REMV REAL ESTATE MANAGEMENT AND VALUATION

Journal homepage: www.remv-journal.com

GLOBAL INFORMATION UNCERTAINTY AND REAL ESTATE STOCK VALUATION IN EMERGING MARKETS: AN INTEGRATED BEHAVIORAL - THEORETICAL AND MACHINE LEARNING FRAMEWORK

Thuy Tu Pham*[1]

[1] *Faculty of Banking, Ho Chi Minh University of Banking (HUB), 56 Hoang Dieu 2, Thu Duc, Ho Chi Minh City, 84, Vietnam, e-mail: tupt@hub.edu.vn, ORCID: 0000-0002-0203-7865*

* *Corresponding author*

ARTICLE INFO

Keywords:

information uncertainty, ESG, uncertainty, behavioral asset pricing, real estate stocks, emerging markets, machine learning

JEL Classification:

C45, C53, D84, G12, G14, R33

ABSTRACT

This study develops an integrated behavioral-theoretical and explainable machine learning framework to investigate how global information uncertainty affects real estate stock valuation in emerging markets. Grounded in Knightian uncertainty and behavioral finance theory, the analysis employs a panel dataset of 28 listed Vietnamese real estate firms from 2013 to 2024, incorporating firm fundamentals, macroeconomic controls, and four key uncertainty indices: ESG Uncertainty (ESGUI), Geopolitical Risk (GPR), World Uncertainty (WUI), and Media Sentiment (WSI). Nonlinear predictive models, particularly XGBoost optimized via Particle Swarm Optimization (PSO), are interpreted using SHAP and LIME to uncover both global and local effects. Results indicate that firm size and book value are the most influential valuation drivers, while global uncertainty indices demonstrate conditional effects. Notably, the interaction between WUI and firm size reveals an inverse U-shaped pattern, supporting the "asymmetric ambiguity response" hypothesis: under heightened uncertainty, investors gravitate towards large firms. The proposed framework offers theoretical consistency, predictive accuracy, and interpretability, contributing to the literature on asset pricing under uncertainty. Findings provide practical insights for ESG communication, risk mitigation, and regulatory design in opaque and sentiment-sensitive emerging markets.

Citation:

Pham, T. T. (2026). Global information uncertainty and real estate stock valuation in emerging markets: An integrated behavioral - Theoretical and machine learning framework. *Real Estate Management and Valuation*, *34*(1), 63-83. https://doi.org/10.2478/remav-2026-0006

1. Introduction

Over the past decade, real estate markets in emerging economies, particularly Vietnam, have undergone pronounced fluctuations driven by global uncertainty shocks. These include the COVID-19 pandemic, geopolitical conflicts, monetary tightening by the U.S. Federal Reserve, and, notably, environment, social, and governance (ESG)-related risks. Such shocks have not only disrupted conventional macroeconomic fundamentals but also intensified informational ambiguity on a global scale, thereby complicating investor expectations and asset pricing dynamics (Ahmed et al., 2025; Tang et al., 2025; Yilmazkuday, 2024). Real estate, being inherently sensitive to policy shifts and investor sentiment, is especially vulnerable to these conditions (Ampountolas et al., 2024).

Despite these developments, most existing studies continue to rely on classical linear models, which inadequately capture the nonlinear, context-dependent impacts of global uncertainty. Key indicators, such as the ESG Uncertainty Index (ESGUI), Geopolitical Risk Index (GPR), World Uncertainty Index (WUI), and World Sentiment Index (WSI), encapsulate forms of Knightian uncertainty, unmeasurable and qualitatively distinct from probabilistic risk in traditional finance (Ellsberg, 1961; Knight, 2022). In such settings, investor behavior may be disproportionately shaped by ESG shocks and emotionally charged or misleading media narratives, making behavioral finance a critical lens to explain market anomalies such as overreaction and noise trading (Barberis et al., 2018).

Although recent literature has begun integrating

ESG factors into asset pricing models (Fan et al., 2024; Hoelscher et al., 2024; Nguyen & Nguyen, 2025; Tang et al., 2025; Truong et al., 2024), there remains a significant research gap in linking broader informational uncertainty, such as GPR, WUI, and WSI, to investor behavior. This gap is particularly evident in the Vietnamese context, where transparency is limited, market cycles are volatile, and sentiment-driven trading is prevalent (Itan et al., 2025). Moreover, few studies leverage machine learning (ML) tools to identify complex nonlinearities and variable interactions under uncertainty.

To address these deficiencies, the study proposes a novel framework grounded in three interrelated pillars: (i) Knightian uncertainty, highlighting the immeasurable nature of global shocks; (ii) behavioral finance, to explain cognitive biases in response to ambiguity; and (iii) explainable machine learning, particularly SHAP (SHapley Additive exPlanations), to uncover variable-level contributions in nonlinear predictive models. Unlike prior ML approaches often lacking theoretical rigor (Ghoddusi et al., 2019), this framework explicitly bridges financial theory and algorithmic inference.

Using a monthly panel of 28 Vietnamese real estate firms (2013–2024), the study employs stock price as the dependent variable and includes firm-specific indicators (EPS, ROE, SIZE), macroeconomic controls (CPI, oil, gold, Fed rate), and global uncertainty indices (ESGUI, GPR, WUI, WSI). A suite of ML algorithms, including Ridge, Lasso, Random Forest, XGBoost, and gradient boosting, are evaluated against traditional models, with interpretability achieved through SHAP values across temporal and structural subgroups (e.g., pre/post-COVID, firm size, and uncertainty regimes).

This study offers three main contributions: (1) a theoretically integrated framework combining global uncertainty, behavioral finance, and interpretable ML; (2) robust empirical evidence from a long-span panel in an emerging market; and (3) a novel approach to modeling asset pricing under complex uncertainty conditions driven by ESG ambiguity, sentiment, and media effects.

2. Theoretical framework

2.1. Knightian uncertainty and global information shocks

The concept of Knightian uncertainty, introduced by Knight (2022) and later expanded by Ellsberg (1961), distinguishes between measurable risk and unmeasurable uncertainty. In classical economic theory, Knight (2022) drew a clear line between quantifiable risk, where probabilities can be estimated, and true uncertainty, where such probabilities are inherently unknowable. This latter category, known as Knightian uncertainty, is characterized by ambiguity regarding both the likelihood and the consequences of potential events. In financial contexts, such uncertainty renders traditional probabilistic models inadequate for comprehensive asset pricing.

Ellsberg (1961) reinforced this view through experimental evidence demonstrating that individuals tend to exhibit greater aversion toward ambiguity than toward measurable risk. This foundational insight explains why global information shocks, such as ESG uncertainty, geopolitical tensions, or media-driven sentiment, can trigger disproportionately irrational responses in financial markets.

In the modern landscape, indices such as the ESG Uncertainty Index (ESGUI), Geopolitical Risk Index (GPR), World Uncertainty Index (WUI), and World Sentiment Index (WSI) serve as empirical proxies for various forms of Knightian uncertainty, capturing the degree of informational ambiguity embedded in the global business environment. Recent studies have highlighted that these forms of uncertainty can exert a substantial influence on investor expectations and asset valuation, particularly in the real estate sector, which is highly sensitive to both macroeconomic fundamentals and market sentiment (Nguyen & Nguyen, 2024).

2.2. Behavioral finance and asset pricing under uncertainty

Behavioral finance extends traditional models by accounting for psychological biases and emotional responses in investment decisions. Under elevated uncertainty, investors tend to overreact to negative information and engage in herding behavior, leading to systematic mispricing and market inefficiencies (Barberis et al., 2018).

Knightian uncertainty, characterized by unknown probabilities, amplifies behavioral anomalies such as noise trading (Shefrin & Statman, 1985) and ambiguity aversion. In such environments, investors increasingly rely on heuristics and unofficial information sources, including emotionally charged social media content, to form expectations (Akin & Akin, 2024). These behaviors complicate valuation and increase volatility, especially in emerging markets with weak informational infrastructure.

Unlike quantifiable risks, global information uncertainty, spanning ESG ambiguity, geopolitical instability, macroeconomic unpredictability, and media sentiment, operates primarily through behavioral channels. Rather than analyzing each source in isolation, this study emphasizes how investor sentiment mediates the relationship between uncertainty and asset pricing, explaining heterogeneous market reactions to similar shocks across sectors and geographies.

In today's highly connected markets, real estate equities are particularly sensitive to informational shocks. Beyond macro fundamentals, such as interest rates and GDP, high-ambiguity signals can alter beliefs, trigger cognitive biases, and distort price discovery (Baker et al., 2016; Pástor & Veronesi, 2013). These effects are especially pronounced in cyclical sectors like real estate, where overreaction, flight-to-safety, and herding behaviors are common (Wang & Zhu, 2025). To capture these dynamics, the study incorporates four uncertainty dimensions:

1) ESG Uncertainty (ESGUI): Focuses on ambiguity in ESG-related market reactions.
2) Geopolitical Risk (GPR): Reflects sensitivity to conflicts and sanctions.
3) Macroeconomic Policy Uncertainty: Affects investment via interest rate and regulation ambiguity.
4) Media-Driven Sentiment: Encompasses misinformation and emotional contagion in digital environments.

This behavioral framework underlies the study's approach to modeling volatility in real estate stock valuation.

2.4. Integrating the theoretical framework into explainable machine learning models

In increasingly complex and uncertainty-driven financial markets, the application of machine learning (ML) models has become a dominant trend in empirical asset pricing research. However, a persistent limitation of many ML-based financial studies is the lack of robust theoretical grounding. A major challenge lies in the "black-box" nature of ML models, which complicates the process of interpretation and their reconciliation with established financial theories. Integrating Knightian uncertainty and behavioral finance theory into machine learning models adds value not only in predictive performance but also in explanatory power and theoretical consistency.

Models, such as XGBoost and Random Forest, are capable of capturing complex nonlinear relationships between global uncertainty indices and asset prices. However, to ensure interpretability and enable behavioral hypothesis testing, explainable machine learning techniques such as SHAP (SHapley Additive exPlanations) serve as a critical theoretical–empirical bridge. SHAP allows for the quantification of the marginal contribution of each uncertainty factor under varying market conditions, facilitating empirical investigation of behavioral phenomena such as ambiguity aversion or emotional spillover effects.

3. Literature review

3.1. Real estate stock valuation in emerging markets

Real estate equity markets in emerging economies, such as Vietnam, Indonesia, and Thailand, are marked by pronounced cyclicality, limited information transparency, and strong responsiveness to macroeconomic shocks and investor sentiment. Recent research has shown that, beyond traditional valuation, determinants like profitability, net asset value, and firm size, behavioral expectations and information uncertainty are increasingly shaping stock price dynamics in this sector (El Oubani, 2024; Vuong & Suzuki, 2022; Yudaruddin & Lesmana, 2024).

Shi et al. (2022) found that investor sentiment, both domestic and global, plays a more substantial role in sectoral returns than conventional macroeconomic variables such as inflation, GDP growth, and interest rates, especially in markets lacking institutional maturity and valuation transparency. Bouri et al. (2022), using the local Gaussian correlation method, demonstrated nonlinear contagion effects between stock markets and REITs across 19 countries during major crises, revealing that even underdeveloped REIT markets are vulnerable to global financial shocks. Investors in emerging markets often react intensely to uncertainty signals, particularly in contexts where credible information is scarce and media influence is emotionally driven (Maurya et al., 2025; Mohammed et al., 2023).

In Vietnam, Hoang Vu et al. (2024) showed that electronic word-of-mouth (eWOM) on social media moderately influences investor information acquisition and decision-making, with information quality and credibility emerging as critical factors. The sharp post-COVID-19 downturn in Vietnam's real estate market further illustrates the dominant role of sentiment and expectations in asset valuation.

