CAUSAL AND EXPLAINABLE MACHINE LEARNING INSIGHTS INTO ROA'S IMPACT ON BANK STABILITY AMID LIQUIDITY AND PANDEMIC SHOCKS

PhD. Pham Thuy Tu*

Abstract: ***Amid growing systemic vulnerabilities in emerging financial markets, this study examines the causal impact of bank profitability, proxied by Return on Assets (ROA), on institutional stability, measured by the Z-score, under liquidity stress and pandemic-induced shocks. Using data from 63 commercial banks across six ASEAN countries (2010–2023), we develop a hybrid framework integrating causal inference, machine learning, and model interpretability. Regularized regressions (Lasso, Ridge, Elastic Net) enhance feature selection, while Double Machine Learning (DML) estimates both average and conditional treatment effects. Optimized via Particle Swarm Optimization (PSO), CatBoost and XGBoost models achieve R^2 above 0.93. SHAP-based analysis reveals nonlinear interactions between ROA, liquidity gaps (FGAP), and COVID-19, indicating that profitability's stabilizing role weakens under high liquidity stress. By bridging explainable AI and causal reasoning, this study offers a novel, interpretable framework for early-warning systems and prudential supervision in volatile and capacity-constrained financial environments.***

• Keywords: *bank stability; return on assets; liquidity gap; double machine learning; SHAP.*

JEL codes: G01, G21, G32, C53, C55

Date of receipt: 31th Jan., 2026 *Date of receipt revision: 20th Mar., 2026*
Date of delivery revision: 11th Mar., 2026 *Date of approval: 28th Mar., 2026*

DOI: https://doi.org/10.71374/jfar.v26.i2.46

1. Introduction

Banking system stability underpins effective financial intermediation, market confidence, and macroeconomic resilience. In emerging economies, particularly within ASEAN, banks play a vital role in channeling capital but remain vulnerable to external shocks due to limited capitalization, thin liquidity buffers, and strong regional interconnectedness. Return on Assets (ROA), representing profitability per unit of assets, serves as a key indicator of operational efficiency and the capacity to accumulate buffers against systemic risk.

Recent disruptions, including the COVID-19 pandemic and global liquidity tightening, have reshaped regional financial risk structures. Evidence from MENASA and ASEAN economies indicates sharp declines in ROA and ROE, heightening insolvency risk and earnings volatility (Muntaqiah & Akhmadi, 2024). This raises a critical question: does ROA causally enhance bank stability, measured by the Z-score, and how does this relationship vary across different risk conditions?

Existing research predominantly employs linear models (e.g., OLS, GMM), which inadequately capture nonlinear, high-dimensional interactions and provide limited interpretability regarding how profitability transmits to stability under systemic stress. In contrast, emerging methodologies integrating Machine Learning (ML), Causal Inference, and Explainable AI (XAI), such as SHAP (Lundberg & Lee, 2017), enable precise causal estimation and interpretability of when and why ROA strengthens or weakens financial resilience.

This study introduces a hybrid analytical framework combining causal inference, ML, and explainability to examine the ROA–stability nexus, emphasizing liquidity risk (FGAP) and pandemic-induced shocks. Feature selection is performed using penalized regressions (Lasso, Ridge, Elastic Net) to address multicollinearity and overfitting. Among these, Ridge regression demonstrates superior robustness and predictive accuracy in noisy, correlated financial data typical of emerging markets (Sun et al., 2024; Tu et al., 2025).

* *Ho Chi Minh City University of Banking; email: tupt@hub.edu.vn*

Using a balanced panel of 63 commercial banks across six ASEAN economies (2010–2023), the study integrates (i) penalized feature selection, (ii) causal estimation via DML, (iii) predictive modeling with eight ML algorithms optimized through PSO, and (iv) interpretability using SHAP analysis. By linking profitability, liquidity stress, and systemic shocks within a unified causal–ML framework, the study enhances predictive precision and offers actionable insights for deