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BRIDGING PREDICTIVE POWER AND INTERPRETABILITY: A HYBRID DEEP LEARNING FRAMEWORK FOR REAL ESTATE PERFORMANCE UNDER SYSTEMIC UNCERTAINTY

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ABSTRACT

This study develops an interpretable hybrid deep learning framework to forecast and explain the financial performance of real estate firms in emerging markets facing macroeconomic uncertainty. Using panel data from 28 listed Vietnamese firms during 2013–2025, a Macroeconomic Uncertainty Index (MUI) is constructed through principal component analysis to integrate five global risk indicators: economic policy, geopolitical, ESG-related, global uncertainty, and world sentiment indices. The proposed XGBoost–CNN model, augmented with SHAP explainability, achieves superior predictive accuracy, reducing RMSE by 54 percent and MAE by 22 percent compared with conventional deep learning models. SHAP analysis, applied to both the composite and individual uncertainty components, enhances interpretability and isolates the marginal influence of each risk factor. Results indicate that earnings per share and firm size jointly explain most of the variation in return on equity and assets, while economic policy uncertainty exerts the strongest macroeconomic impact. The MUI demonstrates a nonlinear moderating role, showing that, under heightened systemic uncertainty, traditional firm–performance relationships may reverse. The framework offers a transparent, data-driven tool for financial forecasting and macroprudential stress testing in emerging real estate markets.

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1. Introduction

In the face of intensifying global volatility, the financial performance of real estate firms in emerging markets has become increasingly exposed to systemic uncertainty arising from multiple macroeconomic sources. These include policy instability, geopolitical tension, shifts in global sentiment, ESG transitions, and broader economic dislocation. Prior studies have often examined these factors in isolation, focusing on Economic Policy Uncertainty (EPU), Geopolitical Risk (GPR), or ESG-related ambiguity (ESGUI). However, in reality, uncertainty emerges from interconnected and overlapping forces. As a capital-intensive and cyclical sector, real estate is particularly sensitive to these shocks (Abaidoo & Agyapong, 2023; Chen et al., 2024; Jiang et al., 2024).

To capture this complexity, recent research has introduced several global uncertainty indices such as the World Uncertainty Index (WUI) and the World Sentiment Index (WSI). While these indices have advanced systemic risk measurement, their independent application often leads to issues of multicollinearity, fragmented interpretation, and incomplete representation of systemic transmission channels (Charles et al., 2018). This study addresses these limitations by constructing a Macroeconomic Uncertainty Index (MUI) using principal component analysis (PCA) to integrate five major uncertainty dimensions - EPU, GPR, ESGUI, WUI, and WSI. The composite index captures latent structures of macroeconomic risk and provides a stable, non-redundant input for financial performance modeling in emerging markets.

Traditional econometric approaches often struggle to model the dynamic, nonlinear, and asymmetric

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effects of uncertainty on firm outcomes. Deep learning architectures, including artificial neural networks (ANN), long short-term memory (LSTM), convolutional neural networks (CNN), and deep neural networks (DNN), offer greater flexibility and predictive power (Fischer & Krauss, 2018; Tin et al., 2024). However, their opacity has limited their adoption in financial decision-making contexts where interpretability is critical. Hybrid models that combine deep learning with machine learning techniques such as XGBoost have shown improved predictive performance (Latif et al., 2024; Wang et al., 2023), yet they too often lack transparency in explaining how uncertainty propagates through financial systems.

To address these challenges, this study develops an interpretable hybrid deep learning framework that integrates XGBoost and deep learning architectures with SHapley Additive exPlanations (SHAP). SHAP is employed to quantify the contribution of each input variable to predicted financial outcomes under two analytical scenarios: first, using MUI as a composite measure of systemic uncertainty; and second, using the five individual uncertainty indices as separate inputs. This dual design enhances model transparency and enables a more nuanced understanding of how different forms of uncertainty interact with firm fundamentals to shape financial performance.

The analytical framework is grounded in behavioral and economic theories, particularly Knightian uncertainty, which distinguishes between measurable risk and unquantifiable ambiguity. Under conditions of high uncertainty, firms and investors may display nonlinear and often defensive responses that traditional models fail to capture. By integrating composite risk measurement, explainable artificial intelligence, and real estate financial modeling, this study advances a more adaptive and interpretable approach to forecasting firm performance under systemic uncertainty.

This study makes three main contributions. First, it constructs a composite Macroeconomic Uncertainty Index (MUI) that integrates five uncertainty dimensions into a unified systemic risk measure for emerging real estate markets. Second, it develops an interpretable hybrid framework combining XGBoost and deep learning, preserving nonlinear predictive power while ensuring transparency through SHAP decomposition. Third, it extends the uncertainty–performance literature to the real estate sector in an emerging markets context, distinguishing between aggregate systemic effects and component-level transmission channels for ROA and ROE.

The paper is organized as follows. Section 2 presents the theoretical framework and related literature. Section 3 describes the data, variables, and construction of the Macroeconomic Uncertainty Index (MUI). Section 4 outlines the empirical methodology. Section 5 reports the results, followed by discussion in Section 6, and Section 7 concludes with policy implications and future research directions.

2. Theoretical Framework and Literature Review

Explaining how ESG dynamics and macroeconomic uncertainty influence the financial performance of real estate firms in emerging markets requires an integrated theoretical foundation. Real estate firms operate in capital-intensive, policy-sensitive, and volatile environments, where institutional and market risks intersect. Linking classical finance theories with behavioral insights and explainable artificial intelligence provides a comprehensive approach to understanding how firms adapt to uncertainty.

At the strategic level, Real Options Theory (Dixit & Pindyck, 2012) explains firms' flexibility under uncertainty and investment irreversibility. Real estate projects, characterized by long-term commitments and ESG exposure, embed options that gain value as volatility rises. Heightened policy or ESG uncertainty, captured by indices such as EPU, GPR, and ESGUI, prompts firms to delay, scale, or reconfigure investments to preserve flexibility and mitigate risk.

Pecking Order Theory (Myers & Majluf, 1984) and the Risk-Based View of Capital Structure describe financing preferences under macroeconomic instability. As inflation, interest rate volatility, or global uncertainty increase, firms favor internal funding to reduce information asymmetry and valuation risk (Chen et al., 2017; González et al., 2016). High uncertainty raises the cost of external capital, encouraging deleveraging and portfolio shifts toward safer assets, especially in liquidity-sensitive property markets.

From a governance perspective, Signaling Theory (Spence, 1973) and Stakeholder Theory (Freeman & McVea, 2001) emphasize ESG disclosure as both a financial and reputational signal. Transparent ESG practices signal governance quality and sound risk management, sustaining investor confidence during volatility (Dhaliwal et al., 2014). Stakeholder engagement further strengthens resilience by aligning environmental, social, and financial objectives.

Behavioral approaches complement these views. Knightian Uncertainty (Knight, 1921) differentiates measurable risk from ambiguity, where decision-making becomes sentiment-driven. Behavioral Asset

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Pricing Theory (Barberis & Thaler, 2002) explains how investor bias and herding amplify volatility. The World Sentiment Index (WSI) captures how behavioral shocks affect valuation and firm outcomes through nonlinear channels.

Finally, Explainable Machine Learning, particularly SHAP (Lundberg & Lee, 2017), extends these theories into empirical modeling. Deep learning models such as CNN and LSTM capture nonlinear interactions between uncertainty and financial outcomes but often lack transparency. SHAP enhances interpretability by decomposing model outputs into variable contributions, clarifying how firm fundamentals (e.g., EPS, SIZE) and macroeconomic risks (e.g., EPU, ESGUI, GPR) jointly shape profitability.

Empirical studies align with this framework. ESG performance strengthens financial resilience by improving governance and stakeholder trust. Morri et al. (2024) show that strong environmental performance enhances profitability under stress, while Kitulazzi et al. (2025) find that ESG benefits depend on ownership, disclosure, and governance quality. Evidence from emerging markets remains mixed, as weak institutions and limited ESG standardization reduce disclosure effectiveness (Ciora et al., 2017). ESG therefore contributes to performance mainly in transparent and credible regulatory systems.

Macroeconomic uncertainty is also a key driver of firm performance. Real estate firms are sensitive to inflation, interest rate movements, and investor sentiment. Global indices such as EPU, GPR, and WUI affect investment flows, valuation, and liquidity (Agoraki et al., 2024; Coën & Desfleurs, 2024). Investors typically shift to safer assets when policy or liquidity risks rise (Ameri, 2023; Freybote et al., 2016). Most studies, however, analyze these factors separately, ignoring their interactions. Recent research supports the use of composite uncertainty measures that integrate multiple risk sources to capture systemic effects (Abaidoo & Agyapong, 2023; Boikos et al., 2024; Jiang et al., 2024). Composite indices provide a more accurate representation of macro-financial complexity (Kaya & Tawadros, 2022; Cantone, 2025).

Advances in data analytics have transformed modeling approaches. Deep learning techniques such as CNN and LSTMoutperform traditional econometric models in capturing nonlinearities and temporal dynamics (Fischer & Krauss, 2018; Xu & Zhang, 2021). In real estate, these models improve valuation and forecasting accuracy (Choy & Ho, 2023; Francke & van de Minne, 2024). Hybrid architectures combining deep learning with XGBoost enhance efficiency and prevent overfitting (Wang et al., 2023; Nichani et al., 2024; Yu et al., 2021). Yet, interpretability remains limited, reducing their usefulness for policy or managerial insight.

To address this, recent research employs Explainable AI techniques such as SHAP, which reveal how firm fundamentals, ESG indicators, and macroeconomic variables contribute to performance (Lundberg & Lee, 2017; Ozturkkal & Wahlstrøm, 2024). The growing adoption of interpretable models reflects the need for transparency and accountability in AI-based financial analysis.

Despite progress, key gaps persist. Few studies integrate ESG, firm characteristics, and macroeconomic uncertainty into a unified model. Most rely on isolated uncertainty measures, neglecting systemic interactions. Explainable deep learning remains underutilized in emerging markets, where volatility and limited data demand interpretable yet accurate models.

This study addresses these gaps by developing a hybrid deep learning framework integrating XGBoost, CNN, and SHAP. The model, applied to Vietnam's real estate sector, constructs a composite Macroeconomic Uncertainty Index (MUI) using PCA based on five indicators, EPU, GPR, ESGUI, WUI, and WSI. This framework enhances predictive accuracy and interpretability while identifying how firm fundamentals, ESG factors, and macroeconomic uncertainty interact to shape financial performance.

3. Data and Variable Description

The study employs a balanced panel of 28 listed Vietnamese real estate firms, observed monthly from January 2013 to June 2025, totaling 4,060 firm-month observations. Firm-level indicators (PB, EPS, SIZE) were derived from audited financial statements, HOSE, HNX, and FiinGroup. Macroeconomic variables (CPI, gold, oil, FED rate) were obtained from the General Statistics Office of Vietnam, the World Bank, and FRED.
Five global uncertainty indices - ESGUI, EPU, GPR, WUI, and WSI - specific to Vietnam were adopted from prior research (Ahir et al., 2018; Baker et al., 2016; Ongan et al., 2025). All variables were adjusted for exchange rates and standardized using Z-scores for scale consistency.

Following the theoretical framework, variables are grouped into dependent, firm-specific, and macro-uncertainty categories (Chen et al., 2017; Morri et al., 2024). Detailed definitions, sources, and expected effects are summarized in Table 1.

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Table 1

Variable Description and Measurement

Category	Variable	Symbol / Measurement	Definition / Description
Dependent Variables	Return on Assets	ROA = Net Income / Average Total Assets	Indicates operational efficiency in utilizing assets to generate profits.
	Return on Equity	ROE = Net Income / Average Shareholders' Equity	Measures profitability relative to equity capital.
Firm-specific (Micro) Variables	Earnings per Share	EPS = Net Income / Number of Shares Outstanding	Represents profitability available to common shareholders.
	Firm Size	SIZE = ln(Total Assets)	Natural logarithm of total assets, proxy for firm scale and market power.
	Price-to-Book Ratio	PB = Market Price per Share / Book Value per Share	Reflects market valuation and investor expectations.
Macroeconomic Indicators	Consumer Price Index	CPI	Proxy for inflation and domestic purchasing power.
	Federal Funds Rate	FED	Global benchmark rate indicating cost of capital.
	Gold Price	GOLD (USD/Ounce)	Safe-haven asset reflecting investor sentiment under uncertainty.
	Oil Price	OIL (USD/Barrel)	Captures global demand and cost-side pressures affecting real estate.
Global Uncertainty Indices	ESG Uncertainty Index	ESGUI	Measures ambiguity in global ESG policies and sustainability discourse.
	Economic Policy Uncertainty Index	EPU	Quantifies unpredictability in fiscal and monetary policy using news-based counts.
	Geopolitical Risk Index	GPR	Reflects geopolitical tensions affecting investment confidence.
	World Sentiment Index	WSI	Text-based index capturing global investor sentiment and behavioral trends.
	World Uncertainty Index	WUI	Quantifies overall macroeconomic uncertainty from EIU country reports.
Composite Measure	Macroeconomic Uncertainty Index	MUI (via PCA)	Composite index derived from ESGUI, EPU, GPR, WSI, and WUI using PCA. Represents systemic and nonlinear macro uncertainty.

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

All input variables are normalized using Z-scores to stabilize scales and facilitate convergence in deep learning optimization routines.

4. Research Methodology

This study develops an empirical framework to examine the nonlinear relationship between macroeconomic uncertainty and the financial performance of Vietnamese real estate firms. The approach integrates hybrid deep learning with explainable artificial intelligence to achieve both predictive accuracy and interpretive transparency.

The hybrid model combines XGBoost with deep learning architectures - ANN, DNN, CNN, and LSTM. Outputs from XGBoost capturing nonlinear feature interactions serve as structured inputs for deep models that learn hierarchical and temporal representations. This layered design leverages the nonlinear learning capacity of XGBoost and the pattern recognition ability of neural networks. Prior studies confirm that such hybrid architectures enhance predictive precision and robustness in financial forecasting (Latif et al., 2024; Mubarak et al., 2024; Zheng et al., 2024).

Systemic uncertainty is represented by a Macroeconomic Uncertainty Index (MUI) constructed through Principal Component Analysis (PCA) of five indicators: EPU, GPR, ESGUI, WUI, and WSI. Standardization ensures scale comparability, and the first four components explain nearly 90% of the total variance. Sampling adequacy is confirmed by a Kaiser–Meyer–Olkin statistic of 0.7544, and Bartlett's test of sphericity is significant ($\chi^2 = 912.46$, $p < 0.001$), supporting the suitability of PCA. A variance-weighted aggregation of the retained components forms the composite MUI, providing a parsimonious and stable measure of systemic uncertainty.

All predictors are normalized prior to training. The dataset is split chronologically into 80% for training and 20% for testing, ensuring that no future observations are used during model estimation. Model performance is evaluated on genuine out-of-sample data, with rolling/expanding window validation conducted as a robustness check. Optimization employs the Adam algorithm with Mean Squared Error (MSE) loss, while regularization techniques—including dropout, early stopping, and L2 penalties—are applied to mitigate

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overfitting. Hyperparameter tuning is performed exclusively within the training sample to prevent data leakage.

Model interpretability is achieved through SHAP values (Lundberg & Lee, 2017), which decompose predictions into the marginal contributions of each variable. SHAP is applied both to the composite MUI and to individual uncertainty indicators, allowing analysis of aggregate and disaggregated effects.

This integrated framework advances beyond traditional econometric models by combining predictive depth with theoretical transparency, offering a data-driven basis for understanding how uncertainty and firm fundamentals jointly shape financial outcomes in emerging markets.

5. Empirical Results

5.1. Descriptive analysis and inter-variable relationships

An exploratory analysis was conducted to examine the statistical characteristics and inter-variable relationships, establishing a quantitative foundation for subsequent modeling. Table 2 reports summary statistics for firm-level, macroeconomic, and uncertainty-related variables over the 2013–2025 period.

Mean ROE and ROA are 2.2% and 1.1%, respectively, with ROE showing greater dispersion (σ = 0.040) and wider range (−33.8% to +33.7%), reflecting heterogeneous profitability among firms. Negative mean values for EPS and PBindicate that several firms experienced profitability or valuation challenges during the sample period. Firm size (SIZE)centers near zero (mean = −0.001) with moderate variability (σ = 0.992), suggesting structural diversity in scale and asset base.

Among macroeconomic indicators, GOLD and OIL display moderate variance, while CPI and FED remain relatively stable. The COVID dummy shows clear polarity (min = −0.802, max = 1.247), marking structural shifts during the pandemic. The composite Macroeconomic Uncertainty Index (MUI) has a mean close to zero but a broad range (−1.933 to +3.511), confirming its ability to capture systemic volatility. Overall, the variables exhibit sufficient variation and scale independence, suitable for nonlinear and multivariate analysis

Table 2

Descriptive statistics

	mean	min	25%	50%	75%	max	std
ROE	0.022	-0.338	0.003	0.012	0.034	0.337	0.040
ROA	0.011	-0.116	0.001	0.006	0.017	0.265	0.022
PB	-0.013	-0.768	-0.561	-0.336	0.139	4.027	0.914
EPS	-0.017	-1.393	-0.483	-0.297	0.227	3.547	0.772
SIZE	-0.001	-2.096	-0.693	-0.033	0.551	3.089	0.992
GOLD	-0.065	-0.557	-0.438	-0.395	0.288	1.203	0.494
OIL	-0.002	-2.212	-0.842	-0.114	0.688	1.91	0.994
CPI	0.012	-2.266	-0.567	-0.114	0.549	2.667	0.949
FED	0.000	-0.736	-0.736	-0.59	0.428	2.319	1.000
COVID	0.000	-0.802	-0.802	-0.802	1.247	1.247	1.000
MUI	-0.001	-1.933	-0.551	-0.089	0.392	3.511	0.995

Source: own study.

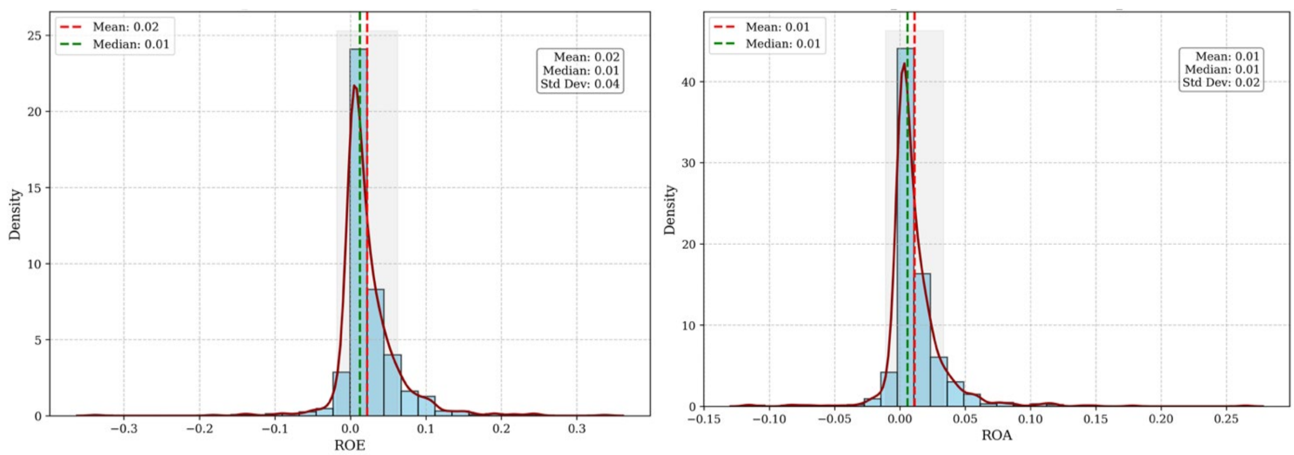

Fig. 1. Distribution of the average Return on Equity (ROE) and Return on Assets (ROA). *Source:* own study.

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Figure 1 illustrates the distribution of financial performance indicators. Both ROA and ROE are positively centered, though ROE shows higher mean and dispersion, indicating stronger equity returns but greater heterogeneity across firms. The left-skewed tail of ROE reflects periods of negative profitability for specific firms during market downturns.

Fig. 2 presents the Pearson correlation matrix among all quantitative variables. The most pronounced relationship is between EPS and ROE (r = 0.86), reaffirming earnings as the primary determinant of shareholder returns, consistent with valuation theory. In contrast, ROA is weakly correlated with both ROE (r = −0.02) and firm-level indicators (EPS, PB, SIZE), confirming that asset efficiency is distinct from equity-based profitability.

