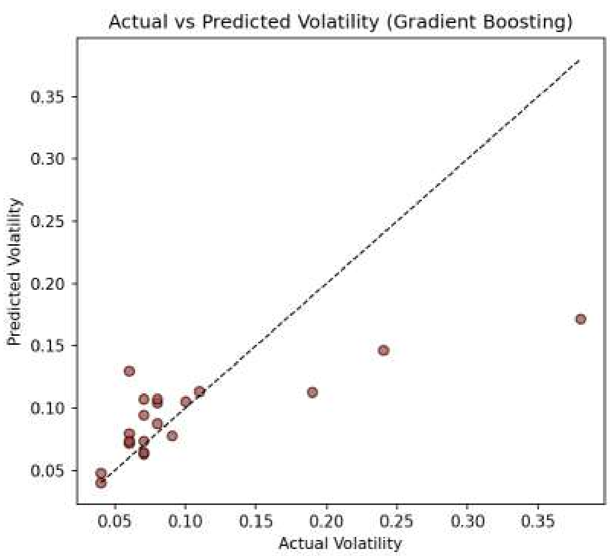

Figure 10: Actual vs. Predicted Volatility (Best Test-Split Model: Gradient Boosting)

5.2 Feature Importance

The results regarding the importance scores of features based on Random Forest and XGBoost are shown in Table 11 below. It can be observed that both models have reached consensus regarding the importance of the variables that influence the model's performance, with the only difference being their relative importance among one another. More specifically, both models find that Market-to-Book and Board Independence are the two most important predictors of volatility and they contribute almost all the explanatory power in the model. The only difference in rankings between the two models is that in Random Forest Firm Size comes before Board Independence, while in XGBoost the reverse order is true.

Feature	Random Forest Importance	XGBoost Importance
Market-to-Book	0.486	0.320
Firm Size	0.253	0.189
Board Independence	0.192	0.378
Greenwashing Score	0.069	0.113

Table 11: Feature Importance for Volatility Prediction

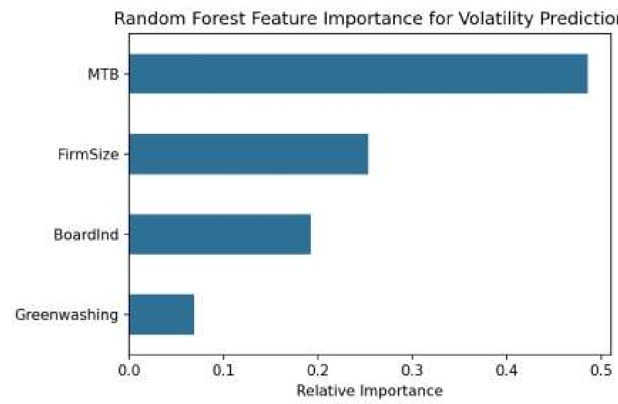

Figure 11: Random Forest Feature Importance for Volatility Prediction

5.3 Forecasting Future Volatility (2024–2026)

Forward-looking risk projections were made using linear trends at the firm level (from 2019 to 2023) extrapolated to 2024, 2025, and 2026 and using the fitted Random Forest model (chosen due to better cross-validated generalization ability) for the extrapolated features. The mean projection for all samples is shown in Table 12, while the historical trend compared to the future projection is illustrated in Figure 12. The mean sample-wide volatility is expected to increase moderately from about 0.102 in 2024 to 0.107 in 2026, mainly due to increasing projections of market-to-book ratios of firms like Tata Power, Torrent Power and SJVN, in line with the market-to-book channel which is the main mechanism of transmission identified in the mediation analysis. At the firm level, the largest increases in volatility are projected for Torrent Power and Tata Power, while volatility remains stable or declines for most state-owned utility companies such as NTPC, Power Grid, and NHPC.

