

Nonlinear associations between ESG uncertainty and financial performance: Explainable machine learning evidence from listed real estate firms in Vietnam

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Abstract

Purpose – This study investigates how ESG-related informational uncertainty is associated with the financial performance of listed real estate firms in Vietnam. It examines whether this relationship is nonlinear and heterogeneous while evaluating the usefulness of explainable machine learning in an emerging market.

Design/methodology/approach – A balanced monthly panel of 28 listed real estate firms covering 2013–2024 is analyzed. Eight machine-learning algorithms are compared, with Particle Swarm Optimization used for hyperparameter tuning. Model interpretability is achieved using SHAP, complemented by partial dependence plots and accumulated local effects to identify nonlinear and heterogeneous associations between ESG uncertainty and return on equity (ROE).

Findings – XGBoost delivers the strongest out-of-sample predictive performance, indicating that the ESG uncertainty-performance relationship is inherently nonlinear. Explainable AI reveals a state-dependent pattern: ESG uncertainty is negatively associated with ROE at low levels, becomes broadly neutral as firms adapt, and is associated with more favorable outcomes only among firms with stronger adaptive capacity under high uncertainty. Large firms are more sensitive to ESG uncertainty, medium-sized firms display more stable adaptive responses, and small firms exhibit weaker responses. These findings represent model-implied associations rather than causal effects.

Originality/value – This study shifts the ESG-performance literature from static ESG levels to ESG-related informational uncertainty and integrates explainable machine learning with SHAP to uncover nonlinear and heterogeneous effects, providing new evidence from Vietnam's listed real estate sector.

Keywords ESG Uncertainty, Machine learning, Explainable AI (XAI)/SHAP, Real Estate Firms, Performance, Vietnam.

Paper type Research paper

1. Introduction

In the context of globalization and increasing pressure for sustainable development, Environmental, Social, and Governance (ESG) principles have evolved from normative guidelines into a strategic

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pillar of the global financial system. As investor expectations and institutional demands intensify, ESG increasingly shapes risk profiles, financing conditions, and firm valuation, particularly in capital-intensive sectors with long investment horizons such as real estate (Newell et al., 2023).

In emerging markets such as Vietnam, where institutional frameworks remain incomplete and transparency is uneven, ESG represents not only an opportunity for sustainable growth but also a source of uncertainty. Rising ESG-related uncertainty has been shown to increase capital costs, weaken investor confidence, and amplify market volatility (Bhatia, 2024). These effects are especially pronounced in real estate, where long-term capital dependence makes firms highly sensitive to changes in ESG-related expectations and regulatory credibility (Nguyen & Nguyen, 2025).

Recent research has shifted attention from static ESG scores to ESG uncertainty, defined as the volatility and ambiguity surrounding ESG policies, disclosures, and expectations. Unlike conventional ESG indicators, ESG uncertainty captures instability in the information environment. This dimension is particularly relevant in emerging markets with fragmented disclosure practices and weak ESG standardization (Bin-Feng et al., 2024; Chen et al., 2025). Although less directly observable, ESG uncertainty can significantly affect investor perception, financing conditions, and cost structures (Bin-Feng et al., 2024). For instance, Chen et al. (2025) show that firms exposed to higher ESG uncertainty face higher debt financing costs due to increased perceived risk.

To conceptualize these effects, this study draws on three complementary perspectives. Stakeholder Theory suggests that ESG uncertainty may erode trust and legitimacy, increasing external pressure. Agency Theory highlights how opaque ESG environments intensify information asymmetry and agency costs. Real Options Theory implies that the relationship may be nonlinear: moderate uncertainty may encourage strategic adaptation, whereas excessive uncertainty may delay investment and reduce profitability. Together, these perspectives suggest that ESG uncertainty may affect firm performance through heterogeneous and nonlinear channels.

Despite extensive research on ESG and firm performance, most studies adopt linear frameworks. This may be restrictive. Emerging evidence indicates that ESG-related effects are often nonlinear and context-dependent. Firms may adapt to moderate uncertainty, but excessive uncertainty may increase agency costs and financing frictions, ultimately reducing performance (Chen et al., 2025; Morri et al., 2024). These insights motivate the use of methods capable of capturing nonlinear and heterogeneous patterns.

To address this gap, this study combines machine learning models (e.g., XGBoost, Random Forest, SVM) with explainable AI tools (SHAP) to examine the ESG uncertainty-performance relationship in Vietnam's listed real estate sector. Machine learning enables the identification of complex nonlinear patterns, while SHAP improves interpretability by revealing feature importance and model-implied nonlinear regions where associations may change in direction or intensity. These patterns are interpreted as associative rather than causal.

This study addresses three research questions:

(1) How is ESG uncertainty associated with the financial performance (ROE) of real estate firms in Vietnam?

(2) Do model-implied threshold-like regions exist where this association changes in direction or intensity?

(3) To what extent can SHAP-based methods reveal feature importance and nonlinear patterns related to ESG uncertainty?

The study contributes in three ways. First, it extends the ESG-performance literature by focusing on ESG uncertainty as a dynamic risk factor. Second, it integrates machine learning with explainable AI to capture and interpret nonlinear patterns in firm performance. Third, it documents firm-size heterogeneity in Vietnam's real estate sector, where ESG uncertainty plays a particularly important role. These findings contribute to research at the intersection of corporate finance, real estate, and sustainability, while offering practical insights for ESG risk assessment in transitional economies.

2. Theoretical Framework

Understanding the relationship between ESG uncertainty and corporate financial performance requires a framework that captures institutional instability, informational opacity, and investment irreversibility, particularly in emerging markets. This is especially relevant for real estate firms, where profitability depends on long-term financing conditions, stakeholder confidence, and the timing of capital-intensive investments. No single theory fully explains these dynamics. This study therefore integrates Stakeholder Theory, Agency Theory, and Real Options Theory to explain how ESG uncertainty may be associated with return on equity (ROE).

Stakeholder Theory provides the first analytical layer. It posits that firm value depends on aligning the interests of multiple stakeholders, including investors, regulators, and communities (Freeman, 2010). In ESG contexts, this alignment relies on trust, legitimacy, and transparency. ESG uncertainty disrupts these mechanisms by increasing ambiguity in ESG commitments and disclosures. As a result, stakeholders may reassess firm credibility, leading to higher perceived risk, weaker investor confidence, and tighter financing conditions. These effects are particularly pronounced in real estate, where long-term projects rely heavily on external capital. Thus, ESG uncertainty can be associated with weaker performance through a legitimacy and financing channel.

