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NLP-Based Quantification of ESG in Sustainability Reports and Firm-Specific Risk: Evidence from Borsa İstanbul

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Abstract: *This study examines the effect of the sentiment used in ESG (environmental, social, and governance) communication in corporate sustainability reports on firm-specific (idiosyncratic) risks in the Turkish stock market. The analysis focuses on 28 firms listed on the Borsa Istanbul Sustainability Index (XUSRD) between 2014 and 2023, based on a panel of 280 firm-year observations drawn from their publicly available 10-year sustainability reports. First, ESG disclosures in corporate sustainability reports were classified using natural language processing (NLP) techniques and transfer learning. Sentiment analysis was performed for each ESG dimension, and sentiment indices were created based on the analysis results. The data obtained were then analyzed using panel ARDL and panel causality test to test the effect of ESG sentiment on firm risks. The findings reveal that among the ESG dimensions, environmental and governance components play a particularly important role in reducing firm-specific idiosyncratic risk. Also, the results demonstrate the usability of AI-supported analyses in investment strategies and the economic benefit potential of ESG-focused corporate communication. In this context, ESG sentiment is critical not only from a social responsibility perspective but also in terms of risk management and investment decisions.*

Keywords: Sustainability Reporting, ESG Sentiment, Idiosyncratic Volatility, Natural Language Processing, BERT-ESG, Economic Growth

JEL: G10, C80, C23, G32, E44

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1. Introduction

In recent years, the global corporate landscape has witnessed an unprecedented shift toward integrating environmental, social, and governance (ESG) considerations into strategic decision-making and public accountability. As stakeholders ranging from investors and regulators to consumers and civil society demand greater transparency and responsibility from corporations, sustainability reporting has emerged as a critical vehicle for conveying ESG-related initiatives and impacts (Zervoudi et al., 2025). However, despite the proliferation of ESG disclosures, the subjective and often qualitative nature of sustainability reporting poses substantial challenges for systematic analysis, comparison, and integration into financial modeling and risk assessment.

Natural language processing (NLP), a subfield of artificial intelligence concerned with the computational understanding of human language, offers a powerful methodological framework for addressing these challenges. By converting unstructured textual data into structured, quantifiable metrics, NLP enables researchers and practitioners to extract meaningful insights from corporate narratives that were

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previously difficult to evaluate at scale. In the context of ESG, NLP can facilitate the quantification of sentiment, tone, and thematic emphasis within sustainability reports, thus allowing for more nuanced assessments of a firm's ESG posture and communication strategies (Huang et al., 2024).

Corporate sustainability is becoming increasingly important in financial markets, emphasizing the importance firms attach to environmental, social, and governance factors. ESG sentiment scores reflect market perceptions and idiosyncratic volatility, representing sustainability-related risks and significantly influencing investment and portfolio management decisions (Atak, 2024; Horn, 2023). This study assesses the sustainability practices of firms listed on the BIST Sustainability Index using ESG sentiment scores and idiosyncratic volatility, examining their implications for market perception and corporate risk. While prior literature has established links between ESG performance and firm risk, the majority of such studies rely heavily on third-party ESG ratings, which are often criticized for their opacity, subjectivity, and lack of consistency across providers. In contrast, our approach utilizes NLP algorithms to directly assess the sentiment embedded in firms' own sustainability narratives, thereby offering a more replicable method for evaluating ESG communication and its implications.

Through a comprehensive empirical analysis, this study aims to uncover whether and how the tone of ESG disclosures influences the magnitude of idiosyncratic volatility. By parsing ESG-related language in annual sustainability reports, we generate firm-level sentiment scores across environmental, social, and governance dimensions. These sentiment indicators are then used as explanatory variables in econometric models to assess their impact on idiosyncratic volatility, controlling for conventional financial determinants and firm characteristics.

Firm-level analyses of ESG communication not only contribute to understanding corporate behavior but also have broader macroeconomic implications. Since firms collectively shape market sentiment and capital allocation dynamics, the way they communicate sustainability practices can influence overall market stability and investor confidence. Therefore, examining ESG sentiment at the firm level provides insights into how micro-level sustainability communication translates into macro-level financial outcomes, such as systemic risk reduction and improved market efficiency (Erem Ceylan, 2021; Hoang, 2025; Zhao et al., 2024). This perspective underscores the necessity and originality of the present study, which links corporate ESG narratives to the broader functioning of financial markets in an emerging economy context.

This study provides empirical evidence that ESG sentiment, as captured through NLP-based textual analysis, holds significant explanatory power for variations in idiosyncratic volatility. It underscores the importance of not only what firms disclose about their ESG efforts, but how they communicate these disclosures an insight that adds depth to the ongoing dialogue on ESG transparency, accountability, and its financial consequences. In the study, following the introduction section 2 provides a review of the relevant literature. Section 3 outlines the methodology employed in the study and presents the data and variable definitions. Section 4 reports empirical results. Finally, section 5 concludes the paper with a summary of the results, discussion of the findings, policy implications, limitations of the study, and future research suggestions.

2. Literature Review

The impact of environmental, social and governance factors on firms' financial risk has been widely studied in the literature and assessed in different contexts. These studies generally focus on various types of firm risk (aggregate, systematic, idiosyncratic risk) and provide empirical analysis across different markets.

Many studies find a negative relationship between ESG performance and firm risk. Focusing on the US market, Lee and Koh (2024), Horn (2023), Perera et al. (2023), Perera et al. (2024) and Jung et al. (2023) find that firms with high ESG performance have lower systematic and idiosyncratic risk. This suggests that especially environmental factors play a role in reducing systematic risk, while social and governance factors play a role in reducing idiosyncratic risk (Horn, 2023; Lee & Koh, 2024; Perera et al., 2023). It is also emphasized that carbon efficiency and carbon disclosures are factors that reduce risk perception in the markets (Jung et al., 2023).

