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# Bank Stability Under ESG Uncertainty: Evidence from Threshold Regression, Causal Forest and SHAP Explanations

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**Abstract**

This paper investigates the nonlinear effects of ESG-related macroeconomic uncertainty on bank stability in Vietnam, an emerging market undergoing rapid financial transformation. Using an integrated empirical framework that combines panel threshold regression, Causal Forest estimation, and SHAP explanations, the analysis explores how ESG-related uncertainty interacts with income diversification and FinTech development to influence bank resilience. The results indicate an inverted U-shaped relationship between ESG uncertainty and bank stability, suggesting that moderate uncertainty enhances governance discipline, whereas excessive uncertainty erodes resilience. Income diversification (IDI) and FinTech growth (G_FINTECH) also display threshold-dependent and nonlinear impacts, where moderate diversification strengthens stability, and FinTech becomes stabilizing only beyond a maturity threshold. Robustness tests using alternative measures of bank stability (non-performing loans - NPL) and ownership heterogeneity confirm that private banks are more sensitive to ESG shocks than state-owned counterparts. The study contributes by introducing a novel hybrid framework integrating threshold models with causal machine learning to capture nonlinear and heterogeneous effects, providing new evidence from Vietnam's nascent ESG and FinTech landscape, and offering policy implications for regulators and banks to manage ESG uncertainty, optimize diversification, and promote sustainable FinTech-driven stability.

**Keywords:**
Bank Stability;
ESG Uncertainty;
Income Diversification;
FinTech; Threshold Regression;
Causal Forest;
SHAP.

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## 1- Introduction

The stability of the banking system is widely recognized as a foundational pillar of macro-financial resilience, particularly within emerging market economies (EMEs), where financial volatility often propagates rapidly into systemic crises [1]. As financial systems in EMEs such as Vietnam deepen their integration into global markets and evolve in complexity, their exposure to a range of external shocks, including environmental, social, technological, and regulatory disruptions, has become markedly pronounced [2, 3]. In this context, maintaining banking stability transcends the strategic interests of individual institutions to become a critical macroprudential objective, one essential for preserving public trust and ensuring systemic integrity [4]. Two interrelated forces, ESG uncertainty and rapid fintech evolution, present profound, systemic challenges to banking stability in EMEs. First, the intensifying emphasis on Environmental, Social, and Governance (ESG) integration, alongside increasing regulatory demands for ESG transparency, has introduced substantial operational and strategic uncertainties for banks [5, 6]. This uncertainty is particularly acute in EMEs like Vietnam, where underdeveloped ESG frameworks amplify risks associated with credit evaluation, asset pricing, and long-term strategic planning [7, 8].

Concurrently, the disruptive momentum of Financial Technology (Fintech) is reshaping competitive dynamics across the banking sector. While Fintech fosters financial inclusion, operational efficiency, and product innovation, it also

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introduces new systemic vulnerabilities, including technology-driven contagion risks, regulatory arbitrage, and cybersecurity threats [9-11]. Traditional banks in Vietnam are thus compelled to undertake extensive business model adaptations under simultaneous pressures of competition and regulatory expectations.

A persistent structural fragility in EME banking systems lies in their overreliance on net interest income as the primary revenue source, reflecting a narrow and risk-prone business model [12, 13]. Diversification through non-interest income sources, such as fee-based services, asset management, and bancassurance, is theoretically posited to enhance stability by distributing income volatility [14, 15]. However, recent evidence points to a non-linear dynamic, where diversification benefits may diminish, or even reverse, beyond critical thresholds.

Despite the expanding literature on banking stability, critical analytical gaps persist in understanding how environmental, social, and governance (ESG) uncertainty interacts with the structural features of emerging financial systems. First, prevailing empirical approaches rely predominantly on linear econometric models, which are often ill-equipped to detect non-linear threshold effects or capture the intricate interactions among financial, technological, and sustainability-related variables. Second, the moderating influence of structural factors such as income diversification and FinTech development on the ESG–stability nexus remains underexplored, particularly in emerging market contexts where institutional frameworks and digital ecosystems are still evolving [14]. Third, the integration of advanced machine learning techniques, especially interpretable approaches such as SHapley Additive exPlanations (SHAP), into the empirical analysis of financial stability is remarkably limited [16-21], despite their potential to uncover high-dimensional and context-specific nonlinear patterns.

In response to these theoretical and methodological gaps, this study pursues three key objectives: (i) to empirically assess the impact of ESG-related uncertainty on banking stability in Vietnam, an emerging market at the frontier of ESG and FinTech transformation; (ii) to evaluate how income diversification and FinTech development moderate the relationship between ESG uncertainty and bank stability; and (iii) to apply advanced threshold regression models integrated with causal machine learning techniques, specifically SHAP analysis, to identify non-linearities and enhance model interpretability.

Accordingly, the study addresses the following core research questions: Does ESG uncertainty significantly undermine banking stability in emerging economies such as Vietnam? To what extent do income diversification and FinTech development mitigate or amplify the destabilizing effects of ESG uncertainty? Are there threshold effects that characterize these dynamics, and can interpretable machine learning effectively identify and explain these inflection points?

This research makes three major contributions to the literature. First, it provides novel empirical evidence from Vietnam, a representative emerging market economy undergoing rapid ESG and FinTech transitions, thereby extending the comparative finance and sustainable banking literature to underexamined contexts. Second, it introduces an integrative analytical framework that combines non-linear econometric modeling with interpretable machine learning, offering a more robust methodological lens for disentangling complex financial dynamics. Third, the findings yield actionable policy implications for regulators and bank executives seeking to design stability-oriented ESG strategies, promote prudent income diversification, and leverage FinTech development without compromising systemic resilience.

## 2- Theoretical Framework and Literature Review

### *2-1- ESG Uncertainty and Banking Stability*

The rising prominence of Environmental, Social, and Governance (ESG) considerations in banking is grounded in Stakeholder Theory, which asserts that firms must serve the interests of a broad set of stakeholders, not only shareholders, but also regulators, clients, investors, and communities [22]. As ESG standards gain global traction, they have evolved from ethical considerations into strategic imperatives. However, in emerging markets where ESG regulatory frameworks are often nascent or fragmented, these expectations may conflict, creating significant compliance costs, reputational risks, and strategic uncertainty.

Uncertainty Management Theory further posits that in highly uncertain environments, such as those shaped by evolving ESG norms, organizations tend to enhance transparency and strategic flexibility to maintain legitimacy [23]. Accordingly, ESG uncertainty may exert dual effects: at moderate levels, it can foster improvements in governance and risk oversight; yet beyond certain thresholds, it may hinder strategic alignment and destabilize financial institutions.

Empirical evidence supports this theoretical duality. While some studies highlight ESG transparency as a contributor to financial resilience, others reveal that ESG implementation under weak institutional contexts can increase systemic risk [3]. For instance, ESG dimensions have been found to elevate default risk under certain conditions [24], and ESG-governance misalignments have been shown to heighten vulnerabilities in countries such as Indonesia and India [5, 7].

In Vietnam, ESG frameworks remain underdeveloped, yet international commitments such as Net Zero 2050 are intensifying external pressures [2]. Notably, existing studies largely rely on aggregate ESG scores without isolating ESG uncertainty as a distinct and dynamic risk factor. To fill this conceptual gap, this study adopts a nonlinear perspective that models the heterogeneous effects of ESG uncertainty on banking stability more precisely.

### *2-2- Income Diversification and Banking Stability*

The theoretical rationale linking income diversification (IDI) to banking stability stems from Modern Portfolio Theory [25] and Risk-Spreading Theory [26], which advocate for risk mitigation through the diversification of income sources. By expanding into non-interest income streams, such as fee-based services, trading activities, and insurance, banks can reduce dependence on interest rate cycles and improve resilience.

However, diversification is not without potential drawbacks. Agency Theory [27] and Organizational Complexity Theory [28] argue that expanding into non-core areas may heighten agency problems, increase managerial discretion, and raise coordination costs, particularly in banks with limited internal governance capacity. These challenges suggest a nonlinear relationship, where IDI enhances stability up to a threshold, beyond which it may erode performance.

Empirical findings corroborate this nonlinear dynamic. Kaur & Bansal (2024) and Bogari (2024) show that IDI positively contributes to bank stability only within an optimal range [13, 29]. Similarly, Lahouel et al. (2023) highlight that the efficacy of IDI depends on firm capacity and market context [30].