Agency Theory complements this external perspective by focusing on internal dynamics. Jensen and Meckling (1976) emphasize conflicts between managers and shareholders under asymmetric information. In emerging markets, where ESG standards are less developed, ESG uncertainty amplifies these asymmetries. The lack of clear benchmarks creates “informational gray zones” that may enable opportunistic behavior, including selective disclosure, greenwashing, or inefficient allocation of ESG-related investments. This increases agency costs, reduces investment efficiency, and weakens profitability. These effects are especially critical in real estate, where investments are irreversible and governance failures are costly. ESG uncertainty therefore operates not only externally through stakeholder perceptions but also internally through managerial incentives and information asymmetry.

Real Options Theory introduces a dynamic dimension to this framework. Building on Black and Scholes (1973) and Myers (1977), it conceptualizes investment as a flexible decision under uncertainty. This perspective suggests that the ESG uncertainty-performance relationship is likely nonlinear. At moderate levels, uncertainty may increase flexibility, allowing firms to delay investments and gather information, thereby preserving option value. However, beyond a certain level, rising uncertainty may lead to investment postponement, capital misallocation, and declining profitability. This mechanism is particularly relevant in real estate, where project timing and irreversibility are central. Real Options Theory thus explains why ESG uncertainty may generate heterogeneous and state-dependent outcomes rather than uniform effects.

Taken together, these theories form a coherent framework. Stakeholder Theory explains how ESG uncertainty weakens external confidence and financing conditions; Agency Theory shows how it increases internal inefficiencies through information asymmetry; and Real Options Theory clarifies why these effects are nonlinear and dependent on the level of uncertainty. Their integration is particularly appropriate in emerging markets, where ESG institutions are evolving and firms differ in their capacity to absorb uncertainty. ESG uncertainty should therefore be viewed as a multidimensional risk factor affecting legitimacy, governance, and investment timing simultaneously.

This integrated perspective also motivates the empirical approach. If ESG uncertainty operates through nonlinear and heterogeneous channels, linear models may be insufficient. Accordingly, this study employs machine learning combined with SHAP-based interpretability to uncover model-implied patterns in the ESG uncertainty-performance relationship. These patterns are interpreted as associative rather than causal, but are consistent with the mechanisms suggested by stakeholder, agency, and real-options theories.

3. Literature Review

The relationship between ESG and corporate financial performance has become central to sustainable finance. A large body of research argues that ESG enhances firm value by improving reputation, lowering legal and financing costs, and strengthening performance indicators such as ROA and ROE (Dawei & Bin Abdul Lait, 2024; Digar, 2023; Handoko et al., 2024). In this view, ESG functions as a strategic asset that reinforces stakeholder confidence and long-term competitiveness, particularly in capital-intensive sectors.

However, the financial consequences of ESG are contingent on the policy, institutional, and information environments in which firms operate. Heightened policy uncertainty can erode ESG value by tightening financial constraints, shortening managerial decision horizons, and weakening the credibility of sustainability commitments. These mechanisms are particularly pronounced where institutional enforcement and disclosure quality are limited, making it difficult for investors to distinguish substantive ESG engagement from symbolic compliance (Persakis, 2023; Waris & Din, 2023; Zhang et al., 2024). ESG should therefore not be viewed as an unconditional source of firm value. Its capacity to strengthen financial performance depends on whether a stable policy framework and transparent information environment allow sustainability investments to generate credible, long-term economic benefits.

This helps reconcile the mixed empirical evidence. Positive ESG effects are not universal and often weaken or become negative in emerging markets with incomplete regulatory and disclosure frameworks (Hansen & Xie, 2025; Iqbal, 2023). This inconsistency may reflect an underlying nonlinear relationship rather than conflicting evidence. ESG improves performance only after firms exceed a minimum commitment threshold; below it, compliance and adjustment costs may outweigh the benefits (Jin, 2025; Zheng et al., 2025). Linear specifications may therefore conceal turning points and heterogeneous responses. More fundamentally, treating ESG as a static score overlooks the informational risk arising from unstable sustainability expectations, an omission that is especially consequential in emerging markets undergoing institutional transition (Biju et al., 2025; Kim et al., 2025; Syaputra, 2022; Zheng et al., 2025).

Recent research has consequently shifted from ESG levels to ESG-related uncertainty. Conventional indices, including the Economic Policy Uncertainty Index, World Uncertainty Index, and Geopolitical Risk Index, capture broad macroeconomic uncertainty but not instability specific to ESG information (Baker et al., 2016). This distinction has become increasingly important as ESG considerations shape capital allocation and risk assessment.

Ongan et al. (2025) address this gap by developing the ESG-based Sustainability Uncertainty Index (ESGUI), a national-level measure derived from text analysis of monthly reports and ESG-related terms. Unlike static ESG scores, ESGUI captures temporal instability and inconsistency in sustainability communication. Firms may therefore incur financial costs not only from weak ESG performance but also from uncertainty surrounding ESG expectations. Such uncertainty increases informational noise and complicates stakeholder assessment (Bin-Feng et al., 2024), while disagreement in ESG ratings raises debt financing costs, demonstrating that ESG uncertainty constitutes a distinct, pricing-relevant risk factor (Chen et al., 2025).

ESGUI is particularly relevant in emerging markets, where ESG institutions remain underdeveloped and disclosure practices fragmented. Its monthly frequency and adaptability make it suitable for linking macro-level ESG uncertainty with firm-level performance. This is especially important in real estate, where funding access and long-term investment depend heavily on trust and regulatory credibility. Prior studies confirm the sector's sensitivity to ESG conditions (Morri et al., 2024; Newell et al., 2023; Nguyen & Nguyen, 2025), yet evidence on ESG uncertainty, rather than ESG level, remains limited, particularly in transitional economies.

At the same time, conventional empirical methods may not adequately capture the complexity of this relationship. Most studies rely on linear models that assume constant marginal effects, potentially overlooking nonlinear responses and heterogeneous firm behavior. This limitation is significant given recent evidence of context-dependent ESG effects (Jin, 2025; Zheng et al., 2025). Machine learning offers a flexible alternative, with strong capability to model nonlinear relationships and high-dimensional interactions (Handoko et al., 2024; Jin, 2025).