Research on the European market presents similar findings, but underlines regional differences. For example, Anselmi and Petrella (2025) find that there are significant differences between ESG rating providers for European and US firms, but that firms with higher ESG scores generally have lower credit risk, and that this effect is more pronounced in the US market. Capelli et al. (2023) find that the VaR ESG model, which integrates ESG factors into financial risk measures, improves risk estimation.

Studies in Asian markets confirm the effectiveness of ESG performance in mitigating market risks, but reveal that the results in different geographies may differ depending on various factors. Sharma et al. (2025) emphasize that the impact of ESG scores on volatility is limited in the Indian market, but the importance of ESG practices increases during crisis periods. Similarly, studies in the Korean market (Khorilov & Kim, 2024; Kim et al., 2024) show that strong ESG performance reduces firm volatility and this effect increases during crisis periods.

Several studies examining the impact of ESG performance on risk in the Chinese market (Li et al., 2025; Liu & Song, 2025; J. Liu et al., 2024; Naseer, Guo, & Zhu, 2024; Naseer, Guo, Bagh, et al., 2024; Saci et al., 2024; Xu et al., 2025; Zeng et al., 2025) have shown that ESG disclosures and high ESG ratings have mitigating effects on firm risk. In addition, these studies also show that ESG rating discrepancies lead to high volatility and lack of rating standardization negatively affects investor behavior (X. Liu et al., 2024; Zeng et al., 2025).

The impact of ESG performance on financial performance in Türkiye remains a controversial topic in the literature, with various findings regarding the direction and strength of this relationship. Özer et al. (2023) found that ESG scores, particularly the environmental component, have positive and significant effects on companies' financial performance indicators, while the effects of the social and governance sub-dimensions are more heterogeneous. Similarly, an analysis conducted by Yavuz et al. (2025) on companies listed on the Borsa Istanbul-100 index showed that environmental and governance practices had positive effects on performance measures such as ROE and Tobin's Q, but no significant relationship was found with ROA. On the other hand, a study conducted by Özdarak and Akarçay (2022) covering the Turkish machinery sector found no statistically significant effect of sustainability reporting on financial performance. Portfolio-level analyses also indicate that the relationship between ESG factors and market returns is limited. For example, a study conducted by Zehir and Aybars (2020) using European and Turkish stocks found that portfolios constructed based on ESG scores underperformed the overall market returns, and socially responsible investments did not demonstrate a significant advantage in terms of financial returns. Few studies have examined the relationship between ESG performance and firm-level risk in Türkiye. One of these studies is Şahin (2022) examined the relationship between ESG scores, financial performance, and financial risk for firms listed on Borsa Istanbul, finding that higher ESG performance is associated with reduced financial risk. This result highlights that effective ESG strategies can reduce financial volatility and increase corporate resilience.

Studies specific to the energy sector also emphasize the risk mitigating role of ESG performance and highlight the importance of ESG integration, especially in high-risk sectors (Gidage & Bhide, 2024; Naseer, Guo, & Zhu, 2024). Moreover, it has been emphasized that green innovation strategies are important in reducing firm risks and can provide competitive advantage (Lin et al., 2020).

Finally, from a methodological perspective, the literature generally examines the relationship between ESG and risk using different methods such as panel regression models, GMM analyses and structural equation modeling (SEM). This diversity of methods increases the robustness of the findings and allows for in-depth analysis of the ESG debate (Gupta & Chaudhary, 2023; Mefteh-Wali et al., 2024; Ng & Rezaee, 2020; Singhania & Gupta, 2024).

Overall, ESG performance consistently emerges as a key factor in mitigating corporate risks, highlighting the necessity for policymakers and investors to effectively evaluate ESG factors for financial stability. In this context, this study builds upon and extends the existing literature by empirically analyzing the relationship between ESG sentiment and idiosyncratic volatility.

3. Data and Methodology

This study examines how the tone of the ESG communication in the sustainability reports of 28 companies, as shown in Table 1, listed in the Borsa Istanbul Sustainability Index (XUSRD) affects firm-specific risks from 2014 to 2023. The analysis used a dataset consisting of 280 firm-year observations.

Table 1. Sectoral Classification of Firms Included in the Analysis

Sector	Firms
Beverage & Food	AEFES, CCOLA, ULKER
Energy	AKENR, AYGAZ
Banks & Financial Services	AKBNK, HALKB, ISCTR, TSKB, VAKBN, YKBNK
Cement & Construction	AKCNS
Chemicals	AKSA, SISE
Conglomerates / Holdings	KCHOL, SAHOL
Consumer Durables	ARCLK
Defense & Aerospace	ASELS
Automotive	BRISA, DOAS, FROTO, OTKAR, TOASO
Industrial Production	EREGL, POLHO
Telecommunications	TCELL
Airline & Transport	THYAO
Retail & Services	TUPRS

The research was conducted using a three-stage method. In the first stage, ESG-related texts in corporate sustainability reports available on firms' websites were classified into environmental, social, and governance categories using NLP techniques and transfer learning approaches. More specifically, after being decomposed into sentence-level tokens, the ESG dimension that each sentence is related to is determined with the help of classifiers developed by fine-tuning the pre-train-tuning the pre-trained EnvRoBERTa, SocRoBERTa, and GovRoBERTa. In other words, each sentence in the reports was categorized as economic, social, governance, and none with the help of the developed classifiers. In the next stage, sentiment scores in economic, social, and governance dimensions were calculated separately for each report of the firms (Araci, 2019; Yang et al., 2020). In the second stage, sentiment analysis was performed on the classified texts, and sentiment scores were created for each ESG dimension. Since the data set was limited in these two stages, transfer learning and 10-fold cross-validation were applied, thereby increasing the predictive power of the topic classifier and sentiment classifier models. In the third stage, the relationships between the obtained sentiment scores and firm risks were analyzed using panel ARDL and causality tests.

3.1. Evaluation Metrics

The models were assessed based on metrics including accuracy, precision, recall, and F1 score, as outlined in Ng and Rezaee (2020). The predicted outcomes were then matched against the actual labels from the test set. Evaluations were conducted independently for categories E, S, and G, as shown in Table 2, which offers an extensive overview of each assessment metric.

Table 2. Evaluation Metrics

Metric	Description	
Accuracy	Proportion of correctly classified instances	$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$
Precision	Ratio of true positives among predicted positives	$\text{Precision} = \frac{TP}{TP + FP}$
Recall	Proportion of correctly identified actual positives	$\text{Recall} = \frac{TP}{TP + FN}$
F1 Score	Harmonic mean of precision and recall	$\text{F1} = 2 \times \frac{Precision \times Recall}{Precision + Recall}$
ROC-AUC	Model's overall discriminative capability	The ROC (Receiver Operating Characteristic) curve graphically presents the sensitivity and specificity of the model at different thresholds. The AUC (Area Under the Curve) measures the area under this curve, indicating the overall discriminative power of the model.

Note: TP: True Positive; TN: True Negative; FP: False Positive; FN: False Negative

3.2. Developing Environmental, Social, and Governance Classifiers

This study utilized various large language models (LLMs) for sentiment analysis of corporate sustainability reports. General-purpose models, such as RoBERTa and its lighter version, DistilRoBERTa, have been trained on extensive text data and offer robust language understanding capabilities across various tasks. FinBERT, a BERT variant, is specifically trained on financial texts and provides more accurate results in tasks such as sentiment detection in a financial context. Its ESG-focused version, FinBERT-ESG, is adapted to the characteristics of ESG-related texts and can perform more specific analyses. EnvRoBERTa, SocRoBERTa, and GovRoBERTa are other domain-specific models. These are pre-trained RoBERTa variants for environmental, social, and governance-related texts, respectively. They offer higher contextual awareness and interpretation power in relevant sections of ESG reports. These models differ fundamentally in the content of the datasets they were trained on and their contextual expertise, which enables more accurate sentiment analysis specific to ESG sub-dimensions.

This classification process was carried out according to the theme and contextual expression contained in each sentence. For example, the sentence “We reduced our carbon footprint by 12% compared to 2022” refers directly to environmental sustainability and was therefore classified as Environmental, the sentence “A total of 12 social responsibility projects were carried out with the local community throughout the year” is assigned to the Social category due to its emphasis on social contribution and social responsibility, and the sentence “The disclosure policy has been updated in line with the principle of transparency regarding the protection of shareholder rights” is assigned to the Governance category as it addresses corporate governance in the context of transparency and stakeholder rights. The model has learned the contextual meaning of texts through such example sentences and enables accurate classification within the ESG dimensions. Sentences that do not directly fall under the ESG scope or where a clear relationship between dimensions cannot be established are grouped under the “None” heading.

During the classification process, a tokenizer broke down corporate sustainability reports into sentences. Then, a transfer learning-based ESG classifier was developed to determine the ESG sub-dimension to which each sentence belonged. Table 3 shows how different language models performed in terms of accuracy, precision, recall, and F1 score metrics when training ESG classifiers.

Table 3. Performance of the ESG Classifiers

Context	Model	Accuracy	Precision	Recall	F1 Score
Env	FINBERT	0.9375	0.9380	0.9375	0.9377
	DistilRoBERTa	0.9475	0.9488	0.9475	0.9478
	RoBERTa	0.9525	0.9533	0.9525	0.9527
	EnvRoBERTa	**0.9825**	**0.9826**	**0.9825**	**0.9825**
	FinBERT-ESG	0.9300	0.9297	0.9300	0.9298
Soc	FINBERT	0.9050	0.9067	0.9050	0.9039
	DistilRoBERTa	0.9175	0.9175	0.9175	0.9175
	RoBERTa	0.9375	0.9385	0.9375	0.9377
	SocRoBERTa	**0.9975**	**0.9975**	**0.9975**	**0.9975**
	FinBERT-ESG	0.8975	0.8983	0.8975	0.8965
Gov	FINBERT	0.8575	0.8579	0.8575	0.8570
	DistilRoBERTa	0.8550	0.8534	0.8550	0.8541
	RoBERTa	0.8700	0.8692	0.8200	0.8696
	GovRoBERTa	**0,9325**	**0,9327**	**0,9325**	**0,9326**
	FinBERT-ESG	0,8625	0,8637	0,8625	0,8630

According to these results, it is seen that the versions of the RoBERTa architecture (EnvRoBERTa, SocRoBERTa and GovRoBERTa), which is an improved version of the BERT architecture and trained with the masking method, are more successful and suitable for analysis.