In Vietnam, interest income remains dominant, but IDI is gaining relevance as a strategic stabilizer. Studies by Nguyen & Nguyen (2024), Nguyen & Phan (2024), and Huynh (2024) indicate that diversification enhances stability, though outcomes depend on institutional characteristics such as size, governance, and competitive environment [15, 31, 32]. These insights justify the investigation of threshold effects and nonlinearity in the IDI–stability nexus.

### *2-3- Fintech Growth and Banking Stability*

The effects of Fintech development on banking stability are informed by two theoretical lenses. The Technology Acceptance Model (TAM) [33] identifies perceived usefulness and ease of use as key determinants of technological adoption, while the Dynamic Capabilities Theory [21] emphasizes the role of learning, adaptation, and reconfiguration in leveraging innovation effectively.

Fintech adoption presents both opportunities and risks. While it can improve efficiency, financial inclusion, and innovation, it may also introduce instability, particularly when banks lack the absorptive capacity to manage digital transformation. Under such conditions, Fintech may increase cyber vulnerabilities, regulatory arbitrage, and competitive shocks [34]. Conversely, banks with robust digital infrastructures and cohesive strategies can harness Fintech as a stabilizing force [35, 36].

Recent studies confirm the nonlinear nature of this relationship. Koranteng & You (2024) and Zhang et al. (2023) report an inverted U-shaped dynamic: Fintech introduces instability during early adoption phases, but its impact becomes positive once digital infrastructure reaches maturity [37, 38]. In Vietnam, where Fintech is rapidly expanding yet fragmented, findings are mixed. Ngo (2025) notes elevated risk from uncoordinated adoption, while Nguyen (2025) finds that integrated Fintech strategies enhance stability [39, 40]. These dynamics highlight the need to account for the developmental stage and integration depth of Fintech when assessing its impact.

### *2-4- Research Gaps*

Despite substantial theoretical and empirical progress, methodological limitations persist. Most studies rely on linear models, such as OLS, GMM, or fixed effects regressions, which struggle to capture nonlinearities, threshold effects, or interaction terms common in macro-financial settings [14, 32, 40].

To overcome these challenges, threshold regression models offer a suitable alternative by identifying turning points in variable relationships, especially relevant in heterogeneous environments like Vietnam. In parallel, the use of causal machine learning, particularly in combination with SHAP, enhances both prediction and interpretability, enabling nuanced insights for academic and policy applications [17, 19, 20].

This study addresses these gaps by applying a nonlinear, machine learning-enhanced analytical framework to explore threshold effects and interaction mechanisms among ESG uncertainty, income diversification, and Fintech development in the Vietnamese banking sector.

### *2-5- Hypothesis Development*

The preceding theoretical discussion suggests that the effects of ESG uncertainty, income diversification, and FinTech development on banking stability are inherently nonlinear and shaped by threshold dynamics, particularly in emerging markets where regulatory frameworks, technological maturity, and risk governance remain in transition. Grounded in Stakeholder Theory, Uncertainty Management Theory, Modern Portfolio Theory, and Dynamic Capabilities Theory, these relationships are expected to depend on both internal structures and contextual factors.

First, ESG-related uncertainty may initially stimulate adaptive governance and transparency, enhancing stability; yet excessive uncertainty can raise capital costs, impair credit assessments, and intensify compliance risks. Consistent with Uncertainty Management Theory and prior empirical evidence [2, 3, 7], this pattern suggests a nonlinear, inverted U-shaped association:

*H1: The relationship between ESG uncertainty and bank stability follows an inverted U-shaped nonlinear pattern with identifiable threshold effects.*

Second, income diversification can reduce earnings volatility and strengthen resilience as proposed by Modern Portfolio Theory. However, Agency and Organizational Complexity theories imply that excessive diversification increases managerial inefficiencies and risk exposure, indicating a nonlinear moderating role:

*H2: Income diversification moderates the ESG uncertainty–stability nexus through a threshold effect, where benefits peak at moderate diversification levels.*

Third, FinTech expansion may initially destabilize banks due to competitive and regulatory frictions but can enhance inclusion and risk management once technological capabilities mature, as emphasized by Dynamic Capabilities Theory and supported by empirical studies [37-40]. Hence:

*H3: FinTech growth moderates the relationship between ESG uncertainty and bank stability nonlinearly, with stabilizing effects emerging beyond a development threshold.*

Finally, institutional heterogeneity in emerging markets implies that the impacts of ESG uncertainty (ESGUI), income diversification (IDI), and FinTech development (G_FINTECH) may vary by bank size, ownership, and perceived ESG exposure:

*H4: The effects of ESGUI, IDI, and G_FINTECH on bank stability differ across SIZE, ownership type, and internal ESG uncertainty levels.*

To test these hypotheses, the study applies a Panel Threshold Regression (PTR) model to identify nonlinearity and integrates a Causal Machine Learning framework with SHAP analysis to reveal underlying mechanisms and enhance interpretability, providing insights relevant to financial stability policy in emerging markets such as Vietnam.

## 3- Data and Variables

### *3-1- Data*

This study employs an unbalanced panel dataset of Vietnamese commercial banks over the period 2010-2024, which allows for the examination of both long-term dynamics and structural changes in the banking sector. Data on bank-level financial indicators are collected primarily from the State Bank of Vietnam (SBV), audited annual reports of individual banks, and commercial databases. Macro-financial indicators are sourced from the International Monetary Fund (IMF) and the World Bank (WB). Information on the development of the Fintech ecosystem is obtained from the Fintech Vietnam Report, while Vietnam's ESG-related uncertainty index is constructed following the approach of Ongan et al. [41]. This multi-source data construction ensures consistency and reliability, while also capturing a broad spectrum of determinants relevant to both bank-specific performance and the external operating environment.

### *3-2- Variables*

Table 1 summarizes all key variables, including indicators of bank stability, ownership structure, Fintech development, and Vietnam's ESG-related uncertainty index, together with their definitions, and construction methods.

**Table 1. Definition and measurement of variables**

| Variable category | Variable (Symbol) | Measurement strategy |
|---|---|---|
| Dependent Variable | ZSCORE | $ZSCORE_{it} = \frac{ETA_{it}+ROA_{it}}{\sigma(ROA_{it})}$ where, ROA = return on assets, ETA = equity-to-assets ratio, and σ(ROA) = 3-year rolling standard deviation of ROA. Higher ZSCORE indicates greater stability. |
| | NPL ratio | Ratio of non-performing loans to total loans. Used as a robustness check reflecting asset quality and credit risk. |
| Independent Variable | ESG Uncertainty Index (ESGUI) | This study employs the ESG-based Sustainability Uncertainty Index (ESGUI), recently developed by Ongan et al. (2025) [41], to capture policy and regulatory uncertainty associated with environmental, social, and governance dimensions. The index is constructed using text-mining techniques applied to country-level reports published by the Economist Intelligence Unit (EIU). For this analysis, the Vietnam-specific ESGUI time series is utilized, where higher index values indicate greater volatility and unpredictability in ESG-related discourse and policy environments. |
| *Moderating Variables* | Income Diversification Index (IDI) | $IDI_{it} = 1 - [(\frac{NET_{it}}{NII_{it}})^2 + (\frac{NON_{it}}{NII_{it}})^2]$ where, NET = Net interest income; NON = non-interest income; NII = Total operating income = NET + NON Higher IDI reflects greater diversification across interest and non-interest income. |
| | Fintech Growth (G_FINTECH) | Annual growth rate in the number of Fintech firms: $G\_FINTECH_t = \frac{FINTECH_t - FINTECH_{t-1}}{FINTECH_{t-1}} \times 100$ where, $FINTECH_t$ = number of Fintech firms in year t. |
| *Bank-specific Controls* | SIZE | Natural logarithm of total assets, proxy for bank size and economies of scale. |
| | NIM | Net interest margin, calculated as net interest income divided by earning assets. |
| | ETA | Equity-to-assets ratio, reflecting capitalization and solvency. |
| | MS | The ratio of a bank's total assets to the total assets of the entire credit system |
| | CTI | Cost-to-income ratio, proxy for operational efficiency. |
| | OWNER | Dummy variable equal to 1 if the bank is predominantly state-owned, and 0 otherwise. |
| *Macroeconomic Controls* | GDP | Annual growth rate of real GDP. |
| | INF | Consumer Price Index (CPI) inflation rate. |
| | COVID | Dummy variable = 1 for years 2020–2024, capturing COVID-19 pandemic shock. |

By combining bank-level indicators, macroeconomic conditions, and structural developments in the Fintech sector, the dataset provides a comprehensive foundation for assessing the complex interplay between ESG uncertainty, income diversification, Fintech growth, and bank stability in the context of an emerging market such as Vietnam. All variables are carefully cleaned and winsorized at the $1^{st}$ and $99^{th}$ percentiles to mitigate the influence of outliers and ensure the robustness of subsequent empirical analyses.

## 4- Methodology

The empirical methodology employed in this study is structured as a multi-layered approach, integrating semiparametric threshold regression models and causal machine learning techniques. This design allows for the identification of not only the overall relationship between ESG uncertainty and bank stability, but also the heterogeneity in impacts across different groups of banks. The full analytical framework consists of four key stages: (i) Panel Threshold Regression (PTR), (ii) Causal Forest and CATE estimation, (iii) SHAP-based interpretation, and (iv) robustness checks.

### *4-1- Threshold Regression*

Given that financial markets are often subject to nonlinear effects stemming from various uncertainties, this study applies the threshold regression model developed by Hansen (1999) to examine the existence of structural breaks in the relationship between key determinants and bank stability [42, 43]. Specifically, three threshold variables are incorporated in the analysis: ESGUI, which captures ESG-related uncertainty; IDI, which measures the extent of banks' income diversification; and G_FINTECH, which reflects the growth rate of fintech firms in Vietnam. The baseline regression Equation is specified as follows:

$$ZSCORE_{it} = \mu_i + \beta_1 \cdot X_{it} \cdot I(X_{it} \leq \gamma) + \beta_2 \cdot X_{it} \cdot I(X_{it} > \gamma) + \delta' Z_{it} + \varepsilon_{it} \quad (1)$$

where: $ZSCORE_{it}$ denotes the measure of bank stability; $X_{it} \in \{ESGUI_{it}, IDI_{it}, G\_FINTECH_{it}\}$ is the main explanatory variable and the threshold variable; I(·) is an indicator function that equals 1 if the condition is satisfied and 0 otherwise; γ is the optimal threshold value to be determined; $Z_{it}$ represents a set of control variables, including bank-specific characteristics (NIM, SIZE, ETA, CTI, MS, OWNER) and macroeconomic conditions (GDP, INF); $\mu_i$ denotes bank fixed effects, accounting for time-invariant unobserved heterogeneity.

The threshold value $\gamma$ is estimated using a grid search procedure that minimizes the sum of squared residuals (SSR). To ensure statistical validity, bootstrap simulations with 1,000 replications are employed to construct confidence intervals and derive robust critical values for the likelihood ratio (LR) test of threshold significance, following [42, 43] Once the optimal threshold is identified, the sample is split into two regimes, below and above the threshold, and OLS estimations are conducted separately for each regime to assess coefficient heterogeneity. This flexible specification imposes no parametric form on the nonlinear relationship, allowing the data to reveal endogenous threshold effects with high precision.

### 4-2- Causal Machine Learning

While the PTR model is useful for detecting nonlinear breaks in the ESG–stability nexus, it assumes homogeneous treatment effects within each threshold regime. This assumption may not hold, as the effect of ESG uncertainty on bank stability likely varies depending on individual bank characteristics, such as size, income diversification, or exposure to Fintech developments. To address this limitation, the study employs a causal machine learning method, specifically the Causal Forest algorithm, to estimate the Conditional Average Treatment Effects (CATE).

This framework is grounded in the potential outcomes model, where the CATE is formally defined as:

$$\tau(x) = E\,[Y_i(1) - Y_i(0) \mid X_i = x] \tag{2}$$

In this framework, $Y_i(1)$ and $Y_i(0)$ represent the potential outcomes when bank *i* is exposed to high or low levels of ESG uncertainty, respectively, while $X_i$ denotes a set of bank-specific characteristics and macroeconomic conditions. The value $\tau(x)$ enables the identification of heterogeneous responses across banks, thereby detecting institutions that are more vulnerable ($CATE < 0$) or potentially benefit ($CATE > 0$) from ESG shocks.

Causal Forest, introduced by Athey & Imbens (2016) and further developed by Wager & Athey (2018), extends the Random Forest framework to explicitly estimate heterogeneous treatment effects [10, 44]. Rather than minimizing prediction error, the algorithm partitions the data in a manner that maximizes variation in causal impacts across subgroups, aggregating numerous "causal trees" to generate stable estimates of CATE at the individual bank level. The result is a rich distribution of CATE values, capturing the diversity in how banks respond to ESG-related uncertainty.

This approach offers significant advantages over conventional linear models. It not only estimates the average treatment effect (ATE) of ESG uncertainty on bank stability but also uncovers deep heterogeneity in the response of individual institutions. As such, it provides a more comprehensive and realistic depiction of how ESG uncertainty impacts the banking system.

### 4-3- SHAP Analysis

To interpret the mechanism through which ESG uncertainty and related variables affect bank stability, the study applies SHAP, a model-agnostic method based on Shapley value theory from cooperative game theory. SHAP decomposes a model prediction into the marginal contribution of each input feature. The predictive model is represented as:

$$f(x) = \phi_0 + \sum_{j=1}^{M} \phi_1 \tag{3}$$

In this expression, $\phi_0$ represents the base value, while $\phi_j$ denotes the marginal contribution of variable *j* on the predicted outcome [45].

Recent studies show SHAP's effectiveness in explaining complex financial models, particularly in credit risk management, bank stability, and ESG-related portfolio analysis [17, 20]. Building on this literature, SHAP is employed here to interpret Causal Forest results, providing transparent insights into the nonlinear and heterogeneous effects of ESG uncertainty, income diversification, and FinTech development on bank stability. The analysis emphasizes SHAP dependence plots, which visualize nonlinear relationships between predictor values and their SHAP contributions. These relationships are estimated using LOWESS smoothing with 95% bootstrap confidence intervals to ensure robustness. Additionally, SHAP interaction values are computed to reveal how pairs of variables (e.g., ESGUI × IDI or ESGUI × G_FINTECH) jointly influence stability. By integrating SHAP into the empirical framework, this study identifies the relative importance of ESGUI, IDI, and G_FINTECH while uncovering the interaction-driven and nonlinear mechanisms through which they operate. This approach aligns with emerging applications of explainable AI in financial stability research [16, 18-21], offering both interpretability and policy relevance for banking systems in emerging economies such as Vietnam.

### 4-4- CATE Significance and Robustness Tests

Following the estimation of CATEs via the Causal Forest approach, the analysis does not merely describe the distribution of CATEs but also conducts statistical tests to assess the credibility of the findings. Specifically, a one-way analysis of variance (ANOVA) is employed to examine whether there are statistically significant differences across the three CATE groups (Low, Mid, High). These tests provide empirical validation that the heterogeneity in the effects of ESG uncertainty is not only quantitatively observable but also statistically significant. To ensure the robustness of the findings, several sensitivity checks are conducted. First, the primary dependent variable, ZSCORE, is substituted with the non-performing loan ratio (NPL) to examine whether the relationships hold when using an alternative proxy for bank stability. Second, the dataset is stratified by ownership type (state-owned banks versus private banks) to evaluate whether causal effects differ according to institutional characteristics. These robustness checks strengthen the generalizability and credibility of the study's findings and further reinforce the policy implications derived from the empirical analysis.

## 5- Empirical Results

### *5-1- Descriptive Statistics and Correlation Analysis*

Table 2 reports the descriptive statistics of key variables. The average ZSCORE is 2.869 with a relatively small dispersion (std = 0.470), indicating a stable banking environment in Vietnam over the sample period. Both skewness and kurtosis values are close to zero, suggesting an approximately normal distribution consistent with previous findings in emerging markets [1]. This reflects moderate stability but also a potential sensitivity to structural shocks, consistent with the argument that financial systems in EMEs are stable yet fragile.

**Table 2. Descriptive Statistics**

| | Mean | Median | Std | Min | Max | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|
| **ZSCORE** | 2.869 | 2.890 | 0.470 | 1.545 | 4.024 | -0.180 | 0.391 |
| **IDI** | 0.342 | 0.374 | 0.128 | 0.062 | 0.498 | -0.757 | -0.215 |
| **G_FINTECH** | 0.344 | 0.273 | 0.343 | -0.281 | 1.000 | 0.504 | -0.275 |
| **ESGUI** | 18.382 | 18.176 | 5.845 | 11.308 | 28.847 | 0.262 | -1.324 |
| **NIM** | 0.032 | 0.030 | 0.012 | 0.010 | 0.077 | 1.106 | 2.025 |
| **SIZE** | 18.777 | 18.756 | 1.273 | 16.402 | 21.475 | 0.139 | -0.710 |
| **ETA** | 0.092 | 0.081 | 0.039 | 0.043 | 0.237 | 1.454 | 2.255 |
| **CTI** | 0.865 | 0.884 | 0.089 | 0.627 | 1.000 | -0.666 | -0.136 |
| **NPL** | 0.021 | 0.019 | 0.014 | 0.005 | 0.088 | 2.308 | 7.382 |
| **MS** | 0.028 | 0.013 | 0.033 | 0.002 | 0.120 | 1.707 | 1.624 |
| **GDP** | 0.061 | 0.064 | 0.015 | 0.026 | 0.081 | -1.194 | 0.553 |
| **INF** | 0.069 | 0.036 | 0.107 | -0.017 | 0.423 | 2.485 | 5.188 |
| **OWNER** | 0.143 | 0.000 | 0.350 | 0.000 | 1.000 | 2.041 | 2.167 |
| **COVID** | 0.333 | 0.000 | 0.472 | 0.000 | 1.000 | 0.707 | -1.500 |

The ESGUI has a mean of 18.382 and a large standard deviation of 5.845, demonstrating substantial variability in the ESG policy environment. This dispersion highlights that Vietnam's ESG framework is still in flux, with frequent regulatory shifts amplifying uncertainty, a condition theoretically linked to systemic risk under Uncertainty Management Theory [6, 7, 23].

The IDI averages 0.342, reflecting that most banks still rely heavily on traditional interest-based income. The negative skewness and low kurtosis indicate limited diversification, aligning with Modern Portfolio Theory [25], where insufficient diversification limits risk dispersion, and with earlier empirical studies on Vietnam's banks [15].

The G_FINTECH exhibits a mean of 0.344 and high volatility (SD = 0.343). Negative minimum values signal contractionary phases, while peaks near 1.0 correspond to rapid expansion periods. This dynamic, consistent with Dynamic Capabilities Theory [46], suggests that FinTech's influence on stability may be nonlinear, with early expansion generating transitional risks before maturity yields benefits [1, 39]. Control variables such as NIM, ETA, and CTI exhibit normal distributions, confirming data reliability.

Figure 1 shows the probability density of bank stability indicators (ZSCORE and NPL). ZSCORE approximates a normal distribution, implying overall sectoral balance. In contrast, the right-skewed NPL distribution suggests the existence of a small subset of banks with significantly higher credit risk exposure. This heterogeneity underscores the relevance of applying Causal Machine Learning techniques, such as Causal Forest, to capture nonlinearity and bank-specific variations [10, 44].

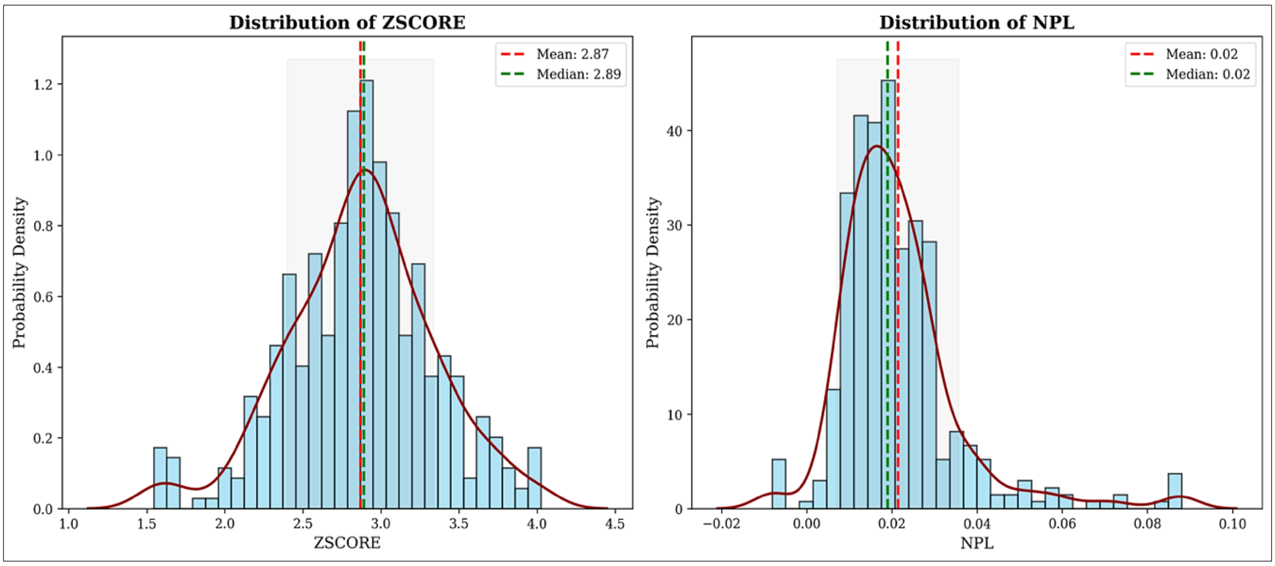


**Figure 1. Distribution of bank stability indicators (ZSCORE and NPL). Note: The figure illustrates the probability density functions of ZSCORE and Non-Performing Loans (NPL), including mean (dashed red line) and median (dashed green line) values.**

Figure 2 presents the correlation matrix. ZSCORE shows positive correlations with ETA (0.29) and G_FINTECH (0.16), indicating that better-capitalized and digitally integrated banks tend to be more stable. These relationships are consistent with theoretical expectations about capital buffers and technology-driven efficiency gains [24, 38]. Conversely, the negative correlation between ZSCORE and CTI (-0.04) confirms the adverse role of low operational efficiency [4].

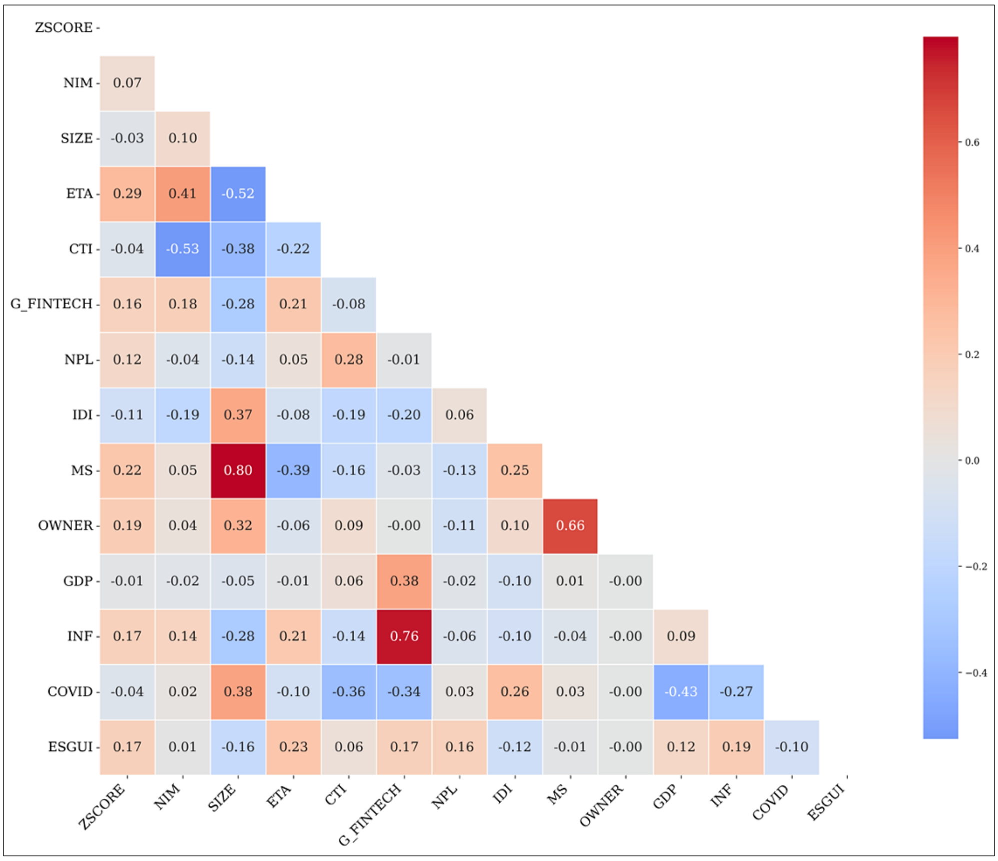


**Figure 2. Correlation matrix of key variables**

The negative correlation between IDI and ZSCORE (-0.11) suggests that incomplete or poorly structured diversification may weaken stability, supporting Hypothesis H2 on the threshold effect implied by Agency Theory [27]. Meanwhile, the mild positive correlation between ESGUI and ZSCORE (0.17) indicates a potential inverted U-shaped pattern, consistent with Hypothesis H1 and Uncertainty Management Theory, where moderate ESG uncertainty strengthens governance discipline before becoming destabilizing at higher levels. The positive link between ESGUI and COVID (0.19) also illustrates how crisis conditions magnify ESG-related uncertainty.

Overall, the relatively low correlation coefficients suggest weak linear relationships, justifying the use of nonlinear and heterogeneous estimation methods such as the PTR and Causal Machine Learning frameworks. These results also support the theoretical premise that the ESG–stability nexus operates through nonlinear mechanisms shaped by bank-specific characteristics and contextual conditions in emerging markets.

### *5-2- Threshold and Moderation Effects via PTR*

The results of the threshold regression, presented in Table 3 and illustrated in Figure 3, confirm the existence of statistically significant nonlinear effects in the relationships between the key variables and bank stability.

**Table 3. Threshold regression results with ESG uncertainty**

| Variable | Threshold | Region | Coefficient | p-value | N |
|---|---|---|---|---|---|
| IDI | 0.4112 | Below | -0.8850 | 0.002 | 273 |
| | | Above | -0.3559 | 0.810 | 147 |
| G_FINTECH | 0.3684 | Below | -0.3205 | 0.052 | 280 |
| | | Above | -0.6736 | 0.056 | 140 |
| ESGUI | 21.6149 | Below | +0.0112 | 0.092 | 280 |
| | | Above | -0.0558 | 0.030 | 140 |

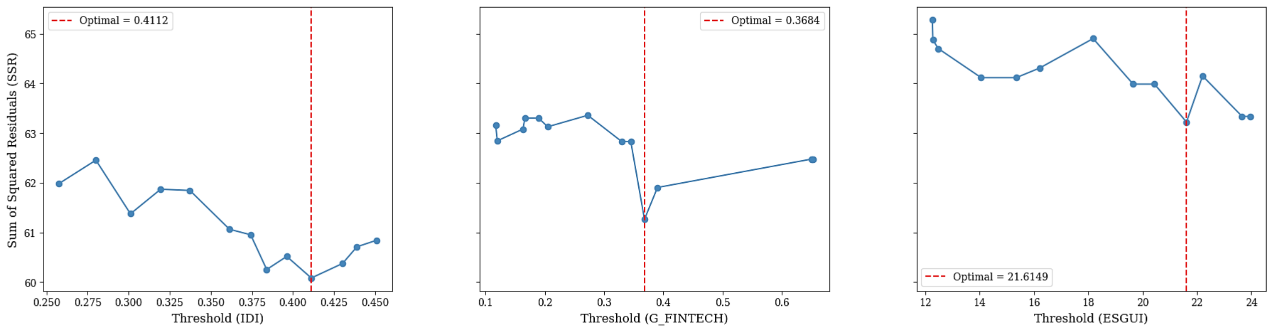


**Figure 3. SSR curves and optimal thresholds for IDI, G_FINTECH, and ESGUI. Note*:* This figure presents the sum of squared residuals (SSR) for different candidate thresholds in the threshold regression models. The red dashed lines indicate the optimal thresholds where the SSR reaches its minimum value.**

For IDI, the optimal threshold is identified at 0.4112. Below this threshold, IDI exhibits a negative and statistically significant effect on ZSCORE (coefficient = -0.8850, $p < 0.01$), implying that low levels of income diversification may undermine bank stability due to insufficient risk buffering capacity from non-traditional income sources. However, above the threshold, the effect becomes statistically insignificant, suggesting the presence of a "moderate-efficiency zone" where the benefits of diversification peak before diminishing. This finding aligns with Modern Portfolio Theory [25] and recent evidence on threshold effects in diversification [29, 30]. These results reinforce Hypothesis H2 regarding the nonlinear relationship between IDI and bank stability.

For G_FINTECH, the identified threshold is 0.3684. Across both sides of the threshold, the effect remains negative and marginally significant ($p \approx 0.05$), with the magnitude becoming more pronounced above the threshold (-0.6736 and -0.3205). This pattern suggests that FinTech expansion, while promoting innovation and financial inclusion in early phases, may generate heightened systemic vulnerability when its growth outpaces regulatory adaptation, risk management capacity, and digital infrastructure maturity. In the Vietnamese context, rapid FinTech proliferation has been accompanied by fragmented oversight, uneven adoption among banks, and limited cybersecurity safeguards, amplifying operational and liquidity risks. The intensified destabilizing effect beyond the threshold thus reflects a "technology–stability trade-off," wherein excessive technological disruption, absent adequate prudential frameworks, undermines institutional soundness. This finding is consistent with emerging evidence in other developing economies where FinTech-driven competition initially enhances efficiency but subsequently increases volatility under weak supervisory regimes [9]. Although the direction contrasts with the initial expectation of stabilization at higher maturity levels, it underscores the importance of regulatory synchronization and gradual FinTech integration for sustainable financial development.

Regarding ESGUI, the optimal threshold is found at 21.6149. Below this threshold, ESGUI exerts a mildly positive effect on ZSCORE (coefficient = 0.0112, p = 0.092), suggesting that moderate ESG uncertainty may promote governance improvements and organizational adaptability. In contrast, above the threshold, the effect reverses and becomes significantly negative (coefficient = -0.0558, p = 0.03), indicating that excessive ESG uncertainty, beyond the system's resilience capacity, poses a pronounced destabilizing risk. This inverted U-shaped pattern is fully consistent with Hypothesis H1 and recent empirical findings in emerging markets [2, 7].

Taken together, the PTR results not only confirm the existence of statistically significant nonlinear thresholds but also highlight the heterogeneous impact mechanisms of each variable, reflecting the institutional context and uneven development characteristics in Vietnam. These findings validate the selection of the PTR approach and lay the foundation for localized causal inference in the subsequent analysis.

### *5-3- Results from Causal Machine Learning*

The CATE distribution illustrated in Figure 4 reveals pronounced heterogeneity in how banks respond to ESG uncertainty. The positive average CATE (0.0021) indicates that most banks tend to improve their stability when facing moderate levels of ESG uncertainty, supporting the argument that ESG shocks can stimulate better governance and adaptive capacity. However, the existence of a subset of banks with negative CATE suggests increased vulnerability, reinforcing the hypothesis that the effect of ESG uncertainty is not uniform, but conditional on institutional and organizational characteristics.

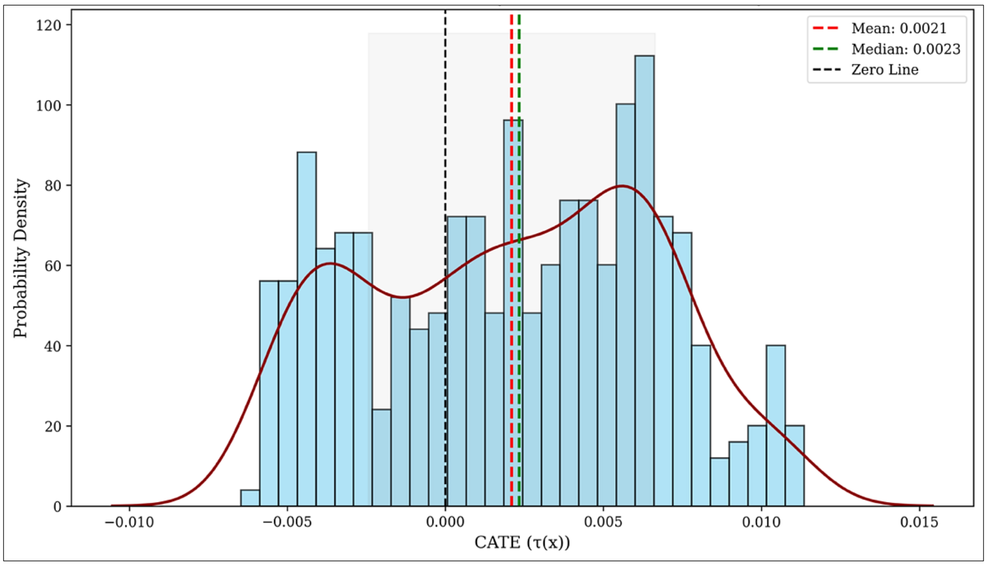


**Figure 4. Distribution of ESG Uncertainty CATE on Bank Stability (ZSCORE)**

The heterogeneous treatment effects (Table 4, Figure 5) reveal statistically significant differences in the causal impact of ESG uncertainty based on bank size (SIZE), FinTech development level (G_FINTECH), and income diversification (IDI).