However, machine learning models are often criticized for their lack of interpretability. To address this, explainable AI (XAI) tools such as SHAP have been developed to decompose predictions into feature-level contributions. Zheng et al. (2025) highlight their usefulness in identifying nonlinear patterns not captured by traditional models. Combining machine learning with SHAP therefore enables both predictive accuracy and interpretability, allowing researchers to examine whether ESG uncertainty exhibits nonlinear, heterogeneous, or threshold-like patterns. These results should be interpreted as associative and model-based rather than causal, but they provide a richer understanding of ESG-related financial dynamics.

Taken together, the literature reveals three gaps. First, most studies focus on ESG levels rather than ESG uncertainty, despite growing evidence that informational instability significantly affects financing and performance (Bin-Feng et al., 2024; Chen et al., 2025; Ongan et al., 2025). Second, although nonlinear ESG effects are increasingly recognized, few studies model them explicitly in a way that captures both heterogeneity and interpretability (Jin, 2025; Zheng et al., 2025). Third, limited research integrates ESG uncertainty, machine learning, and explainable AI in real estate contexts, particularly in emerging markets such as Vietnam.

This study addresses these gaps by integrating ESGUI with machine learning and SHAP to examine nonlinear and heterogeneous associations between ESG uncertainty and firm performance in Vietnam's listed real estate sector. By doing so, it bridges the ESG-performance literature, uncertainty measurement, real estate finance, and interpretable machine learning, providing a more flexible and comprehensive framework for analyzing ESG-related financial risk.

4. Data and Methodology

4.1 Data and Descriptive Statistics

This study employs a balanced monthly panel of 28 listed real estate firms in Vietnam from January 2013 to June 2024, yielding 3,864 firm-month observations. The sample captures the interaction between firm-level performance and time-varying ESG uncertainty in a capital-intensive, policy-sensitive sector characterized by long investment horizons. Data are collected from financial statements, market indicators, macroeconomic sources, and publicly available uncertainty indices.

Firm performance is measured by return on equity (ROE), which captures returns to shareholders and is particularly relevant in emerging markets, where financing constraints and capital structure strongly influence performance. ROE is originally reported quarterly; to align it with the monthly ESGUI series, each quarterly value was assigned to the three corresponding months without interpolation. Thus, the monthly panel represents the temporal alignment of quarterly firm performance with monthly uncertainty rather than independently observed monthly ROE. ROA is employed as an alternative measure for robustness, whereas Tobin’s Q is excluded because consistent market-based valuations are not available for all sampled firms.

The main explanatory variable is the ESG-based Sustainability Uncertainty Index (ESGUI) developed by Ongan et al. (2025). Vietnam is explicitly included in the index’s country coverage, and its monthly ESGUI series was obtained directly from this source without imputation or proxy construction. ESGUI is a national-level measure of volatility and ambiguity in ESG-related information, policies, and expectations. Unlike conventional ESG scores, it captures instability in the information environment rather than the level of ESG performance. The corresponding monthly value was assigned to all sampled firms, reflecting a common uncertainty environment that may affect firm-level ROE through financing costs, investment conditions, market demand, and compliance pressures.

The model includes firm-level and macroeconomic controls. PB and EPS capture valuation and earnings conditions, while SIZE (log of total assets) proxies for scale and financing capacity. At the macro level, GOLD and OIL represent global commodity conditions; CPI captures inflation; FED reflects external monetary conditions; and COVID accounts for the pandemic shock. These variables help isolate ESG uncertainty from broader firm-specific and macroeconomic influences.

For consistency with the empirical design, Table 1 reports variables in the form used in the analysis, including transformed values where applicable.

Table 1. Descriptive statistics for key variables

	mean	min	25%	50%	75%	max	std
ROE	0.022	-0.338	0.003	0.012	0.034	0.337	0.040
ROA	0.011	-0.116	0.001	0.006	0.017	0.265	0.022
PB	-0.013	-0.768	-0.561	-0.336	0.139	4.027	0.914
EPS	-0.017	-1.393	-0.483	-0.297	0.227	3.547	0.772
SIZE	-0.001	-2.096	-0.693	-0.033	0.551	3.089	0.992
GOLD	-0.065	-0.557	-0.438	-0.395	0.288	1.203	0.494
OIL	-0.002	-2.212	-0.842	-0.114	0.688	1.910	0.994
CPI	0.012	-2.266	-0.567	-0.114	0.549	2.667	0.949
FED	0.000	-0.736	-0.736	-0.590	0.428	2.319	1.000
COVID	0.000	-0.802	-0.802	-0.802	1.247	1.247	1.000
ESGUI	0.000	-1.227	-0.840	-0.381	0.666	2.382	0.999

Source: Authors’ calculations

Descriptive statistics indicate substantial variation across variables. ROE has a mean of 0.022 and a standard deviation of 0.040, with values ranging from -0.338 to 0.337, reflecting the cyclical nature of the real estate sector. ROA shows a similar but less volatile pattern. ESGUI has a mean of 0.000 and a standard deviation close to one, ranging from -1.227 to 2.382, confirming significant time variation in ESG-related uncertainty.

Firm-level variables such as PB and EPS exhibit wide dispersion, indicating heterogeneity in valuation and profitability, while SIZE shows moderate variation across firms. Macroeconomic

variables, including GOLD, OIL, CPI, and FED, also vary over time, capturing external economic conditions. The COVID indicator reflects a temporary but significant disruption.

Overall, three observations emerge. First, firm performance is heterogeneous across firms and over time. Second, ESG uncertainty is dynamic rather than static. Third, the variation across variables suggests that the ESG uncertainty-performance relationship is unlikely to be adequately captured by linear models. These features support the use of a nonlinear, machine-learning-based approach in the subsequent analysis.

4.2 Empirical Analytical Framework

To examine the association between ESG uncertainty and firm performance, this study adopts a nonlinear, prediction-oriented framework that integrates machine learning, hyperparameter optimization, and model interpretability. Instead of imposing a predefined linear specification, the approach allows the data to uncover heterogeneous and state-dependent patterns in the relationship between ESG uncertainty and firm performance.

Firm performance is specified as a general nonlinear function of ESG uncertainty, firm-level characteristics, and macroeconomic conditions, formally expressed as:

$$ROE_{i,t} = f(ESGUI_t, X_{i,t}, Z_t) + \varepsilon_{i,t}, \quad (1)$$

Where $ROE_{i,t}$ denotes the return on equity of firm i at time t , $ESGUI_t$ represents ESG uncertainty at time t , $X_{i,t}$ is a vector of firm-specific variables, Z_t captures macroeconomic factors, and $\varepsilon_{i,t}$ is the error term.