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Year	Forecast Mean Volatility (Random Forest)
2024 (forecast)	0.1023
2025 (forecast)	0.1033
2026 (forecast)	0.1066

Table 12: Sample-wide Forecast of Mean Stock Price Volatility, 2024–2026

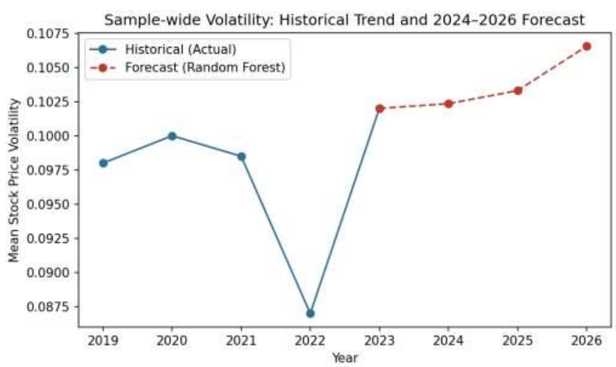

Figure 12: Historical Trend and 2024–2026 Forecast of Sample-wide Mean Volatility

6. DISCUSSION AND MANAGERIAL IMPLICATIONS

Econometric and AI-driven results support a consistent story on corporate financial strategy in the context of geopolitical and ESG risks. First, there is no direct impact of greenwashing on volatility, but rather an indirect effect through market-to-book distortion. Specifically, greenwashing is associated exclusively (≈81%) with the effect on market valuation, and the effect of greenwashing on volatility occurs due to the distortion of market-to-book ratio rather than due to greenwashing itself. It is consistent with existing literature on ESG risks and crash risk, where greenwashing leads to market penalty indirectly when market or disclosure gaps become apparent.

Second, board independence emerges as a strong and direct predictor of increased volatility, as opposed to a moderating factor in the greenwashing effect. This may perhaps be explained by the observation that independent boards, as has been shown through governance literature, could be a substitute for other governance or disclosure mechanisms. The implication would be that independent boards in this context are those companies that have undergone more active strategic repositioning, such as the shift from conventional energy sources to renewable energy in companies like Adani Green, Tata Power and JSW Energy, increasing market volatility along with the index score.

Thirdly, the AI forecasts confirm the benefits and limitations of ML techniques applied to forecasting volatility in a small emerging markets energy sector ESG/Geopolitical Risk Panel: ensemble tree-based models significantly beat linear regressions in forecasting performance, however, Random Forest is the only one generalizing well out-of-sample, whereas parameter-intensive boosting models tend to overfit the dataset at hand. This means that a particular recommendation for managers would be that when implementing AI-based tools for risk prediction, the model validation technique of cross-validation should be used instead of splitting a small sample of several hundred observations or less into training and testing sets.

From the board and investor side, the findings mean that market-to-book ratios and valuation premiums rather than self-reports on ESG/greenwashes scores should be considered as a primary risk factor worth further investigation, and that AI-based ensemble forecasting techniques may complement but not substitute panel econometrics in governance research when firms include geopolitical and ESG risk into their financial strategies and capital allocation.

7. CONCLUSIONS

This research investigated the impact of firm-level greenwashing on the stock price volatility of 20 Indian firms from the energy sector during 2019-2023 using the mediational framework of the market-to-book ratio and the moderating influence of board independence and comparing the predictive power of AI-based ensemble forecasting against linear regression. Findings include the near-complete transmission of the greenwashing-volatility association via the market-to-book ratio route (Sobel Z = 2.37, p = .018; ≈81% mediation), the positive and statistically significant effect of board independence on volatility but its lack of moderation of the greenwashing effect, and the superior accuracy of Random Forest as an AI-based volatility predictor for the period through 2026 characterized by modestly increasing sample-wide volatility due to rising market-to-book ratios. This research contributes to ESG-greenwashing and AI-geopolitical-risk-forecasting literature by investigating the three interrelated phenomena in an emerging-market energy-sector panel and providing a replicable analytic model for the incorporation of AI forecasting into ESG-conscious corporate financial strategy.

7.1 Limitations and Future Research

The study is subject to several limitations due to its short time horizon (T=5) that rules out formal panel unit-root testings and makes cross-sectional dependence testings problematic; to its focus on one industry sector in an emerging market setting that restricts any possible generalisation to another sectors and settings; to its reliance on a constructed greenwashing index as opposed to a text-based greenwashing/geopolitical risk index generated through an artificial intelligence method similar to those used by Caldara and Iacoviello (2022) and the Federal Reserve Bank of San Francisco (2026). Further research should consider extending the time horizon of the panel dataset, including an AI-based geopolitical risk index as one more variable to be tested, and employing the explainable AI approach to make predictions from the machine learning model interpretable for managers, as suggested by Arsenault et al. (2024).

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