Figure 1: ROC-AUC of the Domain-Specific Language Models

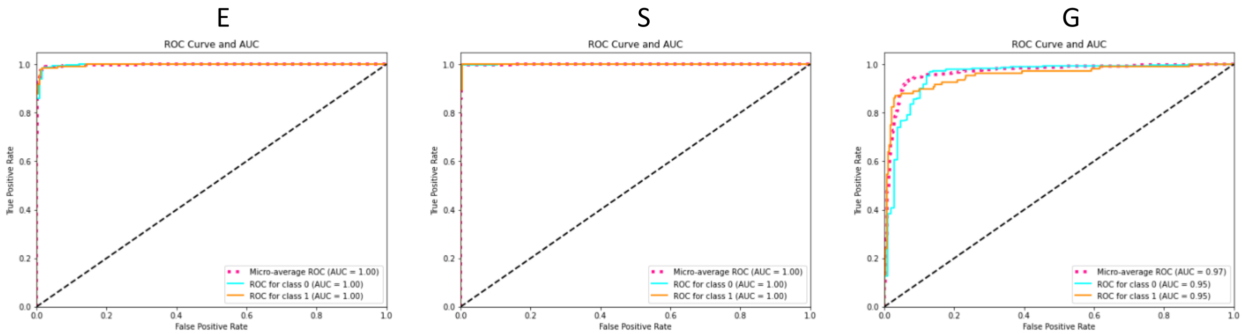

Figure 1 shows a graphical representation of the ROC-AUC of the domain-specific language models EnvRoBERTa, SocRoBERTa and GovRoBERTa. An evaluation of the performance of the three models shows that the models are able to separate classes with high accuracy but with occasional small errors. All three ROC-AUC results are quite high, indicating that the models are reliable, efficient, and usable in practice.

3.3. Estimating of ESG Sentiment Scores

In this study, after determining the ESG dimension of each sentence, its sentiment was also determined. Each sentence was labeled as positive, neutral, or negative according to its meaning. For example, the statement "We reduced our carbon footprint by 12% compared to 2022" reflects a measurable improvement in environmental performance and has been classified as positive. Similarly, the sentence "A total of 12 social responsibility projects were carried out in collaboration with the local community throughout the year" is classified as positive because it reports a socially impactful activity with positive outcomes. Through these examples, the model has gained the ability to measure the sentimental aspect of ESG communication by learning thematic classification and whether sentences contain positive or negative sentiments. The ratio (Pesg,s) for a given sentiment label (s) in each ESG category (environmental, social, governance) was calculated as follows:

$$P_{esg,s} = \frac{N_{esg,s}}{\sum_s N_{esg,s}} \qquad (1)$$

$N_{esg,s}$represents the number of sentences in a given ESG category (esg) tagged with a given sentiment tag (s),$\sum_s N_{esg,s}$ represents the total number of sentences in the respective ESG category, and $P_{env,s}$ represents the observed proportion of sentiment tags (s) in a given ESG category.

Each sentiment tag (s) is then assigned a weight (w_s):

$$w_s \begin{cases} 1, & if\ s = \text{"positive"} \\ 0, & if\ s = "neutral" \\ -1, & if\ s = "negative" \end{cases} \tag{2}$$

The sentiment score is thus a continuous scale, defined as a range from -1 to 1, which accurately reflects the sentiment tone in the Environmental, Social and Governance categories. Values in the negative range represent negative polarity, while values in the positive range indicate positive polarity. As the score approaches 1, positive sentiment is more prevalent and represents an optimistic view of the firm in ESG communication. Conversely, a score approaching -1 indicates a more negative sentiment profile, where there are concerns or challenges that may negatively affect the perception of the firms' ESG practices. This polarity scoring mechanism allows for a more precise interpretation of sentiment perceptions and their impact on firm-specific risk.

The sentiment index (S_{esg}) for each ESG category is calculated as follows:

$$S_{esg} = \sum_s P_{esg,s} \cdot w_s \tag{3}$$

In the equation, S_{esg} represents the sentiment score of the category, $P_{esg,s}$ represents the observed rate for the sentiment tag (s) in a given ESG category, and w_s represents the assigned weight for the sentiment tag.

This methodological framework allows individual sentiment scores to be synthesized through a weighted average. This enables an accurate calculation of the relative impact of each ESG component of the aggregate sentiment measure. Through the use of individual scores and the cumulative weighted sum, this approach creates a balanced view of sentiment, increasing comparability across firms and temporal contexts.

3.4. Estimation of Idiosyncratic Volatility

In this study, firm-specific volatility (IVOL) is calculated using the Fama and French (1993, 1996) three-factor model, following the approach of Ang et al. (2006), Jung et al. (2023) and Perera et al. (2024). This model is based on the idea that stock returns can be explained by market risk, firm size, and value factors. The following regression equation expresses the model.

$$R_{it} - R_{ft} = \alpha_i + \beta_i^{MKT}\left(R_{m,t} - R_{f,t}\right) + \beta_i^{SMB} \cdot SMB_t + \beta_i^{HML} \cdot HML_t + \epsilon_{it} \tag{4}$$

$$\mathrm{IVOL}_{i,m} = \sqrt{Var(\epsilon_{i,t})}\sqrt{N_{i,m}} \tag{5}$$

$$\mathrm{IVOL}_{i,T} = \sum\nolimits_{m=1}^{M} \left(IVOL_{i,m}\right)/M \tag{6}$$

In Equation 4, R_{it} denotes return of stock i at time t, and R_{ft} risk-free rate at time t. α_i represents intercept (alpha) for stock i, while β_i^{MKT}, β_i^{SMB} and β_i^{HML} denote sensitivities of stock i to the market risk factor (MKT), the size factor (SMB – Small Minus Big), and the value factor (HML – High Minus Low), respectively. $R_{m,t} - R_{f,t}$ is the excess return on the market portfolio at time t, SMB_t is the return spread between small-cap and large-cap stocks (size premium), and HML_t is the return spread between high book-to-market and low book-to-market stocks (value premium). Finally, ϵ_{it}represents the idiosyncratic error term for stock *i* at time *t*. In Equation 5, the variable *i* denotes the quantity of trading days associated with stock i during the month m, and relevant observations are subsequently omitted. In Equation 6, M represents the total number of trading months pertaining to stock *i* within the fiscal year *T*. The computation of the monthly idiosyncratic risk is achieved by taking the square root of the daily standard deviation and multiplying it by the monthly trading days corresponding to the stock. The idiosyncratic risk attributed to stock *i* in year *T* is quantified as the average residual standard deviation on a monthly basis for stock *i* (Atak, 2024; He et al., 2022).