The purpose of this framework is not to establish causal effects, but to generate out-of-sample predictions and to interpret model-implied relationships between ESG uncertainty and firm performance.

The analysis begins with data preprocessing to ensure comparability while preserving economic meaning. Extreme values in firm-level variables are controlled through winsorization at the 1st and 99th percentiles. Variables with different scales are standardized where needed to support model stability, particularly for distance- and kernel-based methods. Multicollinearity is assessed using VIF, and redundant variables are removed when necessary. To avoid information leakage, the data are split chronologically: 2013 - 2022 for training and 2023 - 2024 for testing. Cross-validation is performed at the time-block level, ensuring that all firms within the same month are assigned to the same fold.

Eight machine-learning algorithms are estimated: Decision Tree, SVM, kNN, Random Forest, Gradient Boosting, AdaBoost, XGBoost, and LightGBM. These models differ in flexibility and sensitivity to nonlinear interactions, allowing a broad comparison under the same data structure. Tree-based ensembles are particularly suitable given their ability to capture interactions without pre-specification, while SVM and kNN serve as useful nonlinear benchmarks.

Hyperparameters are optimized using Particle Swarm Optimization (PSO) (Kennedy & Eberhart, 1995), a method suited to high-dimensional, non-convex search spaces. Following Qin et al. (2021), the algorithm uses a swarm size of 20, inertia weight of 0.7, and up to 50 iterations. PSO is applied consistently across models with tunable parameters, including SVR, Random Forest, Gradient Boosting, AdaBoost, XGBoost, and LightGBM, ensuring comparability across specifications. Overfitting is controlled through time-series cross-validation, regularization, early stopping (where applicable), and structural constraints in tree-based models. Performance is evaluated using R^2 , RMSE, and MAE, on the out-of-sample test set, and the best-performing model is selected for interpretation.

Interpretability is addressed using SHAP, which decomposes predictions into feature-level contributions. SHAP is used to rank variable importance and to examine how the contribution of ESG uncertainty varies across its range and in interaction with firm characteristics such as SIZE and EPS. These results are interpreted as model-based associations rather than causal effects.

To complement SHAP, Partial Dependence Plots (PDP) and Accumulated Local Effects (ALE) are used to trace the average shape of the ESGUI-ROE relationship. These tools help identify turning regions where the association changes in direction or intensity. The aim is not to estimate structural thresholds, but to characterize nonlinear patterns consistent with the theoretical framework.

This approach enables comparison of predictive models, evaluation of out-of-sample performance, and interpretation of nonlinear ESG uncertainty effects in a manner consistent with stakeholder, agency, and real-options mechanisms. For full reproducibility, detailed data processing, model implementation, and evaluation procedures are provided in Appendix A.

5. Results and Discussion

5.1 Exploratory Data Analysis

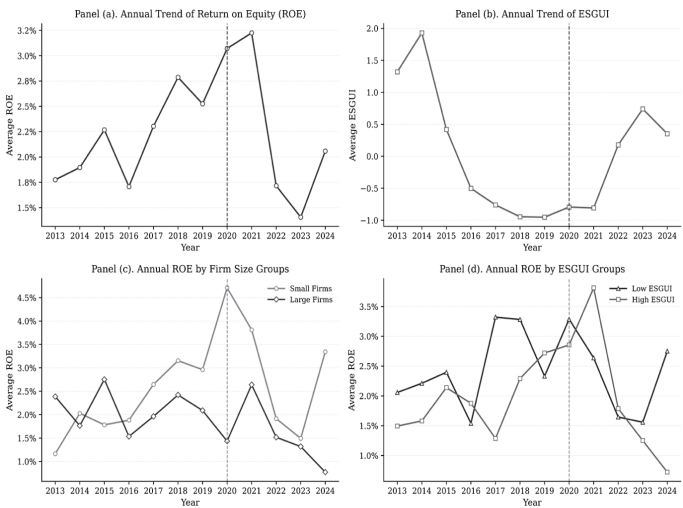
This section provides a preliminary examination of the data prior to formal modeling. The focus is descriptive rather than causal, highlighting time variation, cross-sectional heterogeneity, and empirical patterns that motivate the use of nonlinear and interpretable machine-learning methods. The analysis uses a balanced panel of 3,864 firm-month observations from 28 listed Vietnamese real estate firms over 2013 to mid-2024.

Table 1 shows substantial dispersion in firm performance. ROE averages 0.022, with a standard deviation of 0.040 and a wide range from -0.338 to 0.337, reflecting the cyclical nature of the real estate sector. ESGUI also varies considerably, indicating that ESG uncertainty is a time-varying feature rather than a stable background condition.

Figure 1 summarizes key temporal and cross-sectional patterns. Panel (a) shows that ROE increased steadily before 2020, consistent with favorable financing conditions and market expansion (Nguyen & Nguyen, 2025). This trend weakens after COVID, with profitability becoming more volatile and generally lower, reflecting tighter financial conditions under heightened uncertainty (Bhatia, 2024; Chen et al., 2025). The post-2020 period suggests a less stable environment where uncertainty and capital constraints play a larger role (Bin-Feng et al., 2024; Persakis, 2023).

Panel (b) shows that ESGUI fluctuates markedly over time, with no stable trajectory. This supports the view that ESG uncertainty is dynamic, particularly in evolving institutional contexts (Ongan et al., 2025). Its co-movement with ROE does not imply causality but suggests a potential link through financing conditions, investment decisions, and disclosure credibility (Chen et al., 2025; Chen et al., 2017; Zhang et al., 2024).

Panels (c) and (d) reveal clear heterogeneity. Larger firms achieve higher ROE during expansion periods, consistent with scale advantages and better access to capital (Alabdulkarim et al., 2024), but appear more exposed to downturns (Waris & Din, 2023). Smaller firms show lower but less amplified performance, indicating weaker capacity but lower cyclical exposure. Panel (d) further shows that firms facing lower ESG uncertainty generally outperform those under higher ESGUI, although the gap varies over time. This pattern suggests that the ESGUI-ROE relationship is not constant, consistent with evidence of nonlinear and context-dependent effects (Jin, 2025; Zheng et al., 2025).