**Table 4. Heterogeneity test of ESG uncertainty CATE by bank characteristics**

| Variable | Group | Mean CATE |
|---|---|---|
| | Low | 0.00246 |
| SIZE | Medium | -0.00177 |
| | High | 0.00562 |
| | Low | 0.00294 |
| G_FINTECH | Medium | 0.00140 |
| | High | 0.00198 |
| | Low | 0.00142 |
| IDI | Medium | 0.00230 |
| | High | 0.00260 |

Note: This table reports mean CATE of ESG uncertainty on bank stability (ZSCORE), estimated using Causal Forest. Banks are grouped into terciles (Low, Medium, High) based on SIZE, G_FINTECH, and IDI, respectively.

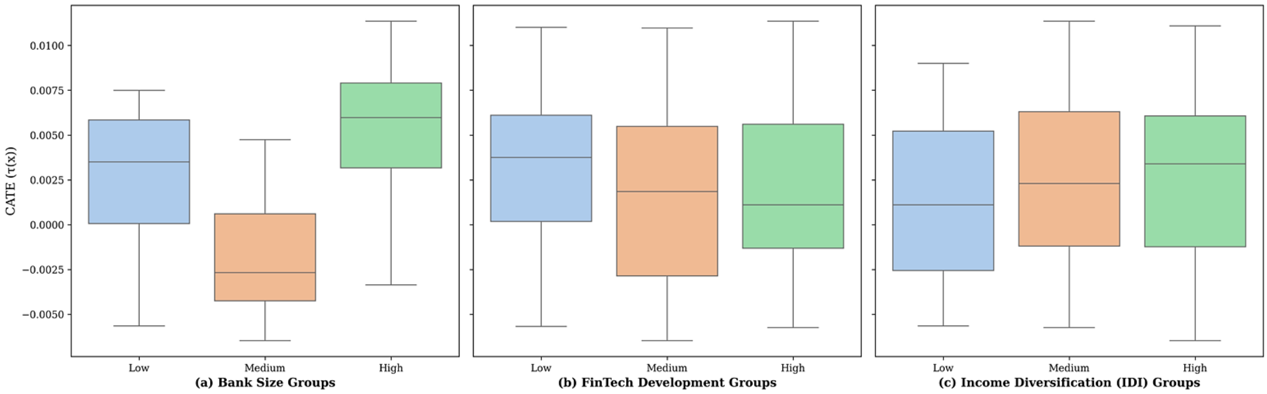


**Figure 5. Heterogeneity of ESG uncertainty effects on bank stability by SIZE, G_FINTECH and IDI. Note: This figure illustrates the distribution of CATE across three key grouping variables. Panel (a) shows significant heterogeneity by bank size, with large banks experiencing the strongest stabilizing effects, while medium-sized banks exhibit weaker impacts. Panel (b) reports heterogeneity by FinTech development. These results confirm that ESG uncertainty does not exert a uniform influence on bank stability but varies depending on structural characteristics, consistent with H4.**

Specifically, large banks exhibit significantly higher CATE values ($p < 0.01$), affirming their superior capacity to absorb risk due to economies of scale. This finding is consistent with Hypothesis H4 and aligns with the "too big to fail" narrative supported by previous literature.

In terms of FinTech development, the effect heterogeneity is statistically significant at the 5% level ($p < 0.05$), suggesting that the degree of FinTech integration may alter how banks respond to ESG uncertainty. However, the direction and strength of this effect remain contingent on the stage of FinTech ecosystem maturity, indicating that the stabilizing influence of FinTech is not universally guaranteed.

For IDI, the observed heterogeneity is marginally significant at the 10% level ($p < 0.10$), implying that the benefits of income diversification are not uniformly distributed across banks. Rather, the stabilizing effect peaks at moderate diversification levels, consistent with Hypothesis H2 and empirical evidence from Bogari (2024) [29] and Lahouel et al. (2023) [30].

These findings reinforce the notion that the impact of ESG uncertainty is context-dependent and moderated by institutional characteristics. Hence, policy recommendations should avoid one-size-fits-all approaches and instead tailor risk management strategies based on bank-specific attributes.

The Causal Forest analysis not only confirms the nonlinear and heterogeneous effects of ESG uncertainty but also provides robust empirical evidence of deep heterogeneity across bank characteristics. These findings underscore the importance of moving beyond average system-wide assessments when evaluating ESG impacts, emphasizing the need to identify vulnerable segments and design tailored policy interventions accordingly.

### *5-4- SHAP Explanations*

The SHAP analysis offers deeper insight into the mechanisms underlying the nonlinear and heterogeneous effects of ESG uncertainty on bank stability. Figure 6 highlights that ESGUI**,** IDI, and G_FINTECH each have a direct but distinct impact on the ZSCORE.

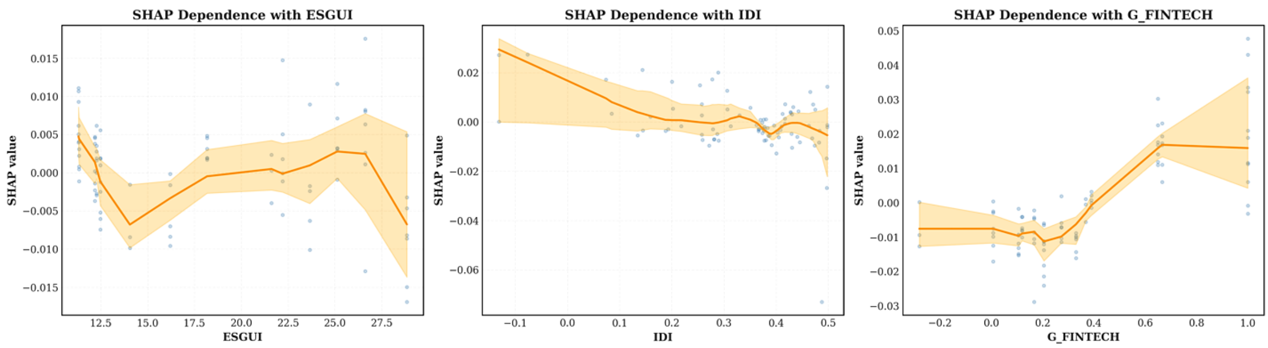


**Figure 6. SHAP Dependence plots of ESG uncertainty, income diversification, and FinTech development. Note: This figure shows SHAP dependence plots derived from the Causal Forest model, illustrating the marginal effects of ESG uncertainty (ESGUI), income diversification (IDI), and FinTech development (G_FINTECH) on bank stability (ZSCORE). The orange line represents the average SHAP effect, with shaded areas indicating 95% confidence intervals.**

For ESGUI, the relationship follows an inverted U-shape: at low levels, ESG uncertainty undermines stability; at moderate levels, it fosters improved governance and transparency, thereby enhancing stability; but at high levels, the effect turns negative again. This pattern is consistent with Hypothesis H1 and supports prior evidence on the dual nature of ESG uncertainty in emerging markets [2, 7].

Regarding IDI, the effect is also nonlinear: banks with moderate income diversification tend to benefit the most in terms of stability, whereas too little or excessive diversification weakens the stabilizing effect. This confirms Hypothesis H2 on the existence of an optimal diversification threshold [30].

In contrast, G_FINTECH exhibits a weaker direct impact; the effect only turns positive at high levels of FinTech development, suggesting that Hypothesis H3 is only partially supported. This result reflects the Vietnamese market's idiosyncrasies, where the FinTech ecosystem is still maturing, in contrast to more developed economies [36].