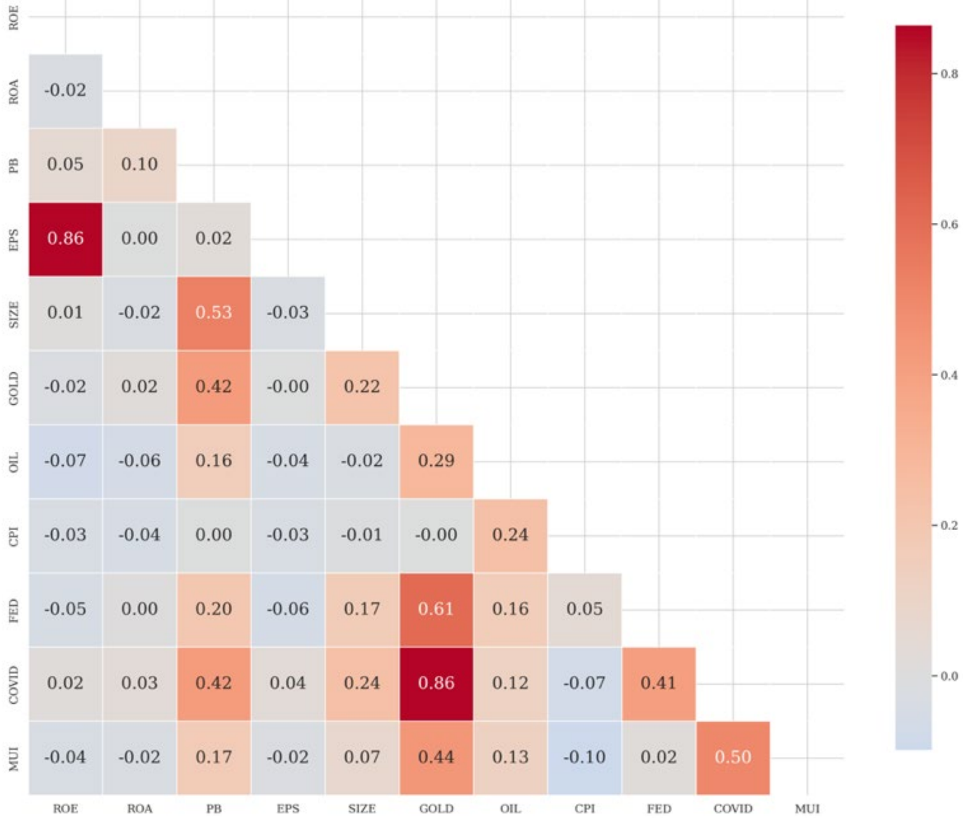

Fig. 2. Correlation matrix of numerical features. *Source:* Authors (2026).

At the macro level, FED and GOLD are moderately correlated (r = 0.61), suggesting monetary policy influences hedging behavior. COVID correlates with both FED (r = 0.41) and SIZE (r = 0.42), indicating pandemic-induced shifts in policy and firm operations. The positive GOLD–COVID correlation (r = 0.24) supports gold's safe-haven role. MUI correlates moderately with COVID (r = 0.50) and GOLD (r = 0.44), reflecting its sensitivity to systemic and behavioral uncertainty, while its weak links with OIL, FED, and CPI (|r| < 0.15) confirm that it captures broader systemic rather than price-based risks. Most pairwise correlations remain below 0.5, suggesting limited multicollinearity and supporting the robustness of subsequent regression and hybrid machine learning analyses.

5.2. Model Performance Evaluation

Table 3 summarizes the predictive accuracy of eight deep learning models for the two dependent variables, ROE and ROA. The models include four standalone architectures (ANN, DNN, CNN, LSTM) and four XGBoost-based hybrids (XGB+ANN, XGB+DNN, XGB+CNN, XGB+LSTM). Performance was evaluated using R^2, RMSE, and MAE as standard metrics.

For ROE, the LSTM model achieved the best standalone performance (R^2 = 0.8443, RMSE = 0.0149, MAE = 0.0090), reflecting its ability to capture sequential patterns and temporal dependencies in financial data, consistent with Fischer and Krauss (2018) and Tin et al. (2024). Other standalone models (ANN, DNN, CNN) showed moderate accuracy, with R^2 between 0.69 and 0.75.

Integrating XGBoost features into deep architectures substantially improved performance across all models. The XGB+CNN achieved the highest accuracy (R^2 = 0.9662, RMSE = 0.0069, MAE = 0.0031), outperforming standalone LSTM by over 12 percentage

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points in R^2 and reducing RMSE by more than half. Comparable results across XGB+ANN, XGB+DNN, and XGB+LSTM confirm the robustness of the hybrid approach. These results align with Wang et al. (2023) and Oukhouya et al. (2023), who highlight the complementarity between XGBoost's nonlinear feature extraction and the representational power of neural networks.

In contrast, ROA predictions exhibited weaker accuracy among standalone models. ANN and CNN produced negative R^2 values (−0.2787 and −0.0059), while LSTM achieved only R^2 = 0.1640, indicating limited predictive capacity for asset-based profitability.

Hybrid models markedly improved ROA forecasts, with XGB+LSTM yielding the best performance (R^2 = 0.7691, RMSE = 0.01104, MAE = 0.00635). The improvement of over 60 percentage points in R^2 relative to standalone LSTM underscores the model's effectiveness in integrating nonlinear, temporal, and uncertainty-related dynamics. Similar evidence from Latif et al. (2024) and Marey et al. (2026) supports the superior stability of hybrid architectures in complex financial settings

Table 3

Forecasting performance of deep learning models for ROE - ROA

	ROE			ROA		
Model	R^2	RMSE	MAE	R^2	RMSE	MAE
ANN	0.6935	0.0209	0.0138	-0.2787	0.02597	0.01657
DNN	0.7489	0.0189	0.0115	0.0569	0.02230	0.01445
CNN	0.7168	0.0201	0.0130	-0.0059	0.02303	0.01481
LSTM	0.8443	0.0149	0.0090	0.1640	0.02099	0.01257
XGB+ANN	0.9658	0.0070	0.0031	0.7689	0.01104	0.00630
XGB+DNN	0.9654	0.0070	0.0031	0.7635	0.01117	0.00636
XGB+CNN	0.9662	0.0069	0.0031	0.7650	0.01113	0.00638
XGB+LSTM	0.9656	0.0070	0.0033	0.7691	0.01104	0.00635

Source: own study.

Figures 3 and 4 illustrate residual distributions and actual-versus-predicted plots for ROE and ROA, respectively. Standalone models produce wide, asymmetric residuals, reflecting weak predictive fit and an inability to capture complex financial dynamics. In contrast, hybrid architectures - particularly XGB+CNN and XGB+LSTM - exhibit compact, symmetric residuals centered around zero, indicating reduced bias and improved model calibration. The scatterplots further confirm this pattern, with hybrid predictions clustering closely along the 45-degree line, demonstrating higher accuracy, stronger correlation, and greater generalizability.

For ROE (Fig. 3), standalone models such as ANN and CNN display broad and skewed residual distributions, while LSTM shows better convergence toward zero, reflecting its strength in capturing sequential dependencies. However, the hybrid configurations significantly outperform all baselines. The XGB+CNN and XGB+LSTM models yield narrow, well-centered residuals and regression slopes approaching unity, confirming near-perfect alignment between predicted and actual ROE values.

For ROA (Fig. 4), standalone models again underperform, consistent with their negative or low R^2 results. Residual plots reveal systematic deviations and noise clustering, implying limited representation of underlying dynamics. Conversely, hybrid models deliver substantial improvement. The XGB+LSTM model, in particular, exhibits stable, non-autocorrelated residuals and tightly grouped predictions within the 0.005–0.015 ROA range, confirming robustness and strong generalization across the central performance spectrum.

To enhance transparency and interpretability, the hybrid deep learning framework is complemented with SHAP, which attributes each prediction to the marginal contribution of its input features. This approach transforms the predictive structure into an interpretable framework, enabling the decomposition of firm performance into firm-specific, macroeconomic, and uncertainty-related effects. Figures 5–7 present the global SHAP summary plots for Return on Equity (ROE), Return on Assets (ROA), and the individual macroeconomic uncertainty components.

Detailed distributions are retained for analytical completeness, while the discussion focuses on the most economically meaningful drivers, namely firm-level determinants (EPS, SIZE) and the primary macroeconomic channel (EPU).

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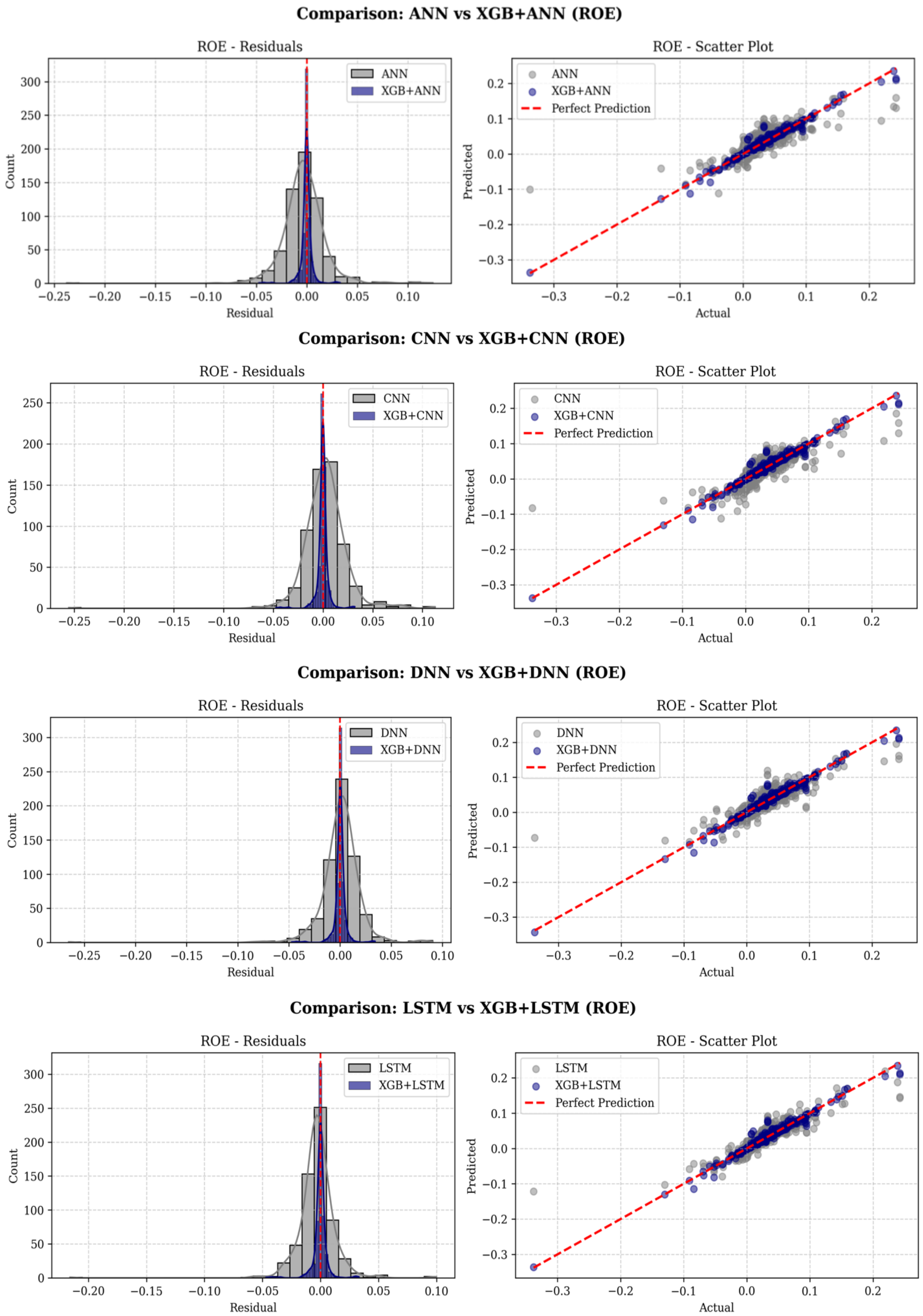

Fig. 3. Residual and prediction comparison between base models and hybrid models (XGBoost-based) for ROE forecasting. *Source:* own study.

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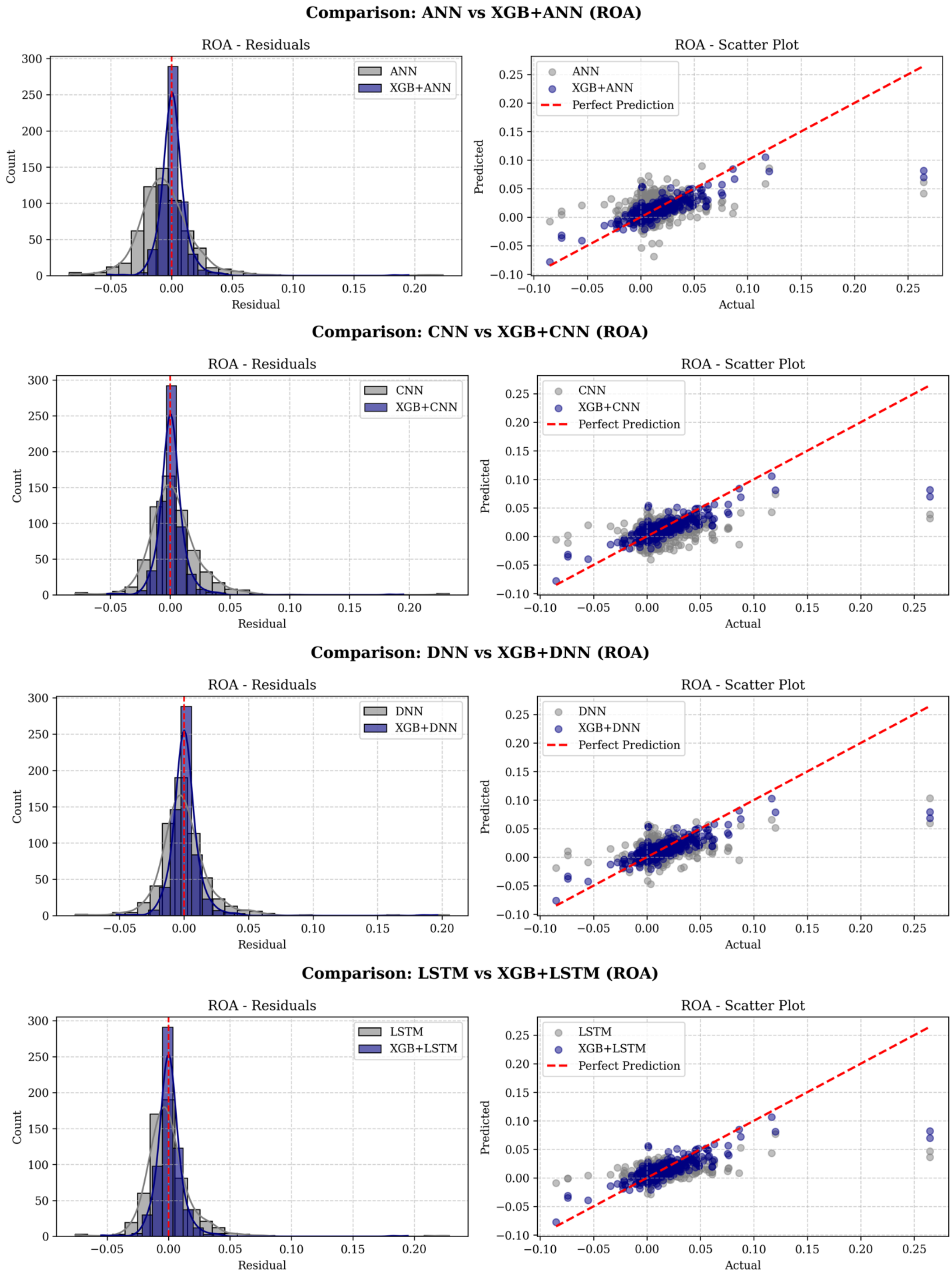

Fig. 4. Residual and prediction comparison between base models and hybrid models (XGBoost-based) for ROA forecasting. *Source:* own study.

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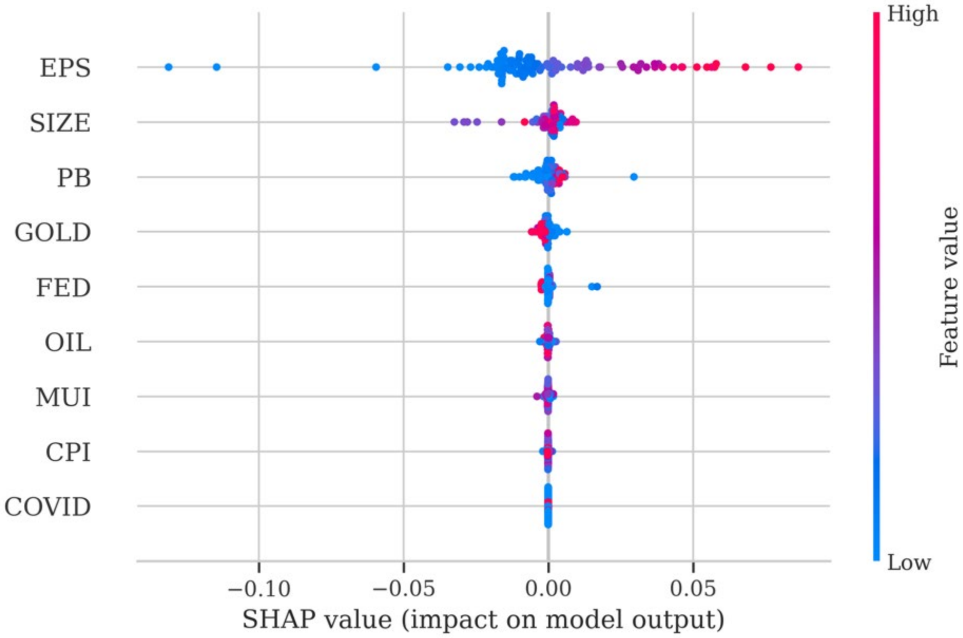

Fig. 5. SHAP summary plot for ROE prediction: feature-level impact on model output. *Source:* own study.

Across model configurations, SHAP results indicate that firm fundamentals dominate, whereas macroeconomic variables exert a secondary and nonlinear moderating influence. For ROE, Earnings per Share (EPS) emerges as the most influential predictor, displaying the widest SHAP dispersion (approximately –0.10 to +0.06). Higher EPS values consistently increase predicted ROE, while lower values reduce it. This pattern suggests that shareholder profitability is largely driven by internal earnings capacity rather than external macro-financial conditions, consistent with the Pecking Order Theory, which emphasizes the resilience of profitable firms under uncertainty.

5.3. SHAP Analysis

Firm size (SIZE) appears as the second most influential determinant. Although its SHAP dispersion is narrower than that of EPS, larger firms consistently contribute positively to predicted ROE, reflecting scale advantages, stronger financing access, and greater resilience to macroeconomic volatility. The joint prominence of EPS and SIZE indicates that firm fundamentals remain the primary drivers of shareholder value in emerging real estate markets. Other firm-level variables, such as the Price-to-Book ratio (PB), show smaller but stable positive contributions, suggesting that market valuation complements internal profitability in shaping equity returns.

Among macroeconomic indicators, GOLD and FED display modest and context-dependent effects. GOLD occasionally shows weak positive SHAP values, consistent with its role as a safe-haven or sentiment indicator during financial stress. Higher FED levels correspond to localized negative SHAP contributions, aligning with the contractionary effects of monetary tightening on capital-intensive sectors. CPI, OIL, and COVID variables exhibit near-zero SHAP distributions, indicating that short-term shocks and inflation dynamics are largely absorbed by firm-level fundamentals within the predictive structure.

For the ROA model, SHAP results (Fig. 6) indicate a shift in predictor importance. While EPS remains relevant, SIZE becomes the dominant driver, highlighting the structural dimension of asset efficiency. Higher SIZE values are consistently associated with positive SHAP contributions, suggesting that larger firms achieve more efficient asset utilization through scale economies and improved capital allocation. EPS continues to affect ROA positively but with a nonlinear pattern, with weaker marginal effects at higher profitability levels, reflecting diminishing returns in asset efficiency. This contrast between ROE and ROA suggests that profitability is largely earnings-driven, whereas efficiency is more structurally determined in emerging real estate markets.

Macroeconomic variables play a secondary role in the ROA model (Fig. 7). FED and OIL show occasional negative SHAP outliers, consistent with tightening financial conditions or higher input costs. GOLD maintains mild positive contributions, acting as a

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sentiment proxy. Systemic indicators such as MUI, CPI, and COVID display near-zero SHAP ranges, indicating that operational efficiency is less directly affected by short-term macroeconomic shocks than shareholder returns.

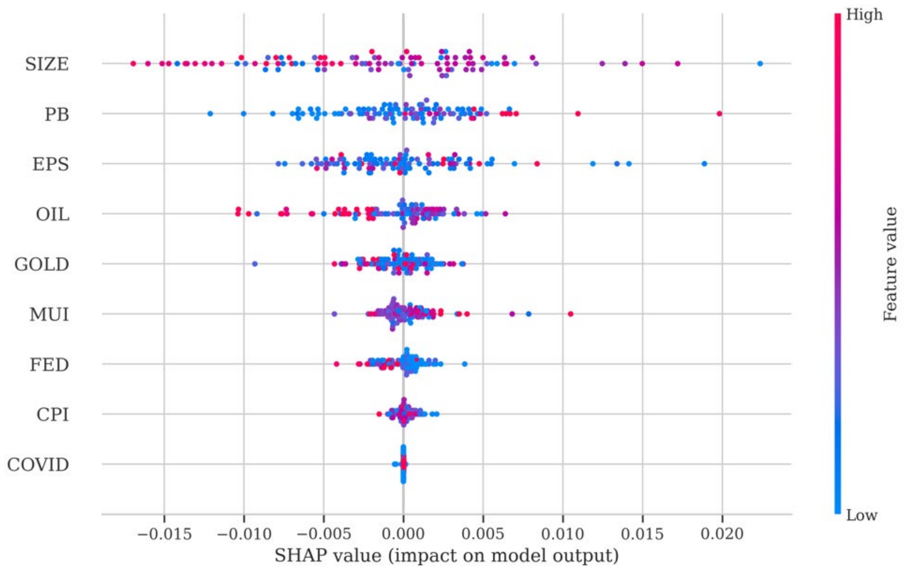

Fig. 6. SHAP summary plot for ROA prediction: feature-level impact on model output. *Source:* own study.

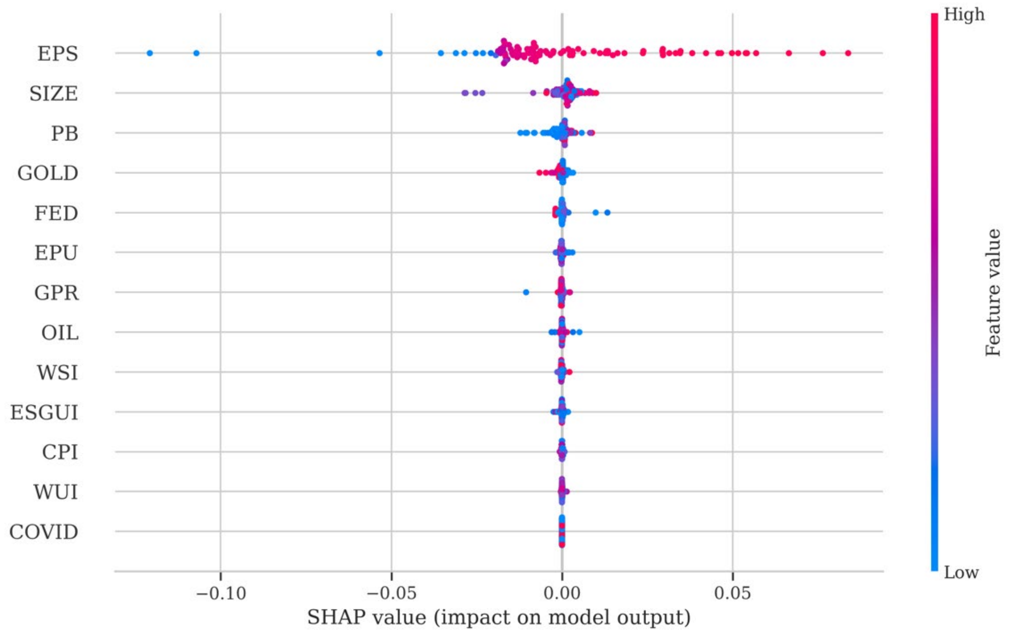

Fig. 7. SHAP Summary for ROE forecasting: individual macroeconomic uncertainty drivers. *Source:* own study.

To further examine systemic risk channels, SHAP analysis is extended to individual uncertainty components - Economic Policy Uncertainty (EPU), Geopolitical Risk (GPR), ESG Uncertainty Index (ESGUI), World Uncertainty Index (WUI), and World Sentiment Index (WSI) - with ROE as the outcome. Among these, EPU shows the strongest effect, with consistently negative SHAP values at higher levels, indicating that policy instability weakens investor confidence and expected profitability.

ESGUI displays moderate negative contributions, acting as a conditional moderator rather than a primary driver, while GPR exhibits irregular and context-dependent effects, becoming relevant mainly during periods of geopolitical stress. In contrast, WUI and WSI show negligible SHAP ranges, suggesting limited transmission of global uncertainty shocks to firm-level profitability in the Vietnamese real estate context.

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Overall, SHAP results indicate a consistent structure: firm fundamentals (EPS, SIZE) dominate performance outcomes, EPU represents the main macroeconomic transmission channel, and other uncertainty measures act as secondary moderators. The composite Macroeconomic Uncertainty Index (MUI) captures these nonlinear interactions, confirming its role as a systemic moderating factor rather than a direct determinant.

These findings support the theoretical coherence of the hybrid framework: the importance of EPS and SIZE aligns with financial resilience arguments in the Pecking Order perspective, while the negative effect of EPU reflects the behavioral impact of macroeconomic uncertainty on expectations and firm performance.

6. Discussion

The SHAP-based analysis reveals how firm fundamentals and macroeconomic uncertainty interact to shape financial performance in emerging real estate markets. Results show that profitability and asset efficiency in Vietnam's real estate sector are mainly driven by internal financial capacity, while external uncertainty acts as a nonlinear but secondary moderator. This reflects a structural asymmetry between internal performance determinants and external risk pressures in transition economies.

The prominence of EPS and SIZE supports the relevance of the Pecking Order and Stakeholder theories under uncertainty. Firms with strong earnings depend less on external financing, enhancing their resilience to shocks. Larger firms benefit from scale advantages, better transparency, and stronger stakeholder trust, enabling stable performance during economic turbulence. These findings highlight internal strength and governance quality as key adaptive shields against systemic volatility.

The negative impact of EPU aligns with Knightian uncertainty and Real Options Theory. Policy ambiguity discourages investment as firms perceive uncertainty as a cost. In emerging economies, weak institutional credibility amplifies this effect, increasing risk premiums and compressing valuations. The limited role of other global indicators, including ESGUI, GPR, and WSI, indicates that external shocks transmit weakly to domestic performance, reaffirming the dominance of local fundamentals.