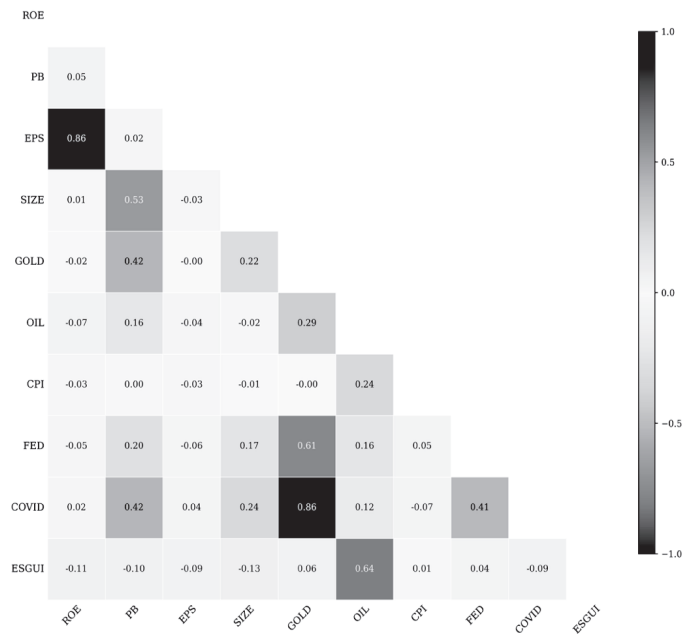


Source(s): Authors' calculations

Figure 1. Trends in Return on Equity (ROE) and ESGUI across Time, Firm Size, and ESGUI Groups

Figure 2 provides a linear benchmark through correlations. EPS and PB are strongly positively correlated ($r = 0.86$), while SIZE and EPS show a moderate positive relationship ($r = 0.53$), consistent with scale-related advantages. ESGUI is negatively correlated with ROE ($r = -0.11$), as well as with EPS, SIZE, and PB, suggesting that higher ESG uncertainty is generally associated with weaker firm conditions. This aligns with evidence that ESG uncertainty raises financing costs and constrains investment (Chai et al., 2023; Chen et al., 2025). ESGUI is also strongly correlated

with gold prices ($r = 0.64$), consistent with periods of macro-financial stress. Its relatively low correlation with other variables suggests that it captures a distinct source of variation.



Source(s): Authors' calculations

Figure 2. Correlation Matrix

Three observations follow. First, ROE and ESGUI vary materially over time, making static specifications restrictive. Second, firm responses differ across size groups, indicating heterogeneity. Third, the combination of time variation, group divergence, and modest linear correlations suggests that the ESG uncertainty-performance relationship is unlikely to be well captured by linear models. These patterns motivate the nonlinear, machine-learning approach used in the next section.

5.2 Machine Learning model training results

To evaluate predictive performance, eight machine-learning algorithms are estimated, including kNN, SVR, Decision Tree, Random Forest, Gradient Boosting, AdaBoost, LightGBM, and XGBoost. Performance is assessed before and after Particle Swarm Optimization (PSO), enabling a consistent comparison across model classes.

Table 2 shows that the effects of PSO optimization vary across models. SVR records the largest improvement in R^2 , confirming its strong sensitivity to hyperparameter selection. Gradient

Table 2. Performance comparison of ML models before and after PSO optimization

Model	R^2 (Before)	R^2 (After)	ΔR^2	$\Delta RMSE$	ΔMAE
Random Forest	0.7998	0.7958	- 0.0040	- 0.0002	- 0.0001
Gradient Boosting	0.7687	0.7817	+ 0.0130	- 0.0006	- 0.0001
XGBoost	0.7902	0.8267	+ 0.0365	- 0.0012	- 0.0007
LightGBM	0.7641	0.7484	- 0.0157	+ 0.0007	- 0.0001
AdaBoost	0.7441	0.7441	0.0000	0.0000	0.0000
kNN	0.6358	0.6358	0.0000	0.0000	0.0000
SVR	0.1927	0.5554	+ 0.3627	- 0.0110	- 0.0119
Decision Tree	0.5190	0.5190	0.0000	0.0000	0.0000

Source: Authors' calculations

Boosting and XGBoost also improve, although to a lesser extent. By contrast, kNN, AdaBoost, and Decision Tree remain unchanged. LightGBM deteriorates slightly overall, whereas Random Forest remains broadly stable, with a small decline in R^2 offset by marginal reductions in RMSE and MAE. Following optimization, XGBoost achieves the strongest overall predictive performance, reporting the highest R^2 together with lower RMSE and MAE.

Two points follow. First, nonlinear ensemble models consistently outperform simpler specifications, indicating that the ESG uncertainty-performance relationship is inherently nonlinear. Second, hyperparameter optimization is not uniformly beneficial. Its effectiveness depends on model structure: it yields substantial gains for parameter-sensitive models such as SVR, moderate gains for boosting methods, and limited or negative effects for more stable algorithms such as Random Forest and LightGBM.

The role of the benchmark model in this study is predictive and interpretive rather than structural. It is used to approximate the underlying data pattern with sufficient flexibility to support post hoc interpretation through SHAP, PDP, and ALE. Accordingly, the purpose of model selection is not to infer causal mechanisms from the training procedure itself, but to identify the specification that provides the most reliable basis for examining nonlinear, model-implied associations between ESG uncertainty and firm performance.

These findings are broadly consistent with prior evidence that ensemble methods often perform well when the underlying ESG-performance relationship is nonlinear and heterogeneous. Zheng et al. (2025) emphasize the usefulness of boosting models in ESG-related prediction, while Jin (2025) shows that tree-based methods are effective in detecting heterogeneous performance patterns. At the same time, the present results also indicate that the relative ranking of models remains data-dependent. In the Vietnamese listed real estate context, XGBoost provides the strongest out-of-sample fit and is therefore selected as the benchmark model for subsequent interpretation.

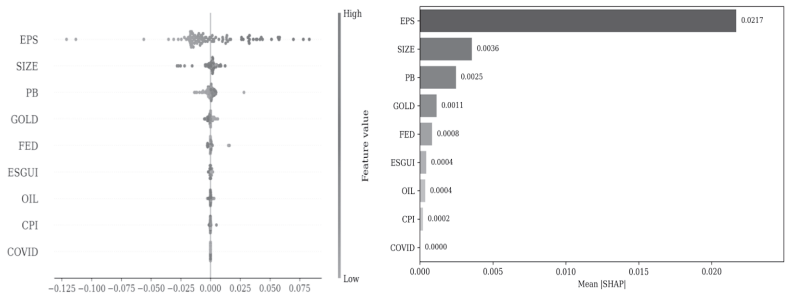
5.3 SHAP-Based model interpretation results

The SHAP-based interpretation bridges predictive performance and economic meaning. Rather than treating the model as a black box, Figures 3 - 5 recover the structure of the ESG uncertainty - performance relationship, directly addressing the research questions on nonlinearity, turning regions, and heterogeneity.