Figure 7 extends the analysis by examining interaction effects. The ESGUI × IDI interaction reveals that the relationship between ESG uncertainty and financial stability is strongly moderated by the degree of income diversification: at moderate IDI levels, the positive effect is pronounced, while excessively low or high levels diminish the benefit. This finding is consistent with Hypothesis H2 and Modern Portfolio Theory, affirming that the stabilizing benefits of diversification are only optimized within a specific range.

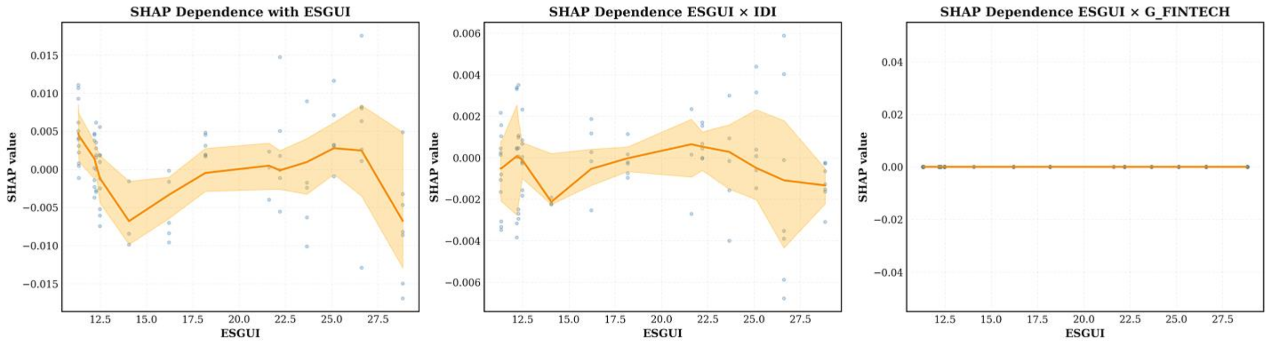


**Figure 7. SHAP dependence plots of ESG uncertainty and interaction effects. Note*:* This figure presents SHAP dependence plots from the Causal Forest model. Panel (a) shows the marginal effect of ESGUI on ZSCORE. Panel (b) illustrates the interaction between ESGUI and IDI, indicating heterogeneous marginal impacts across different levels of IDI. Panel (c) shows the interaction between ESGUI and G_FINTECH, where no substantial interaction effect is detected. The orange line represents the average SHAP value, and shaded areas denote 95% confidence intervals.**

Contrary to theoretical expectations regarding the moderating role of FinTech, SHAP interaction analysis does not identify any statistically significant interaction between ESGUI and G_FINTECH. This suggests that in the context of Vietnam, where the FinTech ecosystem remains fragmented and integration with traditional banking remains limited, FinTech firms currently lack the capacity to significantly alter the ESG–stability nexus. This finding stands in contrast to emerging markets such as Indonesia, where FinTech ecosystems have achieved a certain level of maturity and have demonstrated a stabilizing role under high ESG-related risks [36].

The SHAP results reinforce the findings from PTR and Causal Forest analyses, demonstrating that the effects of ESG uncertainty are both nonlinear and heterogeneous, and are strongly moderated by income diversification, but not yet by FinTech. These results underscore that ESG risk management policies must account for optimal thresholds and firm-specific characteristics, rather than assuming homogeneous impacts across the banking sector.

### *5-5- CATE Significance and Robustness Tests*

Table 5 presents result from one-way ANOVA tests, which detect statistically significant differences in the effects of ESG uncertainty across banks grouped by SIZE, G_FINTECH, and IDI. These tests provide critical empirical support that heterogeneity in ESG effects is not only quantitative but also statistically robust.

Specifically, for SIZE, the ANOVA reveals highly significant differences ($p < 0.01$), with large banks benefiting more clearly from ESG uncertainty, while medium-sized banks may even suffer adverse effects. For G_FINTECH, the effect is also statistically significant ($p < 0.05$), implying that FinTech's stabilizing benefits only materialize at certain levels of development, rather than uniformly across the system. Finally, IDI shows marginal significance ($p < 0.10$), suggesting that while a moderating effect exists, it may not be strongly pronounced, yet still supports the nonlinear role of diversification.

**Table 5.** Heterogeneity test of ESG uncertainty CATE by bank characteristics

| Variable | Group | Mean CATE | ANOVA Test p-value |
|---|---|---|---|
| SIZE | Low | 0.00246 | 0.0000*** |
| | Medium | -0.00177 | |
| | High | 0.00562 | |
| G_FINTECH | Low | 0.00294 | 0.0161** |
| | Medium | 0.00140 | |
| | High | 0.00198 | |
| IDI | Low | 0.00142 | 0.0762** |
| | Medium | 0.00230 | |
| | High | 0.00260 | |

Note: Reported p-values are from ANOVA tests for equality of means across groups. ***p < 0.01, **p < 0.05, *p < 0.10.

In summary, the ANOVA tests confirm Hypothesis H4 by demonstrating that the impact of ESG uncertainty on bank stability is clearly heterogeneous, and is substantially moderated by bank-specific characteristics, including size, FinTech adoption, and income structure. These findings lend empirical support to theoretical arguments emphasizing nonlinear and differentiated responses to ESG shocks within the banking system.

To ensure the robustness of the findings, the study conducts two additional validation tests. First, the primary outcome variable (ZSCORE) is replaced with an alternative measure of bank stability, namely the non-performing loan ratio (NPL). As shown in Table 6, the average CATE remains positive (0.0020), even though NPL is negatively related to stability. This suggests that while ESG uncertainty may increase credit risk in the short term, it does not contradict the main results using ZSCORE. On the contrary, it reinforces the argument of dual and nonlinear effects of ESG uncertainty: although ESG-related pressures may expose latent credit vulnerabilities, in the longer term, they may enhance resilience and strengthen overall bank stability.

**Table 6.** Robustness checks using alternative measure of bank stability (NPL) and ownership type

| Group | Obs. | Mean CATE | Std. Dev. | Min | Median | Max |
|---|---|---|---|---|---|---|
| Full sample | 420 | 0.0020 | 0.0028 | -0.0053 | 0.0020 | 0.0162 |
| Private Banks | 360 | 0.0025 | 0.0017 | -0.0011 | 0.0023 | 0.0088 |
| SOEs | 60 | 0.0004 | 0.0001 | 0.0003 | 0.0004 | 0.0006 |

Note: Table reports descriptive statistics of Conditional Average Treatment Effects (CATE) estimated using Causal Forest. NPL is used as an alternative proxy for bank stability. Ownership heterogeneity is assessed by comparing state-owned banks (SOEs) with private banks.

Second, the data are stratified by ownership structure to test for institutional heterogeneity. The results reveal that joint-stock commercial banks exhibit a significantly higher average CATE (0.0025) compared to state-owned banks (SOEs) (0.0004). This reflects substantial differences in responsiveness to ESG uncertainty. Joint-stock banks tend to be more agile and responsive, thereby exposed to greater risk, yet also more capable of leveraging ESG as a driver of governance improvement. In contrast, SOEs appear largely unaffected, consistent with their lower exposure to market competition and policy-protected structures.

The robustness checks affirm that the effect of ESG uncertainty on banking stability is systemic and consistent. At the same time, the results reinforce the hypothesis of heterogeneity in responses by ownership characteristics, thus underscoring the importance of institutional context when evaluating the role of ESG in banking stability.

## 6- Discussion

The empirical results confirm that the relationship between ESG uncertainty and banking stability is inherently nonlinear, consistent with the theoretical foundations that frame ESG as a dual-faceted force, capable of both introducing risk and fostering resilience through improved governance and innovation [35].

Both the PTR and Causal Machine Learning approaches reveal an inverted U-shaped relationship between ESG uncertainty (ESGUI) and banking stability. This finding supports Hypothesis H1, aligning with the Uncertainty Management Theory, which posits that moderate levels of ESG uncertainty may serve as a catalyst for strategic adjustments, such as enhanced transparency and governance, that bolster institutional resilience. However, beyond a critical threshold, escalating compliance burdens and diminished credit assessment capacity erode bank stability. These findings are consistent with recent empirical work identifying nonlinear ESG impacts in global contexts [38], while also extending the analysis into the underexplored landscape of emerging markets.