3.5. Overview of Model Variables

In the models used in this study, the dependent and independent variables were first defined, followed by the identification of the control variables, as shown in Table 4. The dependent variable in the model is idiosyncratic volatility (IVOL). The independent variables are ESG sentiment scores representing environmental, social, and governance dimensions, which are detailed in the preceding sections.

Additionally, two key control variables were included in the model to ensure more robust and reliable results. One is Growth, representing the firm's growth rate; the other is Free Float Shares, indicating the firm's publicly traded share ratio. The inclusion of growth and free float shares as control variables enables precise analysis of the relationship between ESG sentiment scores and idiosyncratic volatility (IVOL).

Table 4. Variables and Their Definitions

Variable Type	Variable Name	Definition
Dependent variable	IVOL	The idiosyncratic risk of firm i in period t.
Independent variables	Environmental Sentiment	A score that reflects attitudes about environmental sustainability practices and environmentally sensitive policies with data from firms' annual sustainability reports.
	Social Sentiment	A score calculated as a reflection of firms' assessments on social responsibility, equality and social policies through their annual sustainability reports.
	Governance Sentiment	Score based on firms' attitudes on corporate governance, leadership, transparency and ethical practices as stated in their annual sustainability reports.
Control variables	Growth	The growth of firms' assets over time is an indicator that measures financial and economic growth.
	Free Flot Shares	The proportion of freely tradable shares of listed firms that are not held by insiders or strategic investors.

3.6. Overview of Econometric Methods

In this study, the long-run and causal relationships among the variables were examined by employing the Westerlund (2007) panel cointegration test, the Pooled Mean Group (PMG) estimator, and the Dumitrescu & Hurlin (2012) panel causality test. The selection of these econometric methods was based on both the characteristics of the dataset and the need to ensure the robustness of empirical results.

The dataset used in this study consists of 28 firms observed over a 10-year period, forming a short panel structure (N > T). Under such circumstances, traditional time-series cointegration techniques are not suitable, as they cannot capture firm-specific heterogeneity and cross-sectional dependence. The Westerlund (2007) panel cointegration test was therefore adopted since it allows for cross-sectional dependence and heterogeneity across panel units, which are common in firm-level data. This approach provides more reliable inferences about long-run equilibrium relationships, even with relatively short time dimensions. Following the confirmation of cointegration relationships, the PMG estimator was used to estimate long-run coefficients. PMG estimation is particularly appropriate for panels where the cross-sectional dimension is larger than the time dimension, and it accommodates heterogeneous short-run dynamics while assuming homogeneous long-run relationships. This is a realistic assumption for firm-level data operating in similar market environments. In the next step, the Dumitrescu & Hurlin (2012) panel causality test was employed to examine the direction of causal linkages among the variables. This test was preferred because it can handle heterogeneity across firms and remains valid under cross-sectional dependence, making it a robust choice for panels with limited time observations.

Furthermore, several empirical studies have employed similar methods with comparable data structures and sample sizes. For instance, Ramos-Herrera and Prats (2020) and Espoir et al. (2023) have applied these second-generation panel techniques to datasets featuring a small time dimension and a moderate cross-sectional size. These precedents support the methodological suitability of applying Westerlund, PMG, and Dumitrescu-Hurlin tests in this study. Therefore, the selected panel econometric techniques are both methodologically sound and consistent with prior literature, ensuring the reliability of the long-run and causal relationship analyses conducted using firm-level data over the 10-year period.

3.7. Descriptive Statistics and Preliminary Tests

Before starting the analysis, it is important to examine descriptive statistics such as mean, skewness, kurtosis, and correlation matrix, as these provide preliminary insights into the series. According to the descriptive statistics presented in Table 5, the standard deviation of Growth is higher than other variables. Additionally, skewness and kurtosis values are also important among descriptive statistics. If the kurtosis value of the series is higher than 3, it means that the variable is sharp, and if it is lower than 3, it means that the variable is flat (Zhang et al., 2013). Skewness at 0 or close to 0 indicates that the variable has a normal distribution, positive skewness indicates that the series is skewed to the left, and negative skewness indicates that the variable is skewed to the right (Cain et al., 2017). When the values in Table 5 are examined, it is observed that the IVOL, Environmental and Growth variables are skewed to the left, while Governance and Social are skewed to the right. The freefloat series exhibits normal distribution properties as it is close to zero. In addition, while all the series used show a sharp feature, the freefloat series shows a flattened feature. The maximum and minimum values of the dependent variable IVOL respectively are 0.048902 and 0.008542 while the mean value of the series is 0.017581.