Figure 3 establishes the baseline hierarchy of determinants. EPS and SIZE dominate ROE predictions, confirming that profitability and scale remain the core anchors of performance in capital-intensive real estate markets. This is economically intuitive: internal cash generation and balance-sheet strength determine firms' ability to sustain long-cycle investments. Importantly, ESGUI, while not dominant, remains a meaningful contributor, indicating that ESG uncertainty is not peripheral but conditions how fundamentals translate into performance.

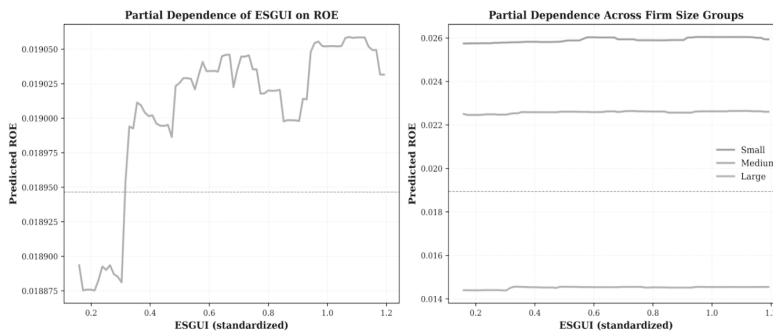
This conditioning becomes evident when moving to functional form. Figure 4 (PDP) shows a clearly non-monotonic ESGUI-ROE relationship, with plateau regions and discrete shifts rather than a single slope. However, given interaction effects, Figure 5 (ALE) provides the suggests. The ALE curve reveals a three-stage pattern: (i) negative effects at low ESGUI, (ii) a neutral transition zone, and (iii) positive contributions at higher ESGUI levels before stabilizing.

This pattern aligns closely with the theoretical framework. In the first stage, the negative slope in Figure 5 reflects stakeholder and agency mechanisms: rising ESG uncertainty erodes credibility,



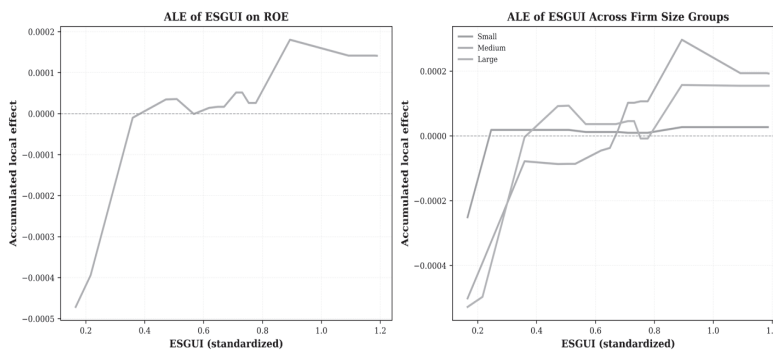
Source(s): Authors' calculations

Figure 3. SHAP summary plot: feature contributions to ROE predictions in XGBoost model.



Source(s): Authors' calculations

Figure 4. Partial Dependence of ESGUI on ROE and Heterogeneity Across Firm Size Groups.



Source(s): Authors' calculations

Figure 5. Estimated Accumulated Local Effects of ESGUI on ROE with Heterogeneous Effects.

increases perceived risk, and intensifies information asymmetry (Bin-Feng et al., 2024; Chen et al., 2025; Freeman, 2010; Freeman & McVea, 2001; Jensen & Meckling, 1976; Zhang et al., 2024). Here, uncertainty acts primarily as a friction, compressing ROE.

The second stage, visible as the flattening region in Figures 4 - 5, represents a transitional regime. ESG uncertainty no longer exerts a strong marginal effect, suggesting that firms begin to adapt through disclosure adjustments, financing strategies, and investment timing. The model captures this balance between adverse and adaptive forces.

The third stage, where Figure 5 shows positive local effects, is particularly revealing. Rather than implying that uncertainty is beneficial, it reflects selection and adaptation. Firms operating under high ESG uncertainty are likely those with stronger governance and financing capacity. This is consistent with real options theory, where firms delay irreversible investments and preserve flexibility (Black & Scholes, 1973; Myers, 1977). The positive slope therefore reflects disciplined adaptation rather than direct gains from uncertainty.

Firm-size heterogeneity further strengthens this interpretation. Figure 4 shows that large firms achieve higher predicted ROE, but Figure 5 reveals that they are also more sensitive to ESGUI changes. This reflects greater exposure to stakeholder scrutiny and financing conditions. Medium firms display smoother and more positive responses in mid-to-high ESGUI ranges, suggesting an optimal balance between flexibility and capacity. In contrast, small firms exhibit weak and unstable responses, indicating limited ability to adjust to ESG uncertainty.

These findings are consistent with prior evidence that ESG effects are nonlinear and context-dependent (D'Amato et al., 2024; Farhadi & Hair, 2025; Thompson, 2025), and that real estate firms are highly sensitive to ESG conditions (Morri et al., 2024; Newell et al., 2023; Nguyen & Nguyen, 2025). Figures 3 - 5 provide a coherent answer to the research questions. ESG uncertainty affects ROE in a nonlinear, state-dependent, and heterogeneous manner; turning regions are indicated; and SHAP-based methods effectively reveal these structures. These results should be interpreted as model-implied associations rather than causal thresholds.

In sum, ESG uncertainty is neither uniformly harmful nor beneficial. Its impact depends on intensity and firm capacity, especially size. The evidence supports a layered mechanism: uncertainty initially generates informational frictions, then interacts with firm adaptation, producing heterogeneous outcomes. This underscores the value of explainable machine learning in uncovering economic patterns that linear models are unlikely to detect.

5.4 Robustness Checks

To assess robustness, this study examines alternative variable definitions, model classes, sample splits, temporal stability, and interpretation consistency. The results consistently indicate that the ESG uncertainty-performance nexus is stable in predictive terms but nonlinear and state-dependent.

Table 3 shows that results are robust to alternative ESG uncertainty measures. Replacing ESGUI with lagged, smoothed, or differenced versions yields similar or slightly higher predictive performance. The best specification uses ESGUI lagged three periods ($R^2 = 0.7591$), indicating delayed transmission of ESG uncertainty. In contrast, replacing ROE with ROA, ΔROE , or ROE volatility sharply reduces explanatory power, suggesting that ESG uncertainty is more closely linked to equity-based performance than to asset efficiency or short-term fluctuations.

The combined results in Table 4 confirm that the findings are not driven by sample composition, temporal segmentation, or interpretation settings. Predictive performance remains stable across subsamples, including the post-COVID period and specifications excluding extreme firms, while clear heterogeneity emerges across firm size. In particular, explanatory power is highest among large firms, suggesting that the transmission of ESG uncertainty depends on firms' capacity to absorb uncertainty and their exposure to market discipline.

Across time windows, model performance is consistently high prior to 2023 but declines in 2023 - 2024. This pattern points to potential structural changes in the market environment and reinforces that ESG uncertainty operates in a state-dependent rather than time-invariant manner.

Finally, results are stable across random seeds and alternative model specifications. ESGUI consistently ranks below core financial variables such as EPS and SIZE, indicating a secondary but persistent role. Thus, ESG uncertainty does not dominate firm performance but conditions how financial fundamentals translate into ROE.

6. Conclusion and Policy Implications

6.1 Conclusion

This study revisits the ESG-performance nexus by examining ESG uncertainty through nonlinear and heterogeneous specifications. The results indicate that its association with firm performance is neither constant nor uniform, but varies across uncertainty levels and firm-size groups. These findings should be interpreted as model-based associations rather than evidence of causal mechanisms.

The analysis identifies a layered pattern. At lower levels, ESG uncertainty is negatively associated with performance, consistent with the view that informational ambiguity may weaken credibility and increase financial frictions. At intermediate levels, the association becomes less pronounced, while higher levels produce more differentiated outcomes. These patterns suggest that firms may respond differently to ESG uncertainty, although the organizational mechanisms underlying such differences are not directly identified.

Table 3. Robustness of Measurement and Model Specification

Specification	Dependent Variable	ESG Proxy	Test R^2	RMSE	MAE
Baseline	ROE	ESGUI	0.7512	0.0302	0.0102
ESGUI lag (1)	ROE	ESGUI_L1	0.7530	0.0301	0.0100
ESGUI lag (3)	ROE	ESGUI_L3	0.7591	0.0299	0.0099
ESGUI MA (3)	ROE	ESGUI_MA3	0.7536	0.0300	0.0100
ESGUI MA (6)	ROE	ESGUI_MA6	0.7568	0.0299	0.0100
Δ ESGUI	ROE	ESGUI_DIFF	0.7576	0.0299	0.0100
Alternative DV	ROA	ESGUI	0.4745	0.0123	0.0048
Alternative DV	Δ ROE	ESGUI	0.2709	0.0264	0.0151
Alternative DV	ROE volatility	ESGUI	0.4317	0.0162	0.0112

Source: Authors' calculations

Table 4. Sample, Temporal, and Interpretation Robustness

Category	Specification / Setting	N / Period	Test R ²	RMSE	MAE	Key Drivers
Subsample	Full sample	3,864	0.7512	0.0302	0.0102	EPS, SIZE, PB
	Post-COVID	1008	0.7215	0.0307	0.0104	
	Exclude top-3 firms	3450	0.7461	0.0305	0.0103	
	Exclude bottom-3 firms	3450	0.7578	0.0299	0.0101	
	Small firms	1242	0.7905	0.0278	0.0095	
	Medium firms	1242	0.7195	0.0310	0.0106	
	Large firms	1380	0.9036	0.0222	0.0073	
Temporal	2019-2020	Test window	0.9769	0.0167	0.0059	
	2020-2021		0.9921	0.0166	0.0059	
	2021-2022		0.9885	0.0169	0.0060	
	2023-2024		0.7512	0.0302	0.0102	
Interpretation	Seed = 7	Random seed	0.7531	0.0301	0.0101	EPS, SIZE, ESGUI EPS, SIZE, PB
	Seed = 21		0.7512	0.0302	0.0102	
	Seed = 42		0.7551	0.0300	0.0100	
	Random Forest		0.7512	0.0302	0.0102	
	XGBoost	Model	0.7878	0.0308	0.0101	
	LightGBM		0.7427	0.0306	0.0101	

Source: Authors' calculations

This evidence helps reconcile the mixed findings reported in the ESG-performance literature. Rather than implying a universal effect, it suggests that inconsistent results may partly reflect nonlinearities and firm heterogeneity that conventional linear models cannot fully capture. Similar levels of ESG uncertainty may therefore be associated with different performance outcomes across firms and market conditions.

Firm size represents an important source of heterogeneity. Larger firms exhibit stronger performance but greater sensitivity to ESG uncertainty, possibly reflecting their higher visibility and market exposure. Medium-sized firms display comparatively stable model-implied responses, whereas smaller firms show weaker sensitivity. Because governance quality, financing flexibility, and adaptive capacity are not directly measured, these factors are treated only as possible explanations for future investigation.

The findings are broadly consistent with stakeholder, agency, and real-options perspectives. ESG uncertainty may affect stakeholder confidence, information frictions, and investment timing, but the study does not separately identify these channels. Their integration nevertheless provides a useful theoretical basis for interpreting the observed nonlinear patterns.

Methodologically, explainable machine learning complements conventional analysis by identifying predictive importance, nonlinear regions, and heterogeneous associations. Its contribution lies in improving the interpretation of complex patterns rather than establishing causality. ESG uncertainty should therefore be considered a dynamic and context-dependent dimension of financial risk.

6.2 Policy Implications

The policy implications remain necessarily cautious because the analysis identifies predictive associations rather than causal effects. Nevertheless, the observed heterogeneity suggests that uniform responses to ESG uncertainty may overlook meaningful differences across firms.

For firms, the findings emphasize the importance of consistent, comparable, and decision-relevant ESG disclosure. Aligning reported information with observable practices may reduce avoidable ambiguity and strengthen disclosure credibility. The analysis does not, however,

establish which internal governance or financing mechanisms improve firms' ability to manage ESG uncertainty.

Firm-size differences further suggest that disclosure approaches should reflect differences in resources and market exposure. Larger firms may benefit from greater consistency across ESG communications, while smaller firms may prioritize standardized and cost-effective disclosure. These implications are indicative rather than prescriptive and require further firm-level evidence.

For investors, ESG evaluation may be strengthened by considering uncertainty alongside reported ESG levels. Because similar uncertainty signals are associated with different performance patterns, assessment should remain firm-specific and sensitive to market context. Explainable methods may support this process but should complement, rather than replace, financial and institutional analysis.

For policymakers, clearer standards and more consistent verification may reduce ambiguity arising from fragmented ESG frameworks. The objective is not to eliminate uncertainty, but to improve the credibility, comparability, and decision usefulness of ESG information. This priority is particularly relevant in emerging markets, where disclosure institutions and enforcement mechanisms remain under development.

6.3 Limitations and Future Research

This study is subject to several limitations. Its focus on a single country and sector limits generalizability. ESG uncertainty is measured at an aggregate level and may not capture firm-specific variation. The results reflect model-based associations rather than causal effects. Finally, the focus on ROE captures only one dimension of performance.

Future research should extend the analysis across contexts, develop firm-level uncertainty measures, integrate causal identification strategies, and examine broader performance outcomes.

Appendix

Appendix A. Methodological Reproducibility and Implementation Details

This appendix provides detailed information to ensure full reproducibility of the empirical analysis presented in this study, including data structure, preprocessing steps, model implementation, and explainability procedures.

A.1. Data Structure and Sample Construction

The empirical analysis is based on a balanced panel dataset of 28 listed real estate firms in Vietnam, covering the period from January 2013 to June 2024 at a monthly frequency. The dataset contains 3,864 firm-month observations.

The panel structure is defined by firm identifier (FIRM) and time index (YEAR), where YEAR is recorded as a monthly timestamp. Observations are sorted chronologically by time and firm to preserve the temporal ordering required for time-series analysis.

Firm performance is measured using return on equity (ROE). The key explanatory variable is the ESG-based Sustainability Uncertainty Index (ESGUI), which captures time-varying uncertainty in ESG-related information. Control variables include firm-level indicators (PB, EPS, SIZE) and macro-financial variables (GOLD, OIL, CPI, FED, COVID).

A.2. Data Preprocessing

To ensure comparability and numerical stability, the following preprocessing steps are applied:

(1) The time variable (YEAR) is converted into a datetime format and used to sort the dataset in ascending chronological order.

(2) The sample is divided into training and testing sets using a strict chronological split: Training sample: January 2013 - December 2022; Testing sample: January 2023 - June 2024.

Continuous variables are standardized using z-score normalization. The scaling parameters are estimated exclusively from the training sample and subsequently applied to the testing sample to avoid information leakage.

Extreme values in firm-level variables are controlled through winsorization at the 1st and 99th percentiles prior to scaling.

This procedure ensures that the model is trained under conditions that mimic real-time forecasting and prevents forward-looking bias.

A.3. Model Specification and Training Procedure

The empirical framework is prediction-oriented and does not impose a predefined functional form. Instead, firm performance is modeled as a nonlinear function of ESG uncertainty and control variables:

$$ROE_{i,t} = f(ESGUI_t, X_{i,t}, Z_t) + \epsilon_{i,t}. \quad (2)$$

Eight machine-learning algorithms are implemented: k-Nearest Neighbors (kNN), Support Vector Regression (SVR), Decision Tree, Random Forest, Gradient Boosting, AdaBoost, XGBoost, LightGBM. These models are selected to represent different levels of flexibility and capacity to capture nonlinear relationships and interactions.

Model performance is evaluated using three metrics: coefficient of determination (R^2), root mean squared error (RMSE), and mean absolute error (MAE), computed on the out-of-sample testing set.

A.4. Time-Series Cross-Validation

To ensure robustness and prevent information leakage, model tuning is conducted using time-series block cross-validation. Specifically, a five-fold expanding window approach is employed:

- (1) Each fold preserves temporal ordering.
- (2) Training sets are sequentially expanded over time.
- (3) Validation sets always follow training sets chronologically.

This approach ensures that future observations are never used to inform past predictions.

A.5. Hyperparameter Optimization

Hyperparameters for selected models (SVR, Random Forest, Gradient Boosting, AdaBoost, XGBoost, LightGBM) are optimized using Particle Swarm Optimization (PSO) following Kennedy and Eberhart (1995). The optimization procedure is defined as follows:

- (1) Swarm size: 20 particles
- (2) Inertia weight: 0.7
- (3) Cognitive parameter: 0.5
- (4) Social parameter: 0.3
- (5) Number of iterations: 30-50

The objective function minimizes the average RMSE obtained from time-series cross-validation on the training sample. Importantly, the testing dataset is not used during the optimization process, ensuring an unbiased evaluation of model performance.

The model with the highest out-of-sample predictive accuracy is selected as the benchmark for interpretation. In this study, XGBoost consistently delivers superior performance across all evaluation metrics. The final model is estimated using the full training sample with optimized hyperparameters and evaluated once on the testing sample.

A.6. SHAP-Based Model Interpretation

To improve interpretability, SHAP (SHapley Additive Explanations) is applied to the final model. SHAP decomposes each prediction into additive contributions from individual features based on cooperative game theory. The analysis includes:

- (1) Global feature importance (mean absolute SHAP values)
- (2) SHAP summary (beeswarm) plots
- (3) Dependence plots showing how ESGUI contributions vary across its range
- (4) Interaction analysis using color-coded features (e.g., EPS, SIZE)

These outputs are interpreted as model-based associations rather than causal effects.

A.7. Partial Dependence and Accumulated Local Effects

To complement SHAP, two additional tools are used:

- (1) Partial Dependence Plots (PDP)
- (2) PDPs illustrate the average marginal effect of ESGUI on predicted ROE, holding other variables constant.
- (3) Accumulated Local Effects (ALE)
- (4) ALE plots estimate localized changes in predictions, accounting for feature interactions and reducing bias caused by correlated variables.

Both PDP and ALE are computed for: the full sample and subsamples defined by firm

size (Small, Medium, Large). Firm size groups are determined using terciles of SIZE based on the training sample. These tools are used to identify model-implied turning regions where the association between ESG uncertainty and firm performance changes in direction or intensity.

All figures (SHAP, PDP, ALE, heatmaps) are generated using Python libraries including matplotlib, shap, and scikit-learn. All figures are exported at a minimum resolution of 600 DPI. Plot styling is standardized using serif fonts to meet journal formatting requirements. All outputs (figures, SHAP values, predictions) are saved as reproducible files.

A.8. Implementation Environment

The analysis is implemented in Python using the following key libraries: pandas, numpy, scikit-learn, xgboost, lightgbm, shap, pyswarms.

All experiments are conducted with fixed random seeds to ensure reproducibility.

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