Methodologically, the study extends explainable AI applications in finance. The hybrid deep learning–SHAP model captures nonlinearities while maintaining interpretability, allowing a nuanced view of how uncertainty moderates firm outcomes. Unlike traditional econometric models, this approach bridges prediction and explanation, advancing transparent and policy-relevant financial modeling for emerging markets.

From a managerial perspective, the evidence emphasizes strengthening internal fundamentals as the most effective buffer against macroeconomic instability. Firms should prioritize profitability, prudent leverage, and transparent disclosure to sustain investor confidence. Policymakers should enhance regulatory consistency, improve policy communication, and promote standardized ESG disclosure to reduce information asymmetry and lower capital costs.

Despite its robustness, the framework does not fully capture behavioral or cross-sectoral dynamics. Future research could incorporate firm-level sentiment measures or extend the model across multiple emerging markets to assess generalizability.

In conclusion, firm-specific fundamentals, particularly profitability and scale, remain the primary drivers of financial performance, while policy-related uncertainty is the main external constraint. In transitional markets, resilience arises less from external stability and more from internal adaptability and transparency.

7. Conclusion and Policy Implications

7.1. Conclusion

This study develops an interpretable hybrid deep learning framework to analyze how macroeconomic uncertainty shapes the financial performance of real estate firms in an emerging market. By integrating a composite Macroeconomic Uncertainty Index (MUI), derived from PCA of five global indicators (EPU, GPR, ESGUI, WUI, and WSI), with firm-level characteristics, the model captures the nonlinear and layered interactions between systemic risk and firm fundamentals.

Empirical results show that firm-specific factors, particularly earnings performance (EPS) and firm size (SIZE), are the dominant drivers of profitability and efficiency. Macroeconomic uncertainty plays a moderating rather than deterministic role, with policy-related risk (EPU) emerging as the most influential dimension. This highlights the critical importance of institutional credibility and policy consistency for firm stability in transitional economies.

The findings reaffirm the explanatory value of Real Options Theory, Pecking Order Theory, and Stakeholder Theory in contexts of uncertainty. Methodologically, the integration of explainable AI,

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operationalized through SHAP, bridges predictive analytics and economic reasoning, improving both model accuracy and interpretability. The study thus contributes to the growing body of research that links financial theory, uncertainty modeling, and interpretable AI for decision-making in emerging markets.

7.2. Policy Recommendations

The findings yield practical implications for investors, firms, and policymakers managing performance under uncertainty. For investors, combining firm-level indicators with the MUI provides a more balanced view of intrinsic value and external risk exposure. The use of explainable AI, especially SHAP-based analytics, enhances valuation transparency by clarifying how macro shocks interact with corporate fundamentals.

For real estate firms, reinforcing internal financial strength remains the most effective defense against systemic volatility. Enhancing profitability, maintaining prudent leverage, and integrating MUI-based monitoring into strategic planning can improve adaptability. ESG initiatives should be embedded within risk management systems, linking sustainability, governance, and financial performance.

From a policy standpoint, institutional credibility and data transparency are essential for reducing systemic uncertainty. Regulators should incorporate composite indices such as the MUI into macroprudential frameworks to detect sectoral vulnerabilities early. Applying SHAP-based diagnostics at the firm level can identify entities most sensitive to policy or liquidity shocks, enabling targeted interventions. Standardized ESG and macro-financial disclosure would further strengthen market confidence and evidence-based policymaking.

Ultimately, sustainable financial performance in emerging markets depends on the alignment between strong corporate governance and consistent macroeconomic policy. Collaborative efforts among investors, firms, and regulators are crucial to building a transparent, adaptive, and resilient financial ecosystem under global uncertainty.

7.3. Limitations and Future Research Directions

While offering theoretical and methodological contributions, the study has several limitations. The PCA-based MUI, although effective in reducing multicollinearity, may mask the distinct effects of specific uncertainty sources such as policy, ESG, or geopolitical risk. The dataset, limited to 28 Vietnamese real estate firms, restricts generalizability across sectors and countries. The analysis also relies on structured quantitative data, excluding behavioral or textual dimensions such as policy discourse, ESG reporting quality, or investor sentiment. Finally, despite strong predictive performance, the findings are interpreted as out-of-sample predictive associations rather than causal effects.

Future research could advance in three directions. First, decomposing the MUI into interpretable subcomponents may clarify individual risk transmission channels. Second, applying the hybrid SHAP-based framework across multiple emerging markets would test its cross-country and cross-sector robustness. Third, integrating unstructured data through natural language processing and sentiment analysis could enrich model interpretability and enhance early-warning capabilities.

Progress toward multi-source, interpretable, and cross-market analytical frameworks represents a promising path for understanding financial resilience under systemic uncertainty.

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Appendix

Appendix A. Factor loadings from PCA of macroeconomic uncertainty indicators

Indicators	PC1	PC2	PC3	PC4	PC5
GPR	−0.2115	0.2559	0.7838	0.5214	0.0602
ESGUI	−0.2060	0.7322	−0.0683	−0.3989	0.5076
WUI	0.5697	0.2064	0.4566	−0.5097	−0.4057
WSI	−0.3135	−0.5809	0.4143	−0.5073	0.3678
EPU	0.7000	−0.1354	0.0307	0.2277	0.6625

Appendix B. Model Hyperparameter Summary

Model	Architecture Details	Activation Function	Optimizer	Epochs	Batch Size	Input Shape
ANN	Dense(64) → Dense(32) → Dense(2)	ReLU (hidden), Linear (output)	Adam	50	32	(13,)
DNN	Dense(128) → Dense(64) → Dense(32) → Dense(2)	ReLU (hidden), Linear (output)	Adam	50	32	(13,)
CNN	Conv1D(64, kernel=1) → MaxPooling1D(1) → Flatten → Dense(32) → Dense(2)	ReLU (conv + dense)	Adam	50	32	(1, 13)
LSTM	LSTM(64, tanh) → Dense(32, ReLU) → Dense(2)	Tanh (LSTM), ReLU, Linear	Adam	50	16	(1, 13)
XGBoost	2 x XGBRegressor (wrapped by MultiOutputRegressor)	–	–	–	–	–
	n_estimators = 100, max_depth = 6, learning_rate = 0.1, subsample = 0.8	–	–	–	–	–
XGB+ANN	XGBoost output → Dense(64) → Dense(32) → Dense(2)	ReLU (hidden), Linear	Adam	50	32	(2,)
XGB+DNN	XGBoost output → Dense(128) → Dense(64) → Dense(32) → Dense(2)	ReLU (hidden), Linear	Adam	50	32	(2,)
XGB+CNN	XGBoost output → Conv1D(64) → MaxPooling1D → Flatten → Dense(32) → Dense(2)	ReLU (conv + dense)	Adam	50	32	(1, 2)
XGB+LSTM	XGBoost output → LSTM(64) → Dense(32) → Dense(2)	Tanh, ReLU, Linear	Adam	50	16	(1, 2)

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