Table 5. Descriptive Statistics and Pairwise Correlation

	IVOL	Environmental	Social	Governance	Growth	Freefloat
Mean	0.017581	0.256566	0.249836	0.053360	44.03404	32.08368
Median	0.016337	0.255956	0.257849	0.047170	23.55000	30.35500
Maximum	0.048902	0.621622	0.468510	0.307692	449.2600	53.95000
Minimum	0.008542	0.000000	0.001449	-0.333333	-10.1600	1.460000
Std. Dev.	0.000335	0.005108	0.004434	0.003135	3.775902	0.769686
Skewness	1.255574	0.348488	-0.380529	-0.544459	3.479484	0.019448
Kurtosis	6.071920	5.219990	3.551161	15.68381	16.99129	1.949090
Correlation	1	-0.0271	-0.0356	-0.0115	0.4447	-0.1012
Observations	280	280	280	280	280	280

Note: *** rejection of the null hypothesis at 1% level of significance, **significant at 5%, * significant at 10% in the whole text. Also, the first numbers given for the series show the test statistics, while the numbers in parentheses show the probability values.

The correlation analysis results for the IVOL dependent variable are also given in Table 5. The correlation coefficients show the linear association between IVOL and each independent variable. In order to avoid the problem of multicollinearity in the correlation analysis, there must be a weak correlation between the independent variables. If the independent variables have a correlation above 0.80, this indicates that there is multicollinearity between the variables (P. Vatcheva & Lee, 2016). When the correlation coefficients of the variables are analyzed, it is seen that this problem does not exist among the independent variables of the study. According to the correlation analysis results, IVOL is negatively correlated with all independent variables except growth.

4. Empirical Results

In this study, the Panel ARDL method (PMG estimator) is used to determine the cointegration relationship between variables, and the Panel Dumitrescu-Hurlin causality analysis is used to determine causality. These methods have been preferred because they are frequently accepted in panel data analysis. In addition, the ARDL method provides an advantage for the study as it can be applied under conditions where the number of observations is low.

In this study, the models expressed in Equation 7, Equation 8 and Equation 9 were used in the analysis of the relationship between IVOL and ESG parameters.

$$\textbf{Model 1}: IVOL_{\dot{\imath}t} = B_0 + Environmental_{it} + Growth_{it} + Freefloat_{it} + e_{it} \quad (7)$$

$$\textbf{Model 2}: IVOL_{\dot{\imath}t} = B_0 + Social_{it} + Growth_{it} + Freefloat_{it} + e_{it} \quad (8)$$

$$\textbf{Model 3}: IVOL_{\dot{\imath}t} = B_0 + Governance_{it} + Growth_{it} + Freefloat_{it} + e_{it} \quad (9)$$

In equation (7), $IVOL_{it}$ is the dependent variable that corresponds to the volatility, B_0 is the intercept; $Environmental_{it}$ is the Environmental ESG scores, $Growth_{it}$ is the asset growth, $Freefloat_{it}$ is free float share of firms and e_{it} represents the error terms. In other models, the control variables ($Growth_{it}, Freefloat_{it}$) and the dependent variable ($IVOL_{\dot{\imath}t}$) remain constant. In equation (8), $Social_{it}$ is the independent variable that corresponds to the Governance ESG scores, while in equation (9), $Governance_{it}$ is the independent variable that corresponds to the Social ESG scores.

4.1. Panel Cointegration Analysis Results

In order to select the appropriate cointegration analysis and unit root tests to be used in the model, the correlation between units should be tested firstly. The Pesaran CD (2004) test, which gives the correlation results between units, is generally used in the literature.

Table 6. Results from Pesaran CD Cross-Section Independence Test

Variables	CD-test value	P-value
IVOL	40.10***	0.000
Environmental	-0.38	0.703
Governance	0.18	0.857
Social	2.05**	0.040
Growth	41.72***	0.000
Freefloat	7.99***	0.000

Note: ***significant at 1%, **significant at 5%.

The basic hypothesis of the Pesaran CD (2004) test states that there is no correlation between units in the series, while the alternative hypothesis states that there is correlation between units in the series. When Table 6 is examined, it is observed that the Pesaran CD test probability value is below the 5% significance level for IVOL, Social, Growth and Freefloat and the basic hypothesis is rejected, but the basic hypothesis is accepted for Environmental and Governance. As a result, while there is no correlation between units in the Environmental and Governance series, there is correlation between units in the IVOL, Social, Growth and Freefloat series and there is cross-sectional dependence in these series. In such cases, it is appropriate to use the CIPS unit root test, which takes into account the cross-sectional dependency. The results of CIPS unit root tests at level forms and first difference are shown in Table 7.

In Table 7, the first numbers given for the series show the test statistics, while the numbers in parentheses show the probability values. The results obtained from the CIPS unit root tests analysis show that all series are stationary in the first difference values. According to this result, there is no problem to examining the cointegration relationships of all selected variables with the Westerlund test.

Table 7. Results from CIPS Panel Unit Root Test

Variables	CIPS	
	Level	First Differences
IVOL	-2.969*** (0.001)	-5.150*** (0.000)
Environmental	0.539 (0.705)	-2.627*** (0.004)
Governance	-2.249** (0.012)	-1.764** (0.039)
Social	-0.075 (0.470)	-2.604*** (0.005)
Growth	-1.983** (0.024)	-4.681*** (0.000)
Freefloat	0.567 (0.714)	-2.434*** (0.007)

Note: ***significant at 1%, **significant at 5%, * significant at 10%.

The Westerlund cointegration test states that there is no cointegration relationship between the variables as the null hypothesis, while the alternative hypothesis states that the variables are cointegrated and move together in the long-run. The Westerlund cointegration test results are given in Table 8.