Environmental, Social, and Governance (ESG) considerations are also gaining importance. Nguyen & Nguyen (2024) found that firms with transparent ESG disclosures and sustainability strategies enjoy valuation premiums. Similarly, Kitulazzi et al. (2025) revealed that,

eISSN: 2300-5289 | Received 2025-06-09 | Revised 2025-09-25 | Accepted 2025-09-30

while overall ESG performance may reduce firm value, the social dimension positively affects return on equity and market value, underscoring the differentiated financial impacts of ESG components.

Collectively, these findings call for the incorporation of behavioral dynamics and global uncertainty indices into valuation models to better capture the nonlinear, sentiment-driven nature of real estate equities in emerging markets.

3.2. Global uncertainty indices and empirical evidence

Ongan et al. (2025) introduced the ESG Uncertainty Index (ESGUI), which quantifies abnormal volatility in ESG-related financial news through textual analysis, capturing divergence in investor expectations. Their empirical results indicate that elevated ESGUI levels are associated with stronger negative market reactions, particularly in sectors characterized by extensive ESG disclosures. In the real estate domain, Nguyen and Nguyen (2024) find that during periods of systemic stress, such as the COVID-19 pandemic, firms with transparent and consistent ESG strategies experienced less severe stock price declines, suggesting a market preference for "safe ESG haven" assets during uncertainty.

Caldara and Iacoviello (2022) developed the Geopolitical Risk Index (GPR), based on the frequency and significance-weighted intensity of geopolitical events reported in global newspapers. Their findings confirm that GPR spikes tend to depress equity valuations, particularly in capital-intensive sectors like real estate. Akin and Akin (2024) highlight that real estate firms in emerging markets are especially vulnerable to geopolitical shocks due to their reliance on foreign capital and heightened political exposure. Even absent fundamental deterioration, or investor fears tied to trade conflicts or geopolitical instability can materially suppress valuations.

Ahir et al. (2022) proposed the World Uncertainty Index (WUI), constructed from over 100,000 economic reports across 143 countries. Nguyen and Nguyen (2024) demonstrate that higher WUI levels are associated with lower expected returns on real estate stocks, consistent with the "uncertainty-induced discounting" hypothesis (Gulen & Ion, 2015).

Lastly, Nicolas et al. (2024) introduced the Media Sentiment Uncertainty Index (WSI), leveraging deep learning and natural language processing to measure emotional volatility in financial news. Their findings show that emotionally charged ESG content can trigger widespread sell-offs, particularly among illiquid real estate firms with weak ESG transparency.

The inclusion of ESGUI, GPR, WUI, and WSI in this study is therefore both theoretically grounded and empirically validated, particularly in emerging markets such as Vietnam, where localized uncertainty mechanisms strongly shape investor behavior.

3.3. Integrating theory into explainable machine learning models

Recent studies have increasingly emphasized the integration of explainability techniques, particularly SHAP (SHapley Additive exPlanations), into machine learning (ML) models to enhance transparency and interpretability. Advanced ML algorithms such as XGBoost, Random Forest, and Transformer have proven effective in handling large-scale financial data and capturing complex nonlinear patterns. Deng et al. (2023) report that XGBoost outperforms traditional models in forecasting Chinese stock index movements, especially when combined with investor sentiment variables. Likewise, Transformer models employing self-attention mechanisms have improved both predictive accuracy and interpretability in asset allocation tasks (Ma et al., 2023).

SHAP, grounded in cooperative game theory, offers a robust framework for quantifying the contribution of each input feature to model outputs. Demirbaga & Xu (2024) demonstrate the utility of SHAP in asset pricing, identifying momentum, 52-week highs, and volatility as key return predictors. In fixed income markets, SHAP has become instrumental in revealing the determinants of excess bond returns, thereby demystifying the "black box" nature of ML models (Beckmann et al., 2023; Černevičienė & Kabašinskas, 2024; Ikumapayi & Muhammed, 2024; Yeo et al., 2025).

Moreover, integrating behavioral finance theories, such as overreaction, herding, and emotional contagion, into ML models enhances their explanatory power. Chen and Gao (2024) show that attribution methods like SHAP and Integrated Gradients can effectively identify latent pricing risks while preserving theoretical coherence. In real estate, where valuations are sensitive to ESG, geopolitical, and macro-policy uncertainties, SHAP-based ML models allow for more granular and theoretically consistent risk assessments (Kuppan et al., 2024).

4. Data and methodology

4.1. Data

This study utilizes a monthly-frequency panel dataset comprising 28 real estate firms (including firms with a primary investment focus in real estate) listed on the Ho Chi Minh City Stock Exchange (HOSE) and Hanoi Stock Exchange (HNX), spanning the period from January 2013 to June 2024. The selection of this time frame ensures not only a sufficiently long time series to capture the dynamic behavior of financial variables, but also the inclusion of multiple economic cycles and major periods of instability, such as the COVID-19 pandemic and global interest rate fluctuations.

The panel structure, combining both temporal and cross-sectional dimensions, enables the joint analysis of firm-specific characteristics, macroeconomic variables, global uncertainty, and technical indicators to assess their multidimensional impact on real estate stock price volatility. The dataset is divided into two main groups of variables: the target variable group (P real estate stock price) and the control variable group (including micro, macro, and interaction terms). Variable definitions, descriptions, and processing methods are detailed in Table 1.

Table 1

Descriptive summary of the variables used in the dataset

Variables	Description of meaning
Target variables	
P	Stock price, closing price adjusted according to dividends and splits at time t of company i. The natural logarithm of the stock price, which is used to deal with the problem of skewed distribution and variability, P =Ln (P)
Variables explained	
Micro variable group (collected from firms' financial statements)	
EPS (Earnings per Share)	Profit after tax per share.
ROE (Return on Equity)	Return on equity.
BV (Book Value)	Book value.
SIZE	The natural logarithm of total assets.
Macro variable group (collected from the General Statistics Office of Vietnam)	
CPI	The consumer price index, reflecting inflationary pressures.
GOLD	World gold prices, a safe haven asset, reflect defensive sentiment.
OIL	Brent oil prices, affecting the input cost of the real estate industry.
FED	The US Federal Reserve's operating interest rate, which represents global monetary policy and cross-border capital flows (Caldara & Iacoviello, 2022).
Global information uncertainty group	
ESGUI (ESG Uncertainty Index)	Developed by Ongan et al. (2025).
GPR (Geopolitical Risk Index)	Developed by Caldara & Iacoviello (2022).
WUI (World Uncertainty Index)	Developed by Ahir et al. (2022).
WSI (Media Sentiment Index)	Developed by Nicolas et al. (2024).

Source: Data collected, compiled, and processed by the author.

4.2. Methodology

The study implements a comprehensive machine learning (ML) pipeline that includes the following core steps: data preprocessing, time-based training set partitioning, training of nonlinear predictive models, and interpretation of results using SHAP. The pipeline is designed to ensure transparency, predictive performance, and economic interpretability, especially under conditions of market disruption caused by global informational shocks.

a) Data processing and feature engineering

The raw data, structured as monthly-frequency panel data from 28 listed Vietnamese real estate firms over the 2013–2024 period, are normalized using StandardScaler and treated for outliers via winsorization at the 1st and 99th percentiles to reduce statistical noise.

In addition to micro-level variables (BV, EPS, ROE, SIZE), macroeconomic indicators (CPI, OIL, GOLD, FED), and global uncertainty indices (ESGUI, GPR, WUI, WSI), the study incorporates technical features such as lags, rolling means, dynamic standard deviations (volatility), and interaction terms (e.g., ESGUI × SIZE, WUI × SIZE) to capture nonlinear conditional effects often observed in financial behavior (Černevičienė & Kabašinskas, 2024).

b) Applied machine learning models

A wide range of machine learning algorithms is employed, including:

1) *Regularized linear models:* Ridge, Lasso, Elastic Net – used as benchmarks for comparison against nonlinear models.
2) *Nonlinear ML models:* Decision Tree, Random Forest, XGBoost, LightGBM, AdaBoost, and Gradient Boosting – suitable for data with complex nonlinear interactions and high dimensionality (Deng et al., 2023).

All models undergo hyperparameter tuning using Particle Swarm Optimization (PSO) in conjunction with time-series cross-validation.

c) Model Performance Evaluation and Testing

Model performance is assessed using RMSE, MAE, and the coefficient of determination (R^2). The model with the lowest predictive error and highest explanatory power is selected as the representative. Forecasting results are benchmarked against traditional linear models to validate the superiority of nonlinear ML approaches (Beckmann et al., 2023).

D) Model Interpretation with SHAP, LIME

To overcome the "black-box" nature of machine learning, the study employs SHAP (SHapley Additive exPlanations) to quantify the marginal contribution of each independent variable to the model’s predictions. Based on Shapley game theory, SHAP allows detailed decomposition of variable contributions at the individual prediction level (Yeo et al., 2025).

Additionally, SHAP is used for comparative group analysis (e.g., pre- vs. post-COVID, high vs. low ESGUI periods), providing quantitative evidence for behavioral mechanisms in the pricing of real estate equities (Chen & Gao, 2024).To enhance the interpretability of the machine learning framework, this study incorporates the Local Interpretable Model-Agnostic Explanations (LIME) method alongside SHAP. While SHAP values provide consistent and model-faithful feature attributions across the global dataset (Lundberg & Lee, 2017), LIME allows for localized, case-specific explanations by fitting simple surrogate models around each prediction (Ribeiro et al., 2016). This complementary approach is particularly useful in behavioral finance contexts, where market responses are often nonlinear and heterogeneous. In settings characterized by Knightian uncertainty and information frictions, as in the Vietnamese real estate sector, LIME contributes nuanced insights into how individual firm characteristics and uncertainty indicators jointly shape pricing behavior at the observation level. The entire empirical framework is summarized in Figure 1.

The quantitative methodology in this study not only emphasizes predictive performance but also aims to achieve economic interpretability and behavioral hypothesis testing under conditions of global uncertainty, enabled by the integration of advanced machine learning and modern interpretability techniques such as SHAP.

5. Empirical results and discussion

5.1. Exploratory data analysis

To establish a robust quantitative foundation for interpretable machine learning models, the study conducts an exploratory data analysis (EDA) to examine distributional properties, variability, and latent correlations among key variables. The dataset comprises 3,036 monthly observations from 28 listed real estate firms in Vietnam spanning the period 2013–2024, characterized by high uncertainty, pronounced cyclicality, and volatile investor sentiment in response to global informational shocks.

Descriptive statistics presented in Table 2 indicate significant dispersion among input variables, reflecting heterogeneity in financial characteristics and sensitivity to macroeconomic and global factors across real estate firms. Specifically, the target variable, logarithm of stock price (P), has a mean of 9.105 and a standard deviation of 0.946, indicating relatively high variability across observations. This is visually corroborated in Figure 2, which shows a slightly left-skewed distribution for P, implying a concentration of stock prices around low-to-moderate levels, consistent with the structural composition of the market, where most firms are of small to medium size.

eISSN: 2300-5289

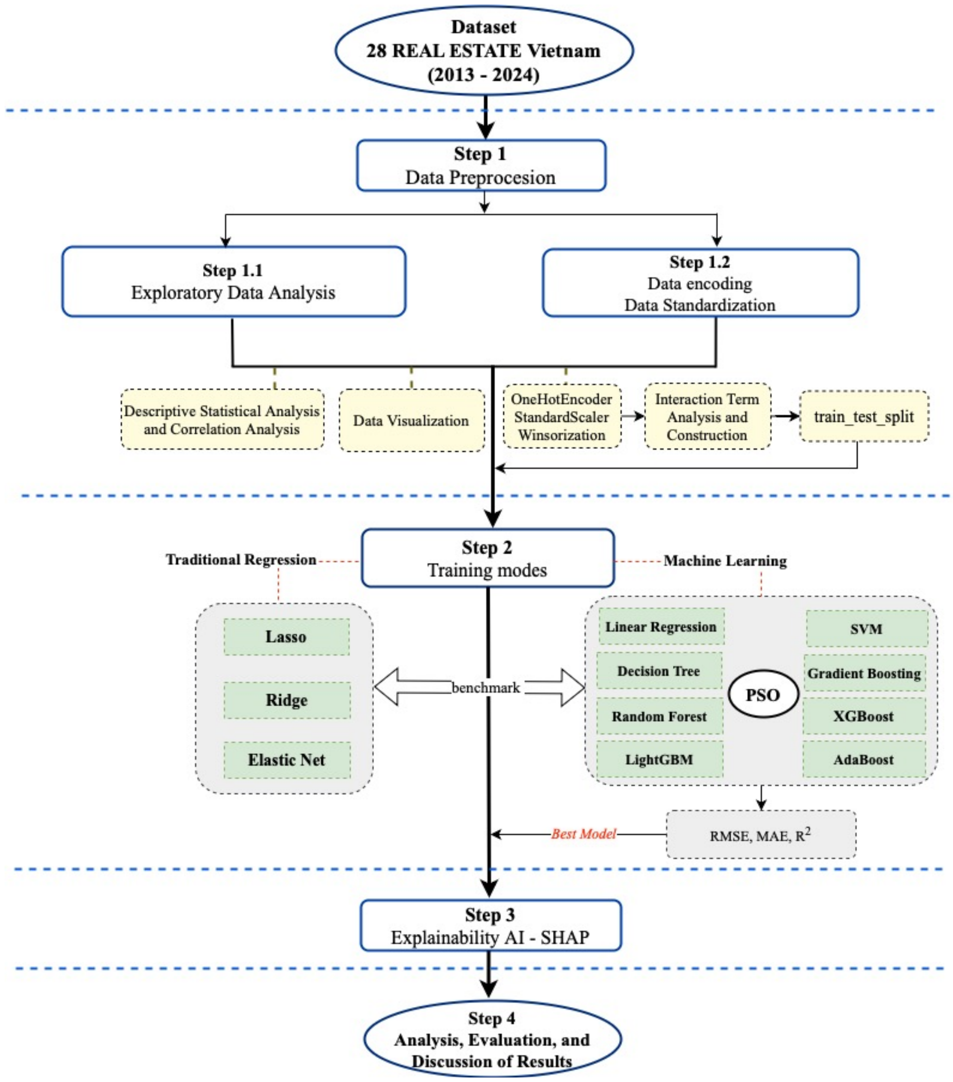

Fig. 1. Experimental Workflow Framework. *Source*: Author's work.

Table 1

Descriptive statistics

	count	mean	std	min	25%	50%	75%	max
P	3036	9,105	0,946	6,522	8,476	9,024	9,745	11,685
EPS	3036	4,807	3,765	-8,96	4,373	5,923	7,091	9,97
SIZE	3036	29,086	1,253	26,296	28,219	29,045	29,775	33,392
BV	3036	9,629	0,417	7,63	9,368	9,544	9,929	11,892
ROE	3036	0,022	0,04	-0,338	0,003	0,013	0,034	0,337
GOLD	3036	1,524	0,332	1,178	1,291	1,326	1,758	3,568
OIL	3036	4,155	0,336	2,936	3,901	4,172	4,404	4,742
CPI	3036	4,608	0,004	4,59	4,605	4,607	4,61	4,62
FED	3036	0,015	0,017	0,003	0,003	0,005	0,023	0,055
COVID	3036	0,391	0,488	0,000	0,000	0,000	1,000	1,000
GPR	3036	4,604	0,266	4,068	4,413	4,592	4,742	5,765
ESGUI	3036	2,779	0,342	2,252	2,485	2,693	3,052	3,46
WUI	3036	3,494	0,188	3,045	3,367	3,466	3,638	4,06
WSI	3036	1,438	0,924	-1,427	0,698	1,3	2,275	3,404

Source: Generated by the authors using Python.

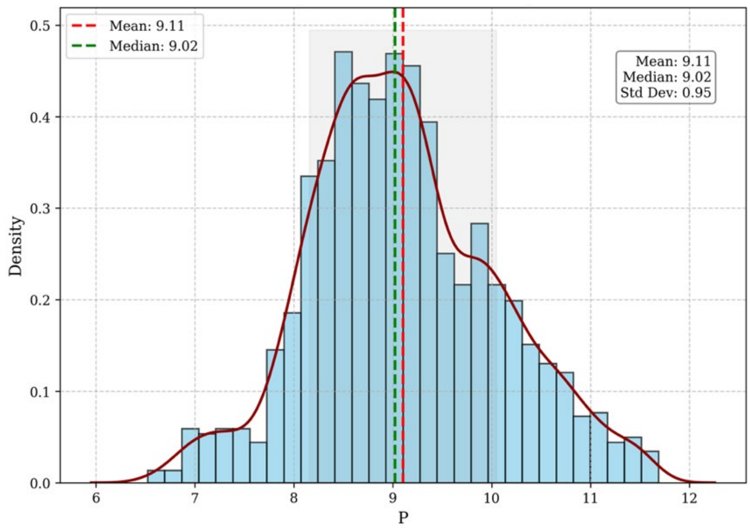

Fig. 2. Empirical Distribution of real estate stock prices in the Vietnamese market (2013–2024). *Source*: Author (2025).

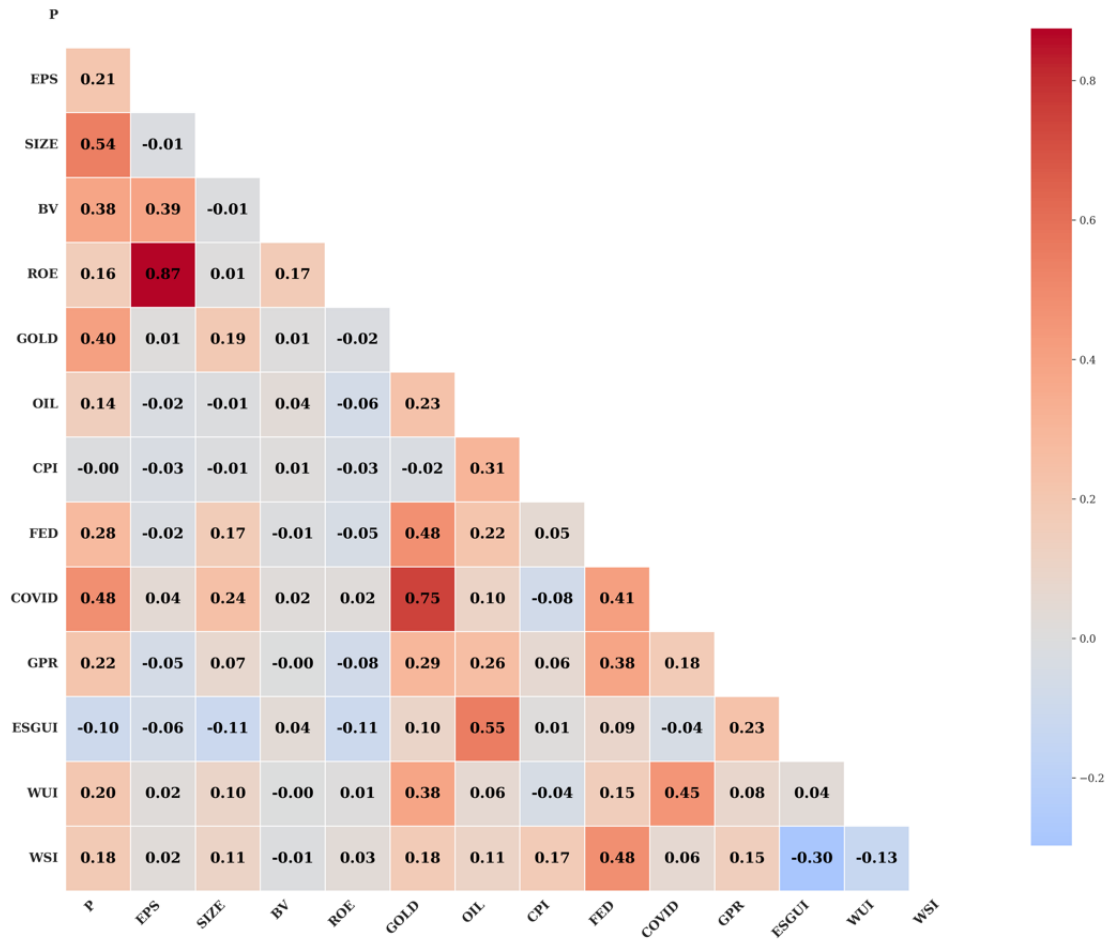

Fig. 3. Correlation matrix of numerical features. *Source*: Author (2025).

The results in Table 1 also reveal that micro-level variables such as EPS, ROE, and SIZE exhibit right-skewed distributions, with some negative values (e.g., minimum EPS of -8.96 and ROE of -0.338), suggesting the presence of prolonged loss-making periods, a common feature during real estate downturns in emerging markets.

Notably, global informational uncertainty indices such as ESGUI, GPR, WUI, and WSI show marked variability. ESGUI ranges from 2.252 to 3.460, while WSI displays a bimodal distribution with values spanning from -1.427 to 3.404. These findings highlight heterogeneous exposure among firms to ESG-related uncertainties and media sentiment volatility, both key

eISSN: 2300-5289

dimensions embodying the Knightian nature of modern investment environments.

The correlation matrix (Figure 3) confirms several economically meaningful comovements, for instance, a positive correlation between SIZE and stock price, and a negative correlation between GPR and ROE, suggesting that geopolitical shocks are often associated with diminished firm profitability. However, most correlation coefficients fall within low to moderate ranges, supporting the rationale for employing nonlinear models to capture complex and non-additive interactions between uncertainty factors and the target variable.

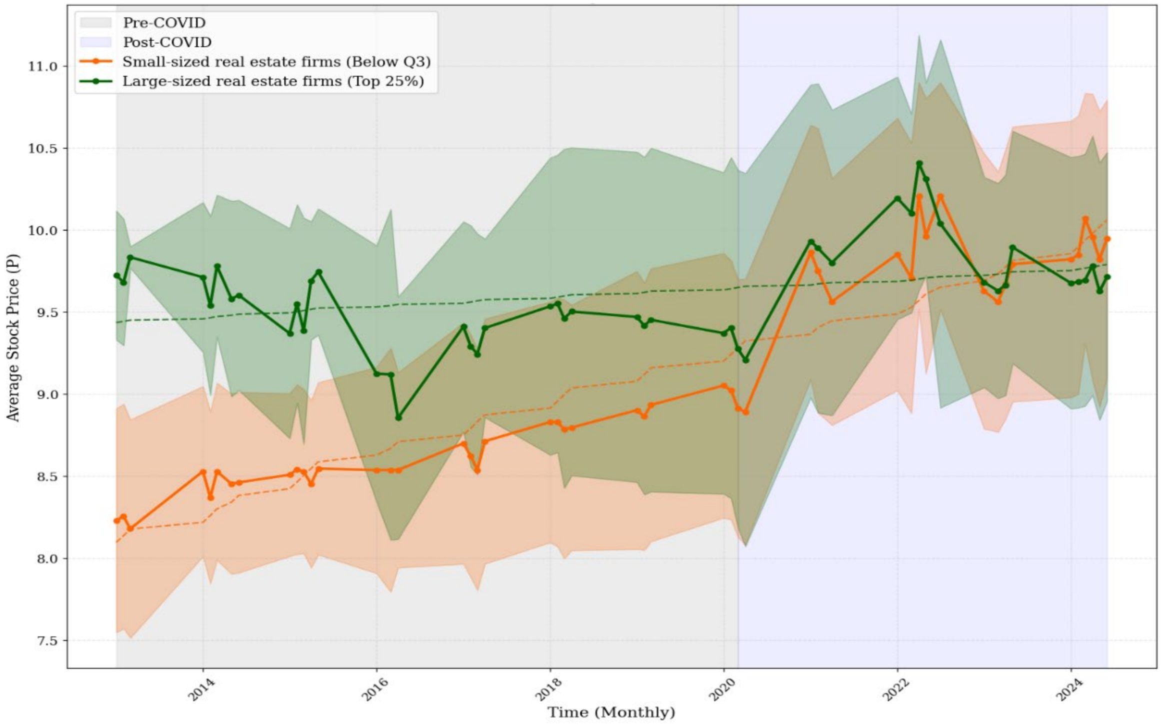

Fig. 4. Real estate stock price trends by firm size (Pre and post COVID). *Source*: Author (2025).

Figure 4 provides a valuable visualization of the dynamic divergence in stock price performance across firm size groups, especially across the pre- and post-COVID-19 periods. The data show a clear post-crisis divergence: large-cap firms exhibit stronger and more sustained price recoveries compared to smaller firms. This finding aligns with the "size effect" hypothesis under Knightian uncertainty, whereby larger firms are better equipped to withstand systemic shocks due to greater capital reserves, easier credit access, and superior informational transparency.

From the perspective of behavioral finance, this trend further illustrates the investor inclination toward a "flight to quality" during periods of crisis, whereby portfolios are reallocated toward assets perceived as relatively safer. The sustained underperformance, or even continued decline, of small-cap equities post-pandemic vividly reflects heightened risk aversion and a shift in investment expectations in response to increasing sources of uncertainty. This analysis also lays the theoretical groundwork for the hypothesis that the interaction between firm size and global informational uncertainty may constitute a critical transmission mechanism within asset pricing models.

Figure 5 to 8 further extend the analysis from Figure 4 by incorporating multiple dimensions of global uncertainty (ESGUI, GPR, WUI, WSI), thereby illustrating the intersection between internal institutional characteristics (firm size) and exogenous informational shocks. The graphical results reveal a pronounced interaction between uncertainty levels and firm size: while large firms exhibit greater resilience to ESG and geopolitical shocks, smaller firms respond more intensely and are significantly more vulnerable, particularly during periods of heightened ESGUI or WSI. This finding aligns with theoretical arguments suggesting that smaller enterprises, typically lacking comprehensive ESG strategies and proactive communication capabilities, are more susceptible to waves of emotionally charged media narratives.

From a behavioral standpoint, such responses may be explained through the lenses of *ambiguity aversion* and *noise trading*. In environments where credible information is scarce, investors tend to overreact or engage in emotionally driven sell-offs rather than rely on fundamental analysis.

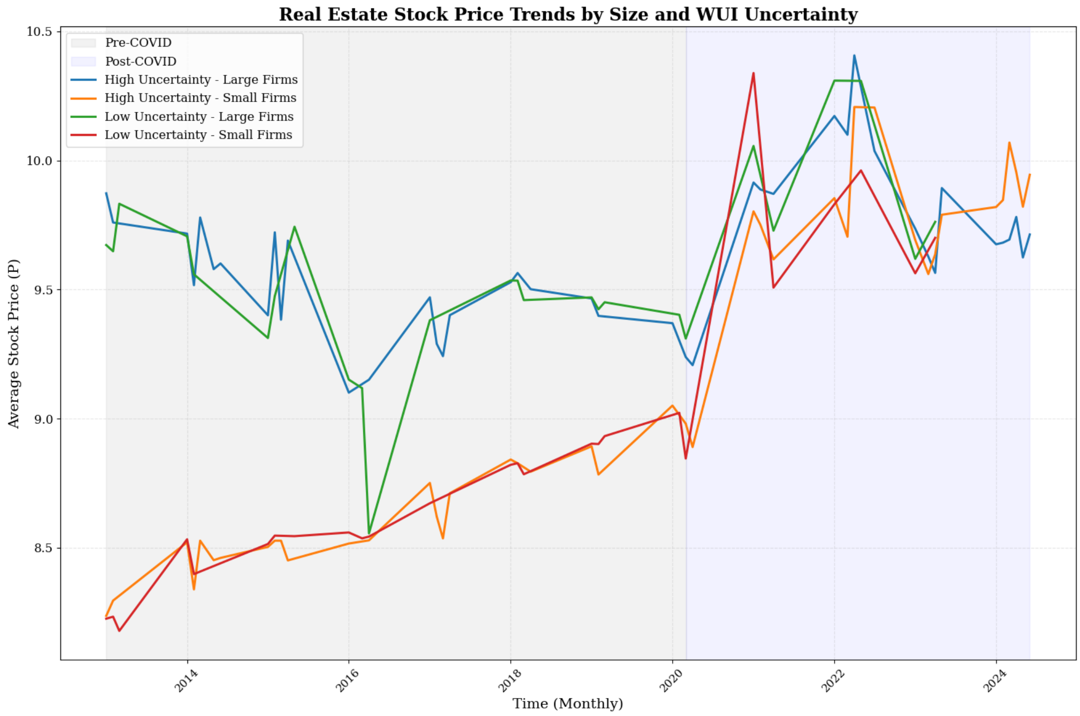

Fig. 5. Real estate stock price trends by firm size and WUI uncertainty dimensions. *Source*: Author (2025)

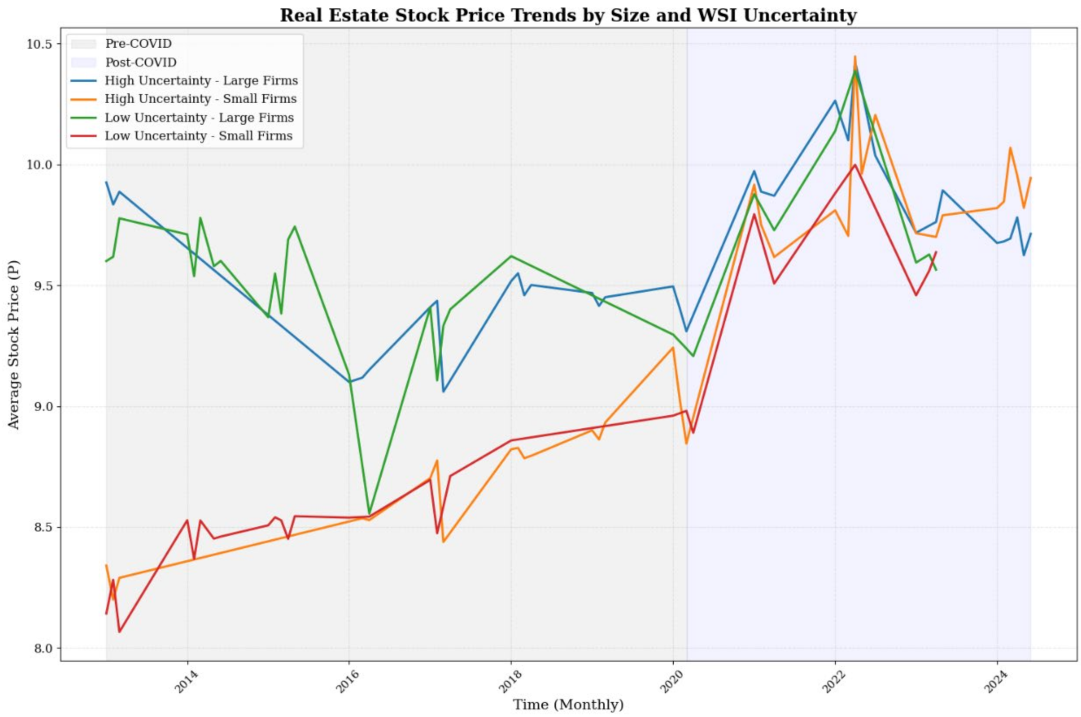

Fig. 6. Real estate stock price trends by firm size and WSI uncertainty dimensions. *Source*: Author (2025)

eISSN: 2300-5289 |

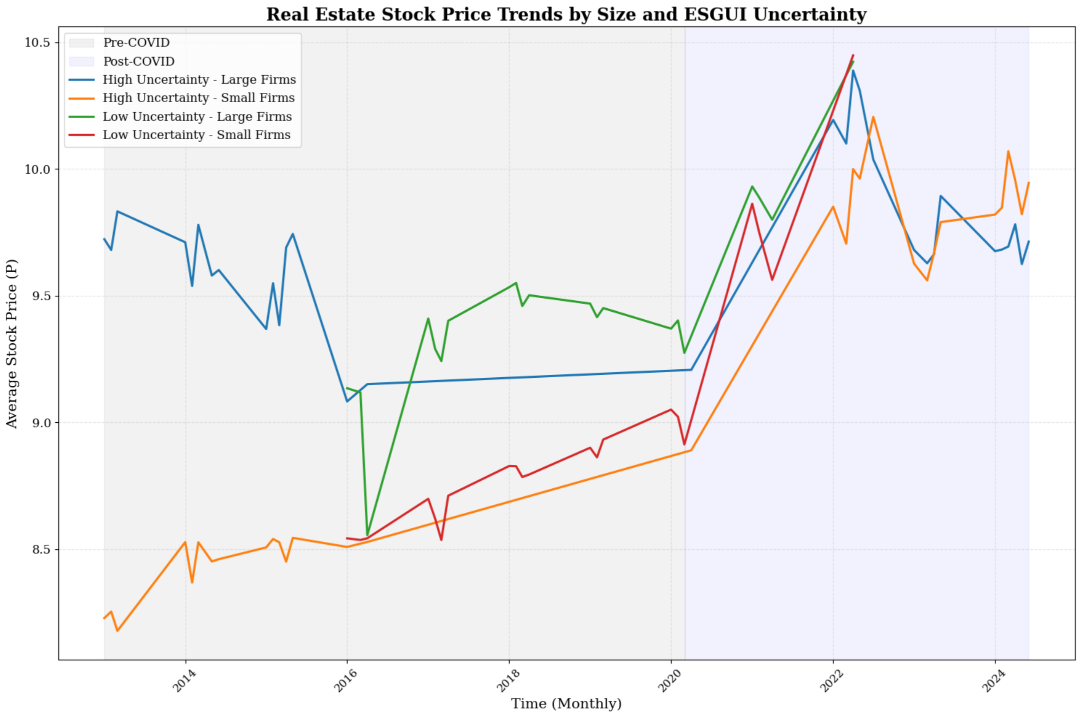

Fig. 7. Real estate stock price trends by firm size and ESGUI uncertainty dimensions. *Source*: Author (2025)

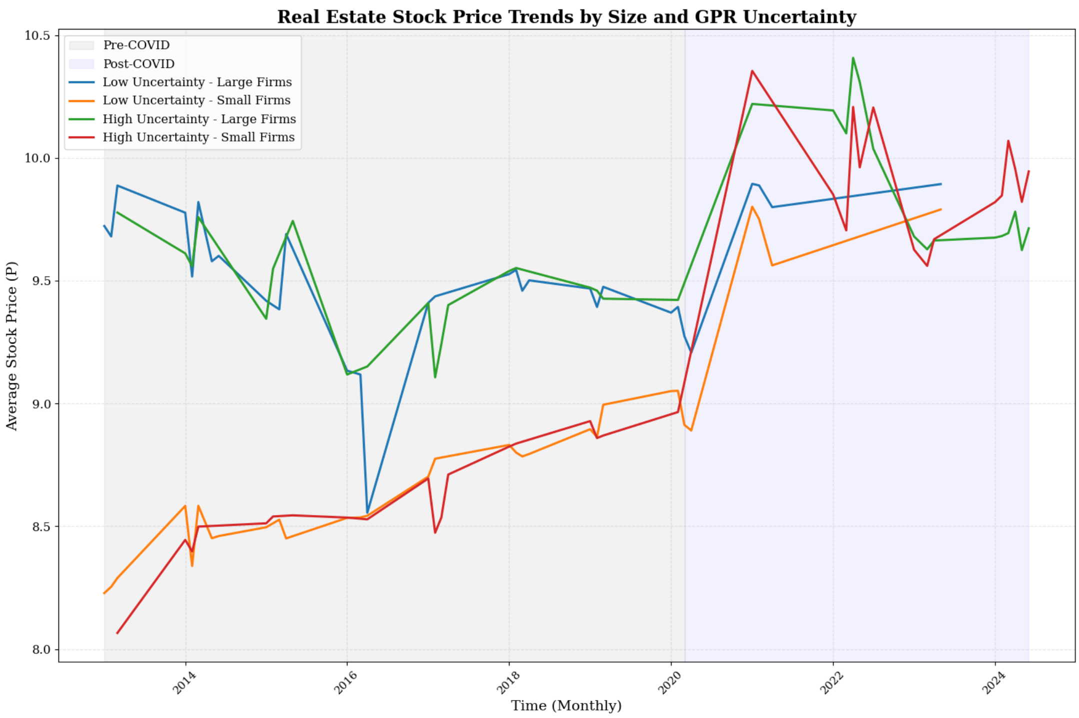

Fig. 8. Real estate stock price trends by firm size and ESGUI uncertainty dimensions. *Source*: Author (2025).

The results presented in Figure 5 to 8 reinforce the empirical foundation of the central hypothesis in the proposed theoretical model, namely, that the impact of global uncertainty on equity valuation is conditional on firm size, and that such nonlinear interactions are a key source of asset price volatility in emerging markets.

In summary, the exploratory data analysis (EDA) clarified the non-normal statistical characteristics and skewed distributional structures of financial, macroeconomic, and global informational uncertainty variables. These findings provide an empirical basis for the assumption of nonlinear and size-dependent mechanisms in the equity pricing process of real estate stocks in emerging markets such as Vietnam.

5.2. Machine learning model performance and benchmarking

Following preprocessing and exploratory analysis, the study proceeded to train and evaluate machine learning models for estimating the target variable, the logarithm of real estate stock prices, across the full dataset. The selected algorithms represent two distinct model categories: (i) standardized linear models, serving as performance benchmarks; and (ii) advanced nonlinear models capable of capturing deep interactions and nonlinearities. The regression outcomes of the three standardized linear models are summarized in Table 3.

The comparative performance in Table 3 shows that the three linear models, Lasso, Ridge, and Elastic Net, produce nearly identical results, with an R^2 of 0.633 and a root mean squared error (RMSE) of 0.572. The mean absolute error (MAE), averaging 0.444, reflects a tendency toward central tendency prediction and indicates limited capability in handling skewed or extreme asset value distributions.

The directional effects and magnitudes of variables influencing real estate stock prices are visualized in Figure 9, based on output coefficients from the Ridge regression.

Table 2

Training performance results using Lasso, Ridge, and Elastic Net regression

Model	R2	RMSE	MAE
Lasso	0,633	0,572	0,444
Ridge	0,633	0,572	0,444
ElasticNet	0,633	0,573	0,444

Source: Generated by the authors using Python.

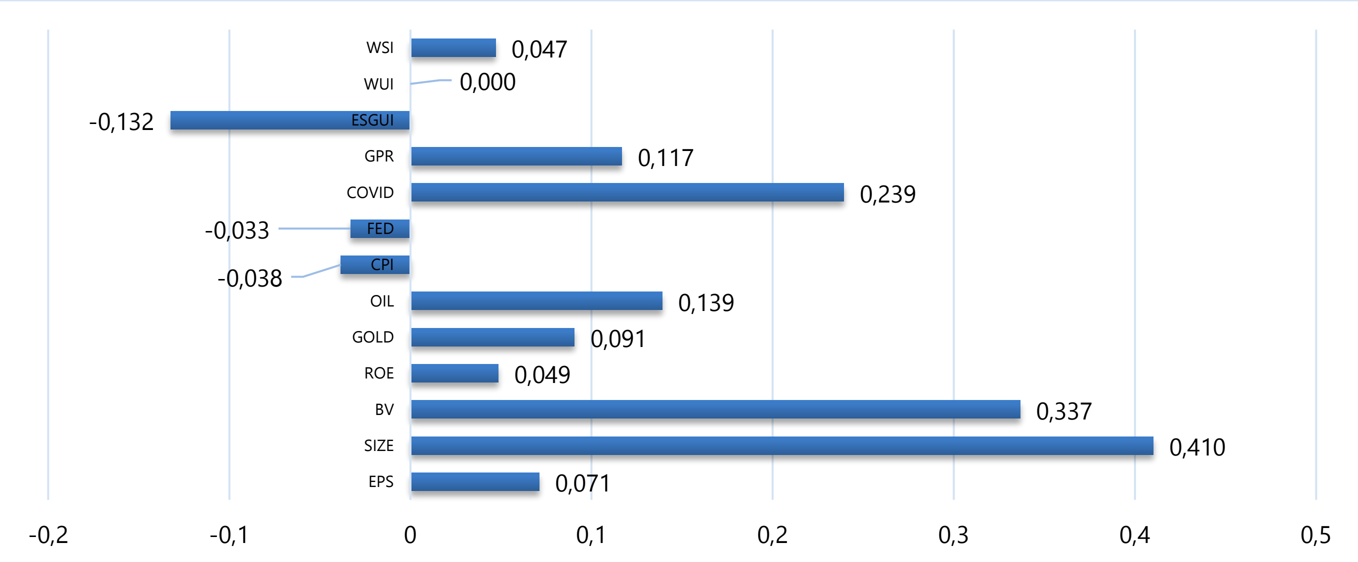

Fig. 9. Importance of control variables on real estate stock prices. *Source*: Author (2025).

Figure 9 indicates that real estate stock prices are significantly affected by firm size and book value. The variables SIZE and BV exert the strongest influence, underscoring the core role of firm scale and asset fundamentals. COVID and GPR also contribute materially, reflecting the impact of global shocks. In contrast, ESGUI has a negative effect, suggesting investor aversion to ESG-related uncertainties. Macroeconomic variables such as FED, CPI, and WUI exert negligible influence, suggesting that domestic fundamentals dominate over global policy effects.

While traditional linear models such as Lasso, Ridge, and Elastic Net provide a reasonable level of explanatory power, their capacity to capture complex, nonlinear relationships between global information uncertainty and equity prices remains inherently limited, an important consideration in the context of modern behavioral finance theory. As the analysis progressed to nonlinear machine learning algorithms, Table 4 demonstrates a marked improvement in predictive accuracy, particularly after hyperparameter optimization via Particle Swarm Optimization (PSO). To alleviate concerns regarding potential overfitting, especially in the case of the XGBoost model, which yielded a notably high out-of-sample R^2 of 0.962, a rigorous validation protocol was employed. The data were randomly partitioned into an 80% training set and a 20% testing set, with all input features standardized to ensure comparability. The PSO algorithm, a population-based metaheuristic search technique, was utilized to systematically explore the hyperparameter space and enhance model calibration. Model

eISSN: 2300-5289 |

performance was assessed on the test set using multiple evaluation metrics, including R^2, RMSE, and MAE, to ensure robustness. The PSO-optimized XGBoost model significantly outperformed a range of benchmark methods, including Ridge, Lasso, Elastic Net, and Linear Regression, while preserving generalizability. These results highlight the empirical advantages of combining advanced machine learning techniques with heuristic optimization in capturing intricate patterns of uncertainty and valuation dynamics in emerging financial markets.

Table 3

Model performance comparison before and after PSO Optimization

Model	Before PSO R2	Before PSO RMSE	Before PSO MAE	After PSO R2	After PSO RMSE	After PSO MAE
Linear Regression	0,632	0,562	0,440	0,632	0,562	0,440
SVR	0,731	0,480	0,364	0,736	0,476	0,369
Decision Tree	0,898	0,296	0,180	0,907	0,282	0,177
Random Forest	0,948	0,211	0,139	0,950	0,206	0,143
Gradient Boosting	0,851	0,357	0,279	0,932	0,241	0,172
XGBoost	0,951	0,206	0,145	0,962	0,181	0,125
LightGBM	0,939	0,229	0,165	0,952	0,203	0,145
AdaBoost	0,779	0,435	0,351	0,786	0,428	0,346

Source: Generated by the authors using Python.

As shown in Table 4, XGBoost demonstrates superior performance after PSO hyperparameter tuning, achieving an R^2 of 0.962 and a reduced RMSE of 0.181, a significant improvement over its pre-optimization results (R^2 = 0.951; RMSE = 0.206). Similarly, Gradient Boosting and LightGBM models show marked gains post-optimization, with R^2 values reaching 0.932 and 0.952, respectively. These results not only affirm the effectiveness of PSO in enhancing model accuracy but also underscore the practical value of machine learning approaches in high-uncertainty, nonlinear data environments.

Notably, XGBoost emerges as the best-performing model across the entire pipeline, excelling not only in predictive accuracy but also in its robustness to datasets characterized by heteroscedasticity, skewed distributions, and strong nonlinear interactions, features endemic to real estate equity markets in emerging economies. Its mean absolute error (MAE) of just 0.125 further confirms the model's consistency in prediction across the value spectrum.

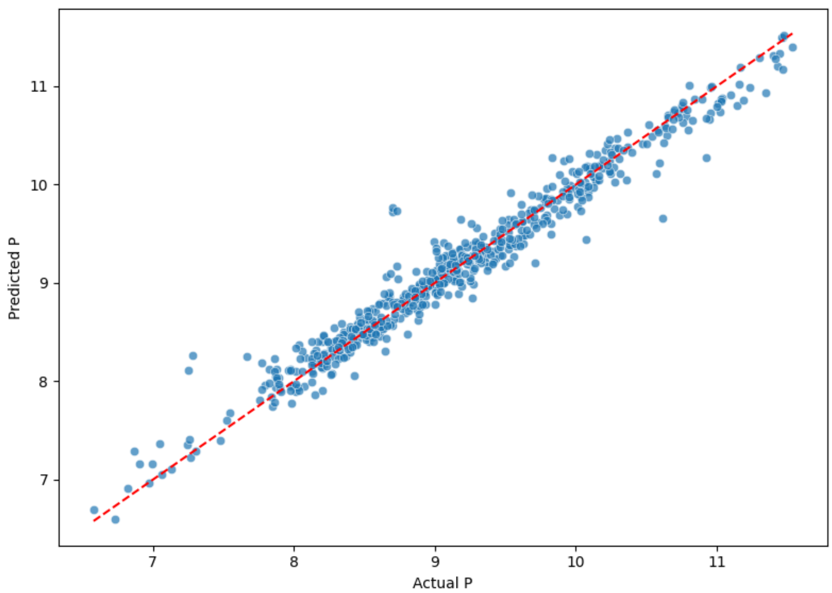

Fig. 10. Best prediction from XGBoost (after PSO). *Source*: Author (2025).

Figure 10 illustrates the relationship between actual stock prices and predicted values from the optimized

XGBoost model. The tight distribution around the 45-degree line indicates not only high accuracy but also strong consistency across all value ranges, especially in extreme pricing regions, areas where traditional linear models often fail. The robust adaptability of XGBoost to abnormal distributions and complex data structures positions it as an ideal tool for modeling market behavior under conditions of global informational uncertainty, a core theme in the theoretical framework of this study.

Overall, the training results suggest that applying modern nonlinear machine learning models, combined with hyperparameter optimization, can significantly enhance the forecasting capabilities of asset valuation models, particularly in data contexts characterized by multiple sources of uncertainty and unpredictable behavioral responses. These findings lay a strong foundation for the next stage in the empirical process, interpreting the model using explainable AI (XAI) techniques, specifically SHAP, to trace and quantify the influence of each uncertainty factor in real estate equity pricing decisions.

5.3. SHAP - LIME Interpretation: unpacking the role of global uncertainty in asset pricing

Following the identification of XGBoost as the model exhibiting superior performance across the entire analytical pipeline, the subsequent stage of this study focuses on uncovering the economic rationale behind the model's predictions using SHAP, LIME. As a state-of-the-art interpretability framework rooted in cooperative game theory, SHAP allows for the quantification of the marginal contribution of each explanatory variable to individual predictions, while maintaining consistency and interpretability, both of which are essential in behavioral finance and asset pricing under uncertainty.

5.3.1. Global SHAP Analysis: hierarchical roles of fundamental and behavioral factors

Figure 11 illustrates the SHAP summary plots for the XGBoost model, offering a global interpretability perspective under the lens of nonlinear and interaction-rich machine learning. The figure reveals a tiered architecture of explanatory relevance, in which firm-specific fundamentals, particularly SIZE and BV (Book Value), emerge as dominant drivers of predicted asset prices. Notably, the distribution of SHAP values for SIZE is asymmetrically right skewed and concentrated in higher feature ranges (in pink), suggesting that larger firms consistently command higher predicted valuations. This finding empirically supports the "size premium" narrative, often associated with enhanced stability and risk-buffering capacity in the face of systemic shocks.

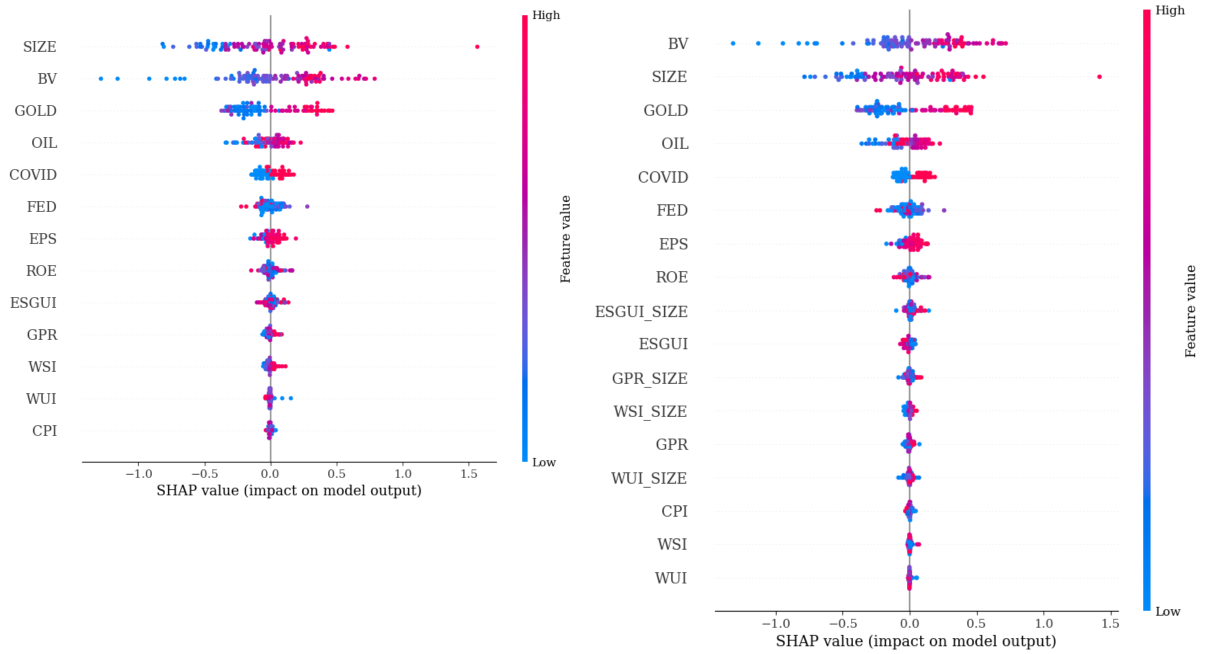

Fig. 11. SHAP Summary plot of feature contributions in the XGBoost model. Source: Author (2025).

Importantly, the visualization enables the identification of feature-value interactions, a key strength of SHAP that extends beyond linear models. For instance, BV demonstrates nonlinear patterns of influence, where moderate book values contribute positively to predictions, but diminishing marginal returns appear at extremes. These dynamics would likely remain obscured under conventional econometric techniques, underscoring the analytical advantage of SHAP in modeling nonlinear valuation behavior under behavioral and informational frictions.

A second cluster of variables, GOLD, OIL, and COVID, reflects cyclical and sentiment-driven effects with heterogeneous and context-sensitive SHAP patterns. GOLD, when elevated, aligns with positive SHAP contributions, suggesting a flight-to-safety behavior in which real estate functions as a tangible hedge against macroeconomic turbulence. Conversely, the COVID variable displays a left-skewed distribution of SHAP values, confirming a consistent downward pressure on valuation during public health crises. These results validate the theoretical expectation that in frontier markets, investor reactions are shaped less by fundamentals and more by perceived environmental shocks.

In contrast, traditional macroeconomic indicators such as FED, CPI, and WUI register marginal SHAP contributions and compressed distributions, suggesting a decoupling of formal economic signals from asset pricing behavior under uncertainty. This decoupling is consistent with the notion that, in Knightian environments, where risks are ambiguous and historical data are uninformative, market agents gravitate toward firm-level heuristics and real-time narratives.

Taken together, these SHAP-based insights not only quantify feature importance but also illuminate nonlinear, sample-specific interactions, affirming the central hypothesis that asset pricing in emerging markets is conditioned by a complex interplay of fundamentals, sentiment, and behavioral asymmetries. The interpretability enabled by SHAP strengthens the empirical credibility of machine learning models in finance, while bridging the gap between predictive accuracy and economic understanding, a requirement increasingly emphasized in the literature on explainable AI (XAI) in economics and finance (Molnar, 2022; Lundberg & Lee, 2017; Doshi-Velez & Kim, 2017).

5.3.2. Conditional effects by firm size: evidence for behavioral nonlinear mechanisms

Although global uncertainty indices such as ESGUI, GPR, WUI, and WSI show average SHAP values close to zero across the model, this does not invalidate their importance. On the contrary, it reflects their inherently conditional effects. To test this hypothesis, the study focuses on a representative interaction term: WUI × SIZE, which captures the joint influence of global policy uncertainty and firm size.

The ANOVA and Kruskal–Wallis tests presented in Table 5 reveal that the SHAP values of the WUI_SIZE interaction term differ significantly across the three firm-size groups, with a p-value approaching zero. This finding confirms that the impact of WUI is not uniform but rather contingent upon firm-level institutional characteristics, a core proposition in modern behavioral finance theory.

Table 4

ANOVA test result

Variable	F-statistic	p-value (ANOVA)	H-statistic	p-value (Kruskal)
WUI_SIZE_SHAP	126,713	1,406e-53	191,592	2,491e-42

Source: Generated by the authors using Python.

Figure 12 (SHAP dependence plot) highlights an inverse U-shaped nonlinear relationship: for small and medium-sized firms, the World Uncertainty Index (WUI) exhibits a negative impact on stock prices (negative SHAP values), whereas for large firms, the effect becomes positive. This provides strong evidence in support of the asymmetric ambiguity responsehypothesis, which posits that under macroeconomic uncertainty, investors tend to shift their optimistic expectations toward large firms, a classic manifestation of “flight to quality.”

Table 5

Mean SHAP values by bank size group

SIZE_GROUP	WUI_SIZE_SHAP
small	-0,0048
medium	-0,0094
large	0,0063

Source: Generated by the authors using Python.

The results presented in Table 6 further reinforce this argument: the mean SHAP value for the interaction term WUI_SIZE is positive for the large-size group (+0.0063) but negative for the small and medium-sized groups (-0.0048 and -0.0094, respectively). Other interaction terms, such as ESGUI × SIZE, GPR × SIZE, and WSI × SIZE, do not exhibit a similar pattern, underscoring that the size-conditional effect is a distinct feature of WUI within the asset pricing model.

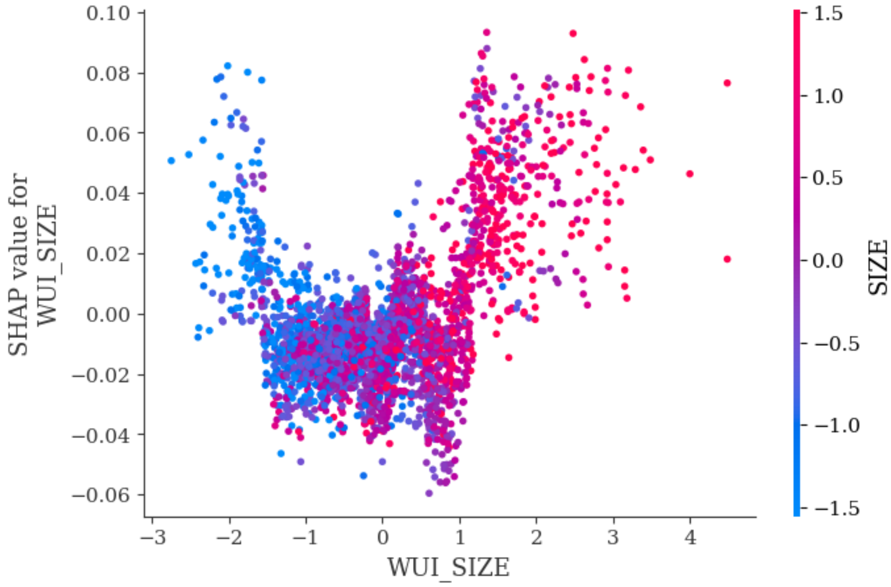

Fig. 12. SHAP dependence plot for WUI_SIZE and firm size interaction. *Source*: Author (2025).

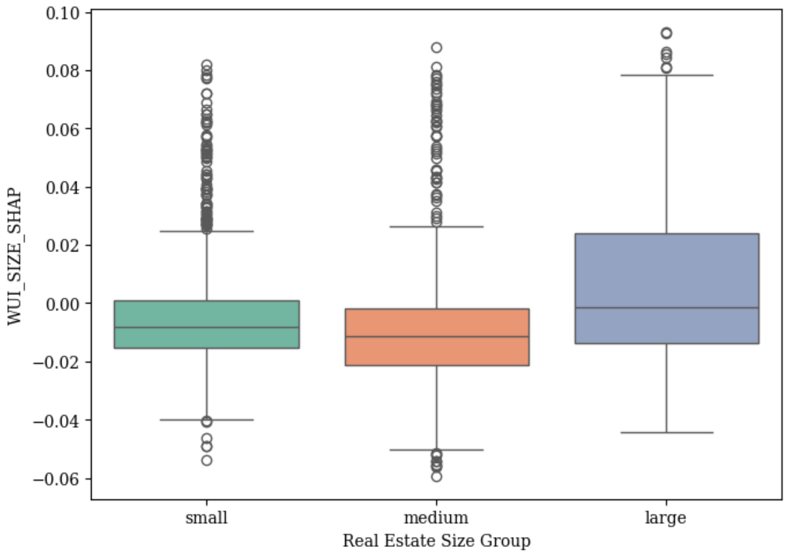

Fig. 13. SHAP value of WUI_SIZE by size group. Source: Author (2025).

Figure 13 summarizes the SHAP distribution of WUI_SIZE across firm size groups, further illustrating the differentiated pricing behavior under conditions of global economic policy uncertainty.

While SHAP results from the XGBoost model indicate that WUI contributes minimally to overall stock price predictions, ANOVA reveals statistically significant differences in SHAP values across firm size groups. This divergence stems from the methodological contrast: SHAP captures feature contributions within nonlinear models, whereas ANOVA assesses mean differences between categorical groups. Thus, WUI's influence, though muted in aggregate, is distinctly segmented by firm size. These findings underscore the complementary strengths of machine learning and traditional statistical methods in revealing how global informational uncertainty shapes market behavior. The analysis affirms that WUI’s impact on real estate stock valuation is heterogeneous and size-dependent, offering methodological and theoretical contributions to uncertainty-driven asset pricing.

5.3.3. LIME-Based Case-Level interpretations

The application of LIME offers a local perspective to complement the global feature attributions derived from SHAP. By generating interpretable linear approximations of the XGBoost model for individual observations, LIME highlights how specific features contribute to each predicted price value. This local decomposition is crucial in capturing idiosyncratic pricing dynamics, particularly in environments shaped by heterogeneous investor sentiment and incomplete information. In selected cases, firm size, gold prices, and COVID-related variables emerged as dominant local factors, although their influence varied across samples, underscoring the nonlinear and context-sensitive nature of asset pricing under uncertainty.

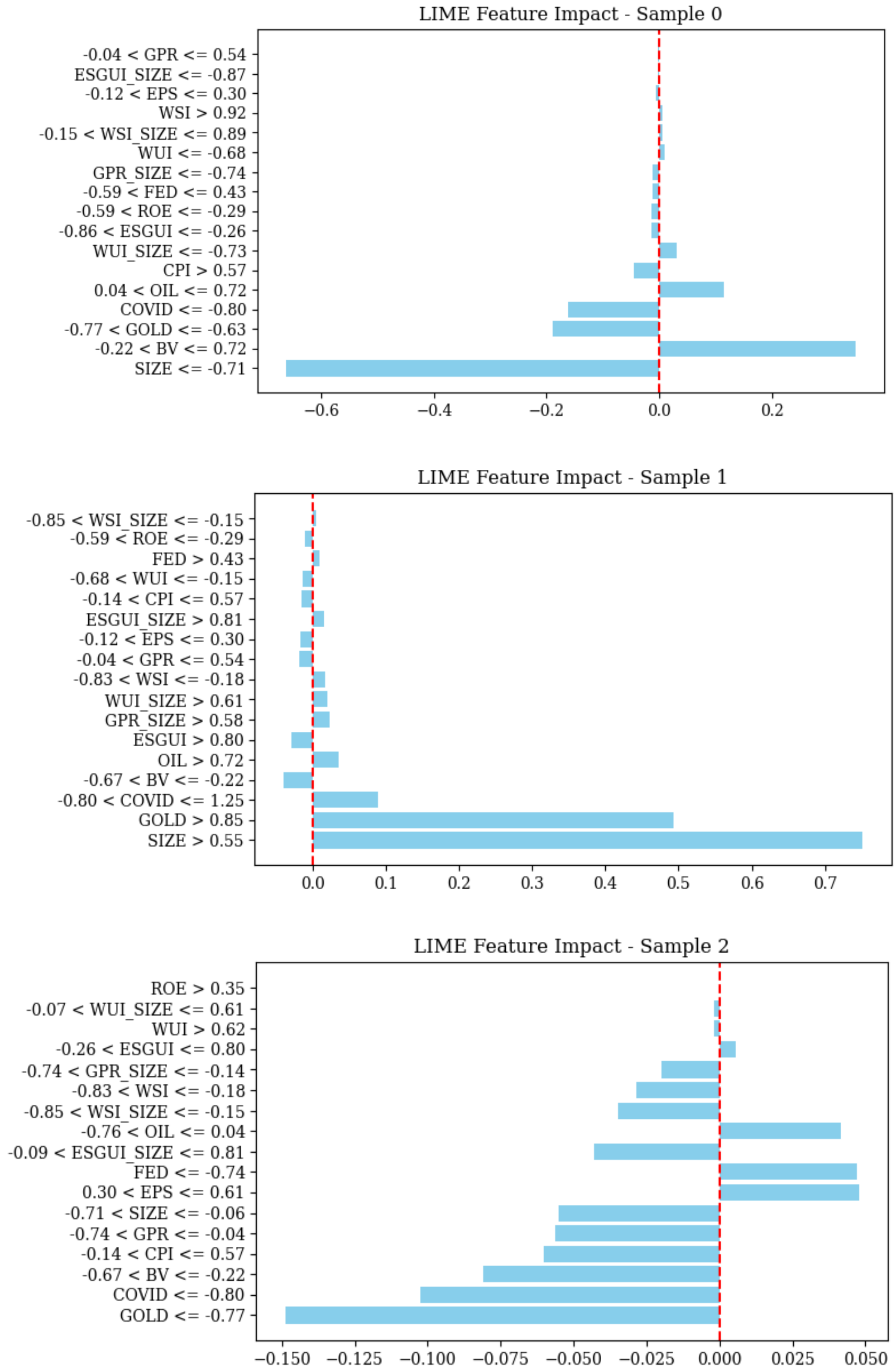

Fig. 14. LIME bar plots for selected samples. *Source*: Author (2025).

For instance, figure 14, in sample #0, low firm size and COVID sentiment significantly reduce predicted valuation, consistent with the "flight to quality" hypothesis. In contrast, sample #1 shows that higher SIZE and GOLD levels increase valuation, reflecting investor preference for macro-resilient firms. These results confirm the nonlinear and investor-specific sensitivity to global uncertainty and highlight LIME's utility in capturing behavioral heterogeneity that global methods may overlook. Figure 14 presents LIME bar plots for selected samples.

Table 7 highlights the feature-wise local interpretability of the XGBoost model using LIME across three representative firm-level samples. The results show strong heterogeneity in how the same variables affect predictions. Notably, SIZE, GOLD, and COVID demonstrate contradictory effects across observations, emphasizing the nonlinear, sample-specific response of the model to uncertainty. Only a few features such as OIL and CPI exhibit consistent directional impacts. This heterogeneity aligns with the theoretical expectation of Knightian uncertainty, where firm valuation is not only data-driven but also context-dependent.

Table 6

Local Interpretability via LIME – Feature impact across three representative samples

Feature (Binned Interval)	Sample 0	Sample 1	Sample 2	Impact Consistency
SIZE	−0.6636	+0.7513	−0.0549	✕ Contradictory
BV	+0.3492	−0.0390	−0.0808	✕ Mixed
GOLD	−0.1899	+0.4931	−0.1489	✕ Contradictory
COVID	−0.1620	+0.0890	−0.1026	✕ Contradictory
OIL	+0.1158	+0.0363	+0.0416	✓ Consistent (+)
CPI	−0.0439	−0.0152	−0.0602	✓ Consistent (−)
EPS	−0.0050	−0.0161	+0.0479	✕ Mixed
ROE	−0.0126	−0.0102	+0.0003	✕ Mixed
FED	−0.0118	+0.0104	+0.0470	✕ Mixed
GPR	−0.0009	−0.0173	−0.0562	✓ Consistent (−)
WUI	+0.0106	−0.0129	−0.0018	✕ Mixed
WSI	+0.0053	+0.0178	−0.0283	✕ Mixed
ESGUI	−0.0132	−0.0282	+0.0055	✕ Mixed
GPR_SIZE	−0.0112	+0.0240	−0.0197	✕ Contradictory
ESGUI_SIZE	−0.0025	+0.0160	−0.0431	✕ Contradictory
WUI_SIZE	+0.0321	+0.0209	−0.0018	✕ Mixed
WSI_SIZE	+0.0065	+0.0057	−0.0346	✕ Mixed

Source: Generated by the authors using Python.

The observed variation supports the notion that local interpretability is essential in explaining behavioral inconsistencies that aggregate models may mask (Molnar, 2025).

5.4. Robust checks

To evaluate the stability and generalizability of the machine learning model under data variation, a robust testing procedure was implemented by re-running the entire modeling pipeline across five different random seeds (0, 42, 123, 2024, and 999). This procedure aligns with best practices in explainable AI, ensuring that performance is not contingent on a particular data split and providing insights into the model's resilience under distributional shifts (Molnar, 2025).

Table 8 summarizes the R^2, RMSE, and MAE scores across the five seeds. The results reveal high and consistent predictive performance, with R^2 values ranging from 0.9598 to 0.9948 and RMSE values fluctuating modestly between 0.0659 and 0.1856. Most notably, the MAE remains consistently low (below 0.14 across all runs), indicating reliable prediction accuracy at the individual observation level. The lowest-performing run (Seed 42) still achieves an R^2 of 0.96, confirming that the model maintains strong explanatory power even under less favorable splits.

Table 7

Robust Performance of the PSO-Optimized XGBoost model across random seeds

Seed	R^2	RMSE	MAE
0	0.9905	0.0937	0.0360
42	0.9598	0.1856	0.1308
123	0.9948	0.0659	0.0289
2024	0.9946	0.0684	0.0308
999	0.9937	0.0743	0.0318

Source: Generated by the authors using Python.

The small variance in error metrics across seeds attests to the model's robustness, suggesting that the feature relationships learned by the PSO-optimized XGBoost model are not overly sensitive to random partitioning or sampling noise. This reinforces the suitability of ensemble-based nonlinear models in settings where uncertainty is both structural and behavioral, as in frontier asset markets.

Furthermore, such stability in model performance under alternative partitions enhances the credibility of subsequent SHAP and LIME interpretations, as it affirms that the explanatory patterns are not artifacts of a single training configuration, but instead reflect genuine, reproducible relationships embedded in the data.

6. Conclusion and Policy Implications

6.1. Conclusion

An integrated framework combining Knightian uncertainty, behavioral asset pricing theory, and explainable machine learning reveals substantial evidence of nonlinear and conditional impacts of global uncertainty on real estate stock valuation in an emerging market context. Using SHAP-based interpretation on a high-performing XGBoost model (R^2 = 0.962), the analysis demonstrates that firm-level characteristics, notably firm size and book value, consistently dominate valuation outcomes.

Global uncertainty indicators, particularly the World Uncertainty Index (WUI) and ESG Uncertainty Index (ESGUI), exhibit limited marginal effects but reveal significant interaction-based influence when conditioned on firm size. The interaction term WUI × SIZE generates highly asymmetric SHAP distributions, confirming that uncertainty acts through firm-specific channels and is amplified by behavioral dynamics under Knightian ambiguity. Such findings are consistent with the literature on ambiguity aversion and "flight to quality" behavior during market-wide shocks (Barberis et al., 2018; Akin & Akin, 2024; Beckmann et al., 2023).

The empirical evidence supports the theoretical proposition that pricing under uncertainty is not only sensitive to informational shocks but is also behaviorally mediated and structurally segmented. The use of explainable machine learning offers a robust methodological enhancement, enabling theoretical hypotheses to be empirically validated in complex, nonlinear contexts (Černevičienė & Kabašinskas, 2024; Demirbaga & Xu, 2024). The joint application of SHAP and LIME establishes a multi-level interpretability framework, enabling both global inference and local diagnostic insight. While SHAP identifies systemic pricing patterns, LIME captures case-specific deviations that reflect investor behavioral heterogeneity and firm-level informational asymmetries. The alignment of model predictions with plausible local explanations strengthens confidence in the model's reliability and transparency, an increasingly important consideration in finance-related AI applications (Doshi-Velez & Kim, 2017).

6.2. Policy recommendations

Implications for investors: Asset pricing under high uncertainty reflects both fundamental signals and behavioral distortions. Firms with larger size, strong balance sheets, and transparent ESG disclosures tend to attract capital flows during periods of elevated uncertainty, functioning as behavioral safe havens. Investment strategies that incorporate firm-specific resilience to global uncertainty, particularly ESG ambiguity and media-driven sentiment, may improve risk-adjusted returns in emerging markets.

Implications for real estate firms: Strategic emphasis on ESG disclosure quality, crisis communication, and reputational risk management is critical. Reducing exposure to sentiment-driven volatility requires not only strong fundamentals but also proactive governance and clarity in information release, especially in response to macro-level informational shocks.

Implications for policymakers: Developing national-level uncertainty indices tailored to local institutional contexts (e.g., ESG, policy, or sentiment indices) can enhance market transparency and investor expectations. Regulatory frameworks that incentivize ESG compliance, minimize information opacity, and mitigate media-based distortion effects are essential for reducing behavioral mispricing in the capital market. Strengthening financial literacy and media standards may also suppress excessive ambiguity-induced reactions among retail investors.

6.3. Limitations and future research

The current framework does not incorporate real-time textual or sentiment data, which could further enrich the measurement of behavioral responses to global shocks. Future extensions may include natural language processing (NLP) models and deep-learning architectures (e.g., transformers) to dynamically model sentiment propagation. Comparative studies across emerging economies could help validate the generalizability of the interaction effects uncovered between firm-level factors and global uncertainty.

References

Ahir, H., Bloom, N., & Furceri, D. (2022). The World Uncertainty Index (NBER Working Paper No. 29763).

eISSN: 2300-5289 | Received 2025-06-09 | Revised 2025-09-25 | Accepted 2025-09-30

https://www.nber.org/system/files/working_papers/w29763/w29763.pdf
Ahmed, F., Sohag, K., Islam, M. M., & Hassan, M. K. (2025). Navigating turbulence: How do geopolitical risks and oil price shocks shape global equity markets? A GVAR approach. *Borsa Istanbul Review, 25*(3), 449–467. https://doi.org/10.1016/j.bir.2025.01.016
Akin, I., & Akin, M. (2024). Behavioral finance impacts on US stock market volatility: An analysis of market anomalies. *Behavioural Public Policy,* •••, 1–25. https://doi.org/10.1017/bpp.2024.13
Ampountolas, A., Legg, M., & Shaw, G. (2024). Real estate investment trusts during market shocks: Impact and resilience. *Tourism Economics, 30*(6), 1557–1579. https://doi.org/10.1177/13548166231219740
Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty*. *The Quarterly Journal of Economics, 131*(4), 1593–1636. https://doi.org/10.1093/qje/qjw024
Barberis, N., Greenwood, R., Jin, L., & Shleifer, A. (2018). Extrapolation and bubbles. *Journal of Financial Economics, 129*(2), 203–227. https://doi.org/10.1016/j.jfineco.2018.04.007
Beckmann, L., Debener, J., & Kriebel, J. (2023). Understanding the determinants of bond excess returns using explainable AI. *Journal of Business Economics, 93*(9), 1553–1590. https://doi.org/10.1007/s11573-023-01149-5
Bouri, E., Gupta, R., & Wang, S. (2022). Nonlinear contagion between stock and real estate markets: International evidence from a local Gaussian correlation approach. *International Journal of Finance & Economics, 27*(2), 2089–2109. https://doi.org/10.1002/ijfe.2261
Caldara, D., & Iacoviello, M. (2022). Measuring geopolitical risk. *The American Economic Review, 112*(4), 1194–1225. https://doi.org/10.1257/aer.20191823
Černevičienė, J., & Kabašinskas, A. (2024). Explainable artificial intelligence (XAI) in finance: A systematic literature review. *Artificial Intelligence Review, 57*(8), 216. https://doi.org/10.1007/s10462-024-10854-8
Chen, D., & Gao, Y. (2024). Attribution methods in asset pricing: Do they account for risk? 2024 IEEE Symposium on Computational Intelligence for Financial Engineering and Economics (CIFEr), 1–8. https://doi.org/10.1109/CIFEr62890.2024.10772752
Demirbaga, U., & Xu, Y. (2024). Empirical asset pricing using explainable artificial intelligence. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4680571
Deng, S., Huang, X., Zhu, Y., Su, Z., Fu, Z., & Shimada, T. (2023). Stock index direction forecasting using an explainable eXtreme Gradient Boosting and investor sentiments. *The North American Journal of Economics and Finance, 64*, 101848. https://doi.org/10.1016/j.najef.2022.101848
El Oubani, A. (2024). Investor sentiment and sustainable investment: Evidence from North African stock markets. *Future Business Journal, 10*(1), 68. https://doi.org/10.1186/s43093-024-00349-x
Ellsberg, D. (1961). Risk, Ambiguity, and the Savage Axioms. *The Quarterly Journal of Economics, 75*(4), 643. https://doi.org/10.2307/1884324
Fan, K. Y., Shen, J., Hui, E. C. M., & Cheng, L. T. W. (2024). ESG components and equity returns: Evidence from real estate investment trusts. *International Review of Financial Analysis, 96*, 103716. https://doi.org/10.1016/j.irfa.2024.103716
Ghoddusi, H., Creamer, G. G., & Rafizadeh, N. (2019). Machine learning in energy economics and finance: A review. *Energy Economics, 81*, 709–727. https://doi.org/10.1016/j.eneco.2019.05.006
Hoang Vu, H. M., Nguyen Tuan Doan, A., Xuan Dinh, A., Minh Trinh, H., & Phi Tran, L. (2024). The relationship between electronic word-of-mouth information, information adoption, and investment decisions of Vietnamese stock investors. *Interdisciplinary Journal of Information, Knowledge, and Management, 19*, 020. https://doi.org/10.28945/5346
Hoelscher, S. A., Sappington, C., & Stros, L. R. (2024). A practical approach to Incorporating ESG risk into equity valuation. *Journal of Applied Business and Economics, 26*(1). Advance online publication. https://doi.org/10.33423/jabe.v26i1.6811
Ikumapayi, N. A., & Muhammed, H. B. (2024). Explainable AI: Making machine learning decisions transparent. https://doi.org/10.2139/ssrn.4909698
Itan, I., Sylvia, S., Septiany, S., & Chen, R. (2025). The influence of environmental, social, and governance disclosure on market reaction: Evidence from emerging markets. *Discover Sustainability, 6*(1), 347. https://doi.org/10.1007/s43621-025-01085-0
Kitulazzi, D., Ametefe, F. K., Karimu, A., & Akinsomi, O. (2025). ESG investing and the performance of JSE-listed real estate firms: A system GMM approach. *Journal of Property Investment & Finance, 43*(2), 222–243. https://doi.org/10.1108/JPIF-11-2024-0149
Knight, F. H. (2022). *Risk, uncertainty and profit* (1921). www.bnpublishing.com
Kuppan, K., Bhaskar Acharya, D. Divya B. (2024). Foundational AI in insurance and real estate: A survey of applications, challenges, and future directions. *IEEE Access: Practical Innovations, Open Solutions, 12*, 181282–181302. https://doi.org/10.1109/ACCESS.2024.3509918
Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. 31st Conference on Neural Information Processing Systems.
Ma, T., Wang, W., & Chen, Y. (2023). Attention is all you need: An interpretable transformer-based asset allocation approach. *International Review of Financial Analysis, 90*, 102876. https://doi.org/10.1016/j.irfa.2023.102876
Maurya, P. K., Bansal, R., & Mishra, A. K. (2025). *Investor sentiment and its implication on global financial markets: a systematic review of literature*. Qualitative Research in Financial Markets. https://doi.org/10.1108/QRFM-04-2024-0087
Mohammed, K. S., Obeid, H., Oueslati, K., & Kaabia, O. (2023). Investor sentiments, economic policy uncertainty, US interest rates, and financial assets: Examining their interdependence over time. *Finance Research Letters, 57*, 104180. https://doi.org/10.1016/j.frl.2023.104180
Molnar, C. (2025). Interpretable machine learning: A guide for making black box models explainable (3rd ed.). Independently published, ISBN-13: 979-8411463330
Nguyen, H. H., & Nguyen, H. T. (2025). Do the ESG factors truly enhance real estate companies' valuation and performance in uncertain times. *Journal of Property Investment & Finance, 43*(2), 190–221. https://doi.org/10.1108/JPIF-03-2024-0036
Nicolas, M. L. D., Desroziers, A., Caccioli, F., & Aste, T. (2024). ESG reputation risk matters: An event study based on social media data. *Finance Research Letters, 59*, 104712. https://doi.org/10.1016/j.frl.2023.104712
Ongan, S., Gocer, I., & Işık, C. (2025). Introducing the new ESG-based sustainability uncertainty index. *Sustainable Development (Bradford), 33*, 4457–4467. Advance online publication. https://doi.org/10.1002/sd.3351
Pástor, Ľ., & Veronesi, P. (2013). Political uncertainty and risk premia. *Journal of Financial Economics, 110*(3), 520–545. https://doi.org/10.1016/j.jfineco.2013.08.007
Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "Why should I trust you?" *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 1135–1144. https://doi.org/10.1145/2939672.2939778
Shefrin, H., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal*

of Finance, 40(3), 777–790. https://doi.org/10.1111/j.1540-6261.1985.tb05002.x

Shi, J., Ausloos, M., & Zhu, T. (2022). If global or local investor sentiments are prone to developing an impact on stock returns, is there an industry effect? *International Journal of Finance & Economics, 27*(1), 1309–1320. https://doi.org/10.1002/ijfe.2216

Tang, C.-H., Liu, H.-C., Lee, Y.-H., & Hsu, Y.-T. (2025). ESG risk, economic policy uncertainty, and the downside risk: Evidence from US firms. *The North American Journal of Economics and Finance, 75*, 102293. https://doi.org/10.1016/j.najef.2024.102293

Truong, T. H. D., Le, N. D. K., & Huynh, T. N. T. (2024). Impacts of Environmental, Social, and Governance (ESG) performance on firm value, profitability, and cash flows: Evidence in Southeast Asia. *Journal of Financial Accounting Research, 1*(26).

Vuong, N. B., & Suzuki, Y. (2022). The moderating effect of market-specific factors on the return predictability of investor sentiment. *SAGE Open, 12*(3), 21582440221114322. Advance online publication. https://doi.org/10.1177/21582440221114322

Yeo, W. J., Van Der Heever, W., Mao, R., Cambria, E., Satapathy, R., & Mengaldo, G. (2025). A comprehensive review on financial explainable AI. *Artificial Intelligence Review, 58*(6), 189. https://doi.org/10.1007/s10462-024-11077-7

Yilmazkuday, H. (2024). Geopolitical risk and stock prices. *European Journal of Political Economy, 83*, 102553. https://doi.org/10.1016/j.ejpoleco.2024.102553

Yudaruddin, R., & Lesmana, D. (2024). The market reaction of real estate companies to the announcement of the Russian–Ukrainian invasion. *Journal of European Real Estate Research, 17*(1), 102–122. https://doi.org/10.1108/JERER-12-2022-0038