The results also validate Hypothesis H2, confirming a threshold effect in the relationship between income diversification (IDI) and bank stability. Specifically, stability is maximized at moderate levels of diversification, while both low and excessively high diversification levels are associated with reduced benefits. This supports the theoretical proposition of an optimal diversification point, rooted in Modern Portfolio Theory and corroborated by studies such as [30]. However, in contrast to findings in more developed financial systems, where diversification often yields more linear gains, the results for Vietnam highlight more pronounced nonlinearities, likely due to the limited internal risk management capacity of banks to effectively absorb the complexities of highly diversified income streams.

The findings related to FinTech development (G_FINTECH) provide partial support for Hypothesis H3. Stability-enhancing effects only emerge after surpassing a development threshold, suggesting that in the early stages of FinTech ecosystem growth, heightened competition, regulatory lag, and operational integration challenges may initially elevate systemic risks. These outcomes differ from prior studies in contexts such as Indonesia (Yudaruddin et al. [36]) and Africa, where FinTech integration more rapidly contributes to stability. This discrepancy underscores the importance of institutional readiness and market maturity in shaping FinTech's role in banking resilience [37, 38].

The heterogeneity analysis, based on bank size, ownership structure, and ESG uncertainty levels, confirms Hypothesis H4. ANOVA results show that ESG uncertainty does not affect all banks uniformly: large banks tend to experience clearer stability benefits due to greater resources and stronger compliance capabilities, whereas medium-sized banks are more vulnerable to ESG-driven instability. Additionally, banks with higher levels of FinTech adoption show a nonlinear trajectory toward improved stability once critical thresholds are reached. Likewise, income diversification exerts a moderating effect that varies significantly across bank types. These patterns are theoretically supported by the Heterogeneous Treatment Effects framework [10, 44] and emphasize the role of micro-level heterogeneity in shaping how banks respond to ESG-related shocks.

Overall, the findings affirm that the impact of ESG uncertainty on banking stability is nonlinear, threshold-dependent, and heterogeneous, shaped significantly by organizational traits and contextual variables. These results validate Hypotheses H1 through H4, while contributing new empirical evidence to support and extend existing theories on nonlinear and heterogeneous financial responses to ESG shocks, particularly within the under-researched environment of emerging markets.

## 7- Conclusion and Policy Implications

### *7-1- Conclusion*

This study provides novel empirical evidence on how ESG-related uncertainty (ESGUI) affects banking stability in Vietnam, an emerging market undergoing profound institutional and financial transformation. Employing a hybrid methodological framework that integrates Panel Threshold Regression, Causal Forest estimation, and SHAP interpretability, the analysis reveals that the ESG–stability nexus is inherently nonlinear, heterogeneous, and context-specific. The results demonstrate an inverted U-shaped relationship between ESG uncertainty and bank stability, indicating that moderate uncertainty enhances governance discipline and adaptive capacity, while excessive uncertainty beyond a critical threshold undermines stability. This pattern validates the predictions of Uncertainty Management Theory and confirms that the relationship between sustainability pressures and financial resilience is not monotonic but threshold dependent.

Furthermore, income diversification plays a crucial moderating role. The interaction between ESG uncertainty and the Income Diversification Index (IDI) suggests that diversification can mitigate the adverse impacts of ESG uncertainty, but only within an optimal range, where moderate diversification strengthens resilience, whereas excessive or insufficient diversification reduces its stabilizing effect. In contrast, FinTech development (G_FINTECH) exhibits a mixed influence. Contrary to theoretical expectations, rapid FinTech expansion without adequate regulatory or technological maturity may heighten systemic risks rather than enhance stability, and no robust evidence of an interaction between ESGUI and FinTech is observed. These findings underscore the incomplete integration of Vietnam’s FinTech ecosystem and its limited capacity to buffer ESG-induced volatility.

Finally, heterogeneity analyses using ANOVA and Causal Forest confirm that these effects vary significantly across bank types, sizes, and ownership structures. Overall, the study extends nonlinear financial stability theory by providing the first empirical evidence from Vietnam on the differentiated impacts of ESG uncertainty, income diversification, and FinTech development, while demonstrating the methodological value of combining econometric and explainable AI approaches to enhance model interpretability and policy relevance.

### *7-2- Policy Implications*

The results of this study highlight that banks do not respond homogeneously to ESG-related uncertainty; their resilience depends critically on internal income structures, technological maturity, and ownership characteristics. Accordingly, ESG risk governance and macroprudential policy design must recognize institutional heterogeneity rather than applying uniform, system-wide standards. A key priority for policymakers is to reduce ESG uncertainty through transparent, consistent, and predictable regulatory frameworks. Establishing unified ESG reporting standards, harmonized taxonomies, and clear supervisory guidelines can substantially lower compliance burdens and informational asymmetries. By enhancing regulatory clarity, authorities can transform ESG uncertainty from a destabilizing risk into a catalyst for improved corporate governance and long-term stability.

Furthermore, the nonlinear moderating effect of income diversification underscores the need for banks to pursue balanced diversification strategies. Excessive dependence on interest-based income amplifies vulnerability to credit and market shocks, while over-diversification may generate inefficiencies and agency problems. Therefore, maintaining moderate, well-managed diversification, supported by sound risk management and internal control mechanisms, can optimize resilience without incurring excessive operational complexity. At the same time, the findings on FinTech development suggest that digital transformation should be promoted cautiously and in tandem with regulatory oversight. In emerging markets like Vietnam, where FinTech ecosystems are still fragmented, uncoordinated technological expansion may initially destabilize the system. Thus, regulators should prioritize phased integration, cybersecurity resilience, and innovation sandboxes to foster a secure environment for FinTech–bank collaboration.

Collectively, these insights call for a coordinated approach in which ESG governance transparency, optimal diversification, and prudent technological innovation jointly contribute to a more sustainable and stable banking sector in emerging economies.

### *7-3- Limitations and Future Research*

While this study contributes novel insights into the interplay between ESG uncertainty, income diversification, and FinTech development in the banking sector, several limitations should be acknowledged. The ESG Uncertainty Index (ESGUI), although robust in capturing macro-level policy and informational volatility, is a text-derived construct based on the frequency and dispersion of ESG-related terms in Economist Intelligence Unit (EIU) reports. Consequently, its reliance on textual data may introduce potential measurement bias, as it reflects the intensity of ESG discourse at the national level rather than firm-level practices or disclosure behavior. This limitation may also arise from linguistic nuances, media emphasis, or institutional reporting differences that influence the frequency of ESG-related terminology. Future research could mitigate this limitation by triangulating ESGUI with firm-level ESG performance metrics, disclosure-based indices, climate-risk databases, and sentiment-driven data sources, thereby improving both measurement accuracy and interpretive depth. Integrating such multidimensional ESG indicators would enable a richer understanding of how uncertainty interacts with institutional and market-level sustainability factors.

Moreover, the empirical scope, centered on Vietnam as an archetypal emerging market, offers contextually rich but geographically bounded insights. Extending this analytical framework to a broader cross-country setting, particularly within the ASEAN bloc and other emerging financial systems, could yield valuable comparative perspectives on institutional heterogeneity, regulatory maturity, and technological diffusion in shaping ESG-related stability outcomes.

Looking ahead, the methodological integration of causal machine learning and interpretable AI presents a promising avenue for deepening the understanding of nonlinear financial-environmental interactions. As global finance transitions toward sustainability-oriented paradigms, future scholarship should not only refine measurement but also explore the policy design and governance mechanisms that can translate ESG-driven uncertainty into long-term systemic resilience.

## 8- Declarations

### *8-1- Author Contributions*

Conceptualization, P.D.V. and P.T.T.; methodology, P.D.V.; software, P.T.T.; formal analysis, P.T.T.; investigation, P.D.V.; resources, P.D.V.; data curation, P.T.T.; writing—original draft preparation, P.D.V. and P.T.T.; writing—review and editing, P.D.V. and P.T.T.; visualization, P.T.T.; supervision, P.D.V.; project administration, P.D.V.; funding acquisition, P.D.V. All authors have read and agreed to the published version of the manuscript.

### *8-2- Data Availability Statement*

The data presented in this study are available on request from the corresponding author.

### *8-3- Funding*

The authors received no financial support for the research, authorship, and/or publication of this article.

### *8-4- Institutional Review Board Statement*

Not applicable.

### *8-5- Informed Consent Statement*

Not applicable.

### *8-6- Conflicts of Interest*

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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