Table 8. Westerlund Cointegration Test Results

	Statistics	Gt	Ga	Pt	Pa
Model 1	Value	-2.070	-6.228	-9.908	-6.100
	Z-value	-1.649	0.951	-2.078	-2.012
	P-value	0.050**	0.829	0.019**	0.022**
	Statistics	**Gt**	**Ga**	**Pt**	**Pa**
Model 2	Value	-2.040	-6.391	-11.435	-7.136
	Z-value	-1.469	0.791	-3.586	-3.206
	P-value	0.071*	0.786	0.000***	0.001***
	Statistics	**Gt**	**Ga**	**Pt**	**Pa**
Model 3	Value	-2.272	-7.002	-15.346	-9.099
	Z-value	-2.851	0.195	-7.447	-5.470
	P-value	0.002***	0.577	0.000***	0.000***

Note: *** rejection of the null hypothesis at 1 % level of significance, **significant at 5 %, * significant at 10 %.

According to the obtained Westerlund cointegration results, for Model 1, the null hypothesis has been rejected based on p-value at a 5% significance level for Gt, Pt, and Pa statistics. For Model 2, the null hypothesis has been rejected based on p-value at 1% significance level for Pt and Pa statistics. For Model 3, the null hypothesis has been rejected based on p-value at 1% significance level for Gt, Pt and Pa statistics. As a result, all models have a cointegration relationship in the long run. After determining the cointegration relationship, the coefficients can be estimated using the cointegration estimator. Table 9 shows the PMG estimation results.

According to the obtained robustness PMG estimation results, it is seen that all variables included in the models are statistically significant. The Growth and Freefloat control variables, which are common in all models, have a positive effect on IVOL according to the common results obtained from three separate models. This effect is very small according to the common results of all three models. In addition, the ECT estimates in the three separate models again showed statistically significant and close values. The Environmental variable, which is an independent variable in Model 1, has a statistically significant and negative effect on IVOL. In Model 2, the effect of the Social variable on IVOL is statistically significant and positive. Finally, according to the results in Model 3, the effect of the Governance variable on IVOL was measured, and again, a statistically significant negative relationship was found between the variables.

Table 9. PMG Estimation Results

Variables	Model 1	Model 2	Model 3
Panel-ARDL Analysis Results			
Dependent variable IVOL			
Environmental	-0.0163346***		
	(0.000)		
Social		0.0384169***	
		(0.000)	
Governance			-0.013859***
			(0.000)
Growth	0.0000428***	0.000015***	0.000041***
	(0.000)	(0.000)	(0.000)
Freefloat	0.0001565***	0.0003622***	0.0001404***
	(0.000)	(0.000)	(0.002)
ECT	-0.5199073***	-0.5360093***	-0.5738223***
	(0.001)	(0.000)	(0.001)

Note: Model 1 examines the effect of Environmental on IVOL, Model 2 examines the effect of Social on IVOL, and Model 3 examines the effect of Governance on IVOL. Also, *** rejection of the null hypothesis at 1% level of significance, **significant at 5%, * significant at 10%.

4.2. Panel Causality Results

Table 10 shows the results of the Panel Dumitrescu & Hurlin (2012) causality analysis between the dependent variable and the independent variables. The basic hypothesis of the Dumitrescu-Hurlin causality analysis states that there is no causality relationship between the variables, while the alternative hypothesis states a causality relationship between the variables.

Table 10. Panel Dumitrescu and Hurlin Causality Test Results

Null hypothesis (H_0 Lag length is AIC)	Z-bar Test Statistics	P-value
IVOL ≠ Environmental	-0.9351	0.3498
Environmental ≠ IVOL	5.3446	0.0000***
IVOL ≠ Governance	1.4152	0.1570
Governance ≠ IVOL	4.8987	0.0000***
IVOL ≠ Social	2.6213	0.0088
Social ≠ IVOL	3.7243	0.0002***
IVOL ≠ Growth	3.4389	0.0006
Growth ≠ IVOL	6.1371	0.0000***
IVOL ≠ Freefloat	5.3469	0.0000
Freefloat ≠ IVOL	10.0337	0.0000***

Note: *** rejection of the null hypothesis at 1% level of significance, **significant at 5%, * significant at 10%.

According to the obtained results in Table 10 show that all independent variables in the models are the cause of IVOL. This result indicates the significance of the used models. In addition, there is a bidirectional causality relationship between IVOL and Social, Growth, Freefloat. Finally, a unidirectional causality relationship from Environmental to IVOL was determined between IVOL and Environmental, and a unidirectional causality relationship from Governance to IVOL was determined between IVOL and Governance.

5. Discussion and Conclusion

This study investigates the influence of ESG sentiment scores on idiosyncratic volatility among firms listed on the BIST Sustainability Index, offering a timely contribution to the literature on corporate sustainability and financial risk. The results of the econometric methods used in the study show that the models are suitable for the purpose. Our empirical results reveal a statistically significant relationship between the sentiment embedded in ESG disclosures and the level of idiosyncratic volatility. This situation is valid for the three different models used in the study and all models have a cointegration relationship in the long run according to the Westerlund cointegration results. After determining the existence of the cointegration relationship, the estimated Panel ARDL estimator (PMG estimator) produced very critical results. According to the obtained robustness PMG estimation results, Environmental (E) and Governance (G) variables have a statistically significant and negative effect on idiosyncratic volatility while the effect of the Social (S) variable on idiosyncratic volatility is statistically significant and positive. Moreover, asset growth and free float share of firms which are common in all models, have a positive effect on idiosyncratic volatility according to the common results obtained from three separate models. This effect is very small according to the common results of all three models. Finally, the results of Panel Dumitrescu & Hurlin causality analysis show that all independent variables in the models are the cause of idiosyncratic volatility. This result also points to the significance of the models used for cointegration analysis.

One of the most notable findings is the negative and statistically significant effect of both Environmental and Governance sentiment on idiosyncratic volatility. This result suggests that firms which communicate their environmental and governance practices with a more positive tone experience lower firm-specific risk. From an investor's perspective, this aligns with the expectation that strong and positively framed environmental initiatives signal proactive risk management related to climate exposure, regulatory compliance, and operational efficiency. Similarly, strong governance-related disclosures likely convey trust in management, internal controls, and strategic integrity factors that reduce uncertainty about a firm's long-term stability. Our findings further emphasize that environmental and governance dimensions of ESG are key drivers in mitigating firm-level risk. Firms with stronger performance and positive communication in these dimensions exhibit lower idiosyncratic volatility, suggesting that targeted improvements in environmental and governance practices can enhance financial sustainability.

Across all three models, asset growth and free float share were found to have a positive effect on idiosyncratic volatility, although the magnitude of this effect was relatively small. These results are consistent with established financial theory. Firms in asset growth phases often undertake aggressive investments or strategic shifts, which can introduce higher earnings uncertainty and operational risk. Similarly, a higher free float ratio increases the availability of shares for trading, potentially leading to greater price fluctuations due to more frequent trading and broader investor participation (Bostancı & Kılıç, 1997; Kerestecioğlu & Çalışkan, 2013). Although the effect sizes are limited, the consistency of these findings across models strengthens their reliability and highlights the role of fundamental financial indicators alongside ESG factors.

The presence of causality from all independent variables to idiosyncratic volatility reinforces the structural validity of the cointegration model and strengthens the argument that ESG sentiment is not merely correlated with, but potentially drives, variations in firm-level risk. This has important implications for how investors and risk managers treat sustainability reporting not just as a reputational or compliance tool, but as a material input in financial decision-making.

The findings of this study, which reveal that ESG communication significantly reduces firm-specific idiosyncratic risk, are largely consistent with the broader empirical literature emphasizing the risk-mitigating role of ESG performance. Similar to the results reported by Lee and Koh (2024), Horn (2023), and Perera et al. (2024) for the U.S. market, our evidence supports the view that firms with stronger ESG sentiment experience lower volatility and risk exposure. This alignment suggests that ESG-oriented transparency and positive discourse in sustainability communication strengthen investor confidence and reduce uncertainty about firm behavior. Consistent with Anselmi and Petrella (2025) and Capelli et al. (2023), who found that higher ESG scores reduce credit and market risk in European firms, our results indicate that the positive perception generated by ESG communication enhances firms’ financial resilience, even within an emerging market such as Türkiye. Likewise, our findings resonate with studies in Asian contexts such as Khorilov and Kim (2024) and Kim et al. (2024) which highlight that ESG practices help mitigate firm volatility, especially during times of crisis, suggesting that ESG sentiment acts as a stabilizing mechanism in periods of market uncertainty.

The results of this study offer several important implications for policymakers and regulatory authorities. Encouraging linguistic and emotional transparency in corporate sustainability reporting could strengthen market stability by improving information flow and investor confidence. Moreover, developing standardized ESG reporting frameworks would reduce information asymmetry and promote more accurate risk assessment among market participants. In this regard, ESG-sensitive corporate communication strategies should be viewed as a strategic policy tool that enhances both financial sustainability and market resilience.

Overall, this study reinforces the notion that how firms communicate ESG matters nearly as much as what they disclose. By leveraging NLP to quantify ESG sentiment in sustainability reports, we reveal a significant and economically meaningful relationship between disclosure tone and firm-specific risk. In doing so, we highlight a powerful new frontier in ESG analytics one that blends technology, finance, and sustainability to better understand and manage corporate risk in dynamic and evolving markets like Türkiye.

In sum, the results of this study demonstrate that ESG sentiment, as derived from textual analysis of sustainability disclosures, plays a significant and nuanced role in shaping firm-specific risk in the Turkish Stock Market. Environmental and governance narratives contribute to reduced volatility, signaling firm stability, while social sentiment introduces complexity and, potentially, greater uncertainty. These findings highlight the importance of communication tone in ESG disclosures and position NLP-based sentiment analysis as a critical tool in the financial and sustainability research toolkit.

This study has some important limitations. First, the ESG and financial data used are limited to a specific country and period, and the results may not be generalizable to different markets or time periods. Furthermore, the fact that only 10-year sustainability reports of 28 companies were available for this study limits the generalizability of the results. Another important limitation is the sectoral diversity of the companies included in the analysis. For example, the financial structure, risk profile, and market dynamics of a firm operating in the manufacturing industry are quite different from those of a firm in the banking or finance sector. Therefore, analyzing different sectors together within the same model may not fully reflect the effects of sectoral differences and may limit the generalizability of the findings.

Given these limitations, several areas for future research. First, using a larger dataset that covers more companies and a longer period will significantly enhance the statistical reliability of the analyses and make the results more applicable overall. Additionally, grouping companies by sector and conducting sector-specific analyses will help better identify sector-related dynamics and investor reactions. Performing comparative analyses across different countries or markets would also be beneficial in testing the international relevance and variability of the findings. Moreover, expanding the dataset to include other forms of textual communication such as press releases, integrated annual reports, and investor briefings rather than relying solely on sustainability reports, will allow for a more thorough exploration of corporate behavior and market responses. While this study focuses on firm-level ESG communication and its impact on idiosyncratic risk, the findings also open new avenues for exploring macro-level implications of ESG sentiment. Future research could extend this framework by investigating how aggregated ESG communication patterns across firms influence broader economic indicators such as financial stability, market volatility, and capital flows. Such analyses would provide valuable insights into the transmission mechanisms through which corporate-level sustainability practices affect the overall economy. Examining these macroeconomic dynamics would not only deepen the theoretical understanding of ESG-finance interactions but also guide policymakers in designing more effective sustainability-driven economic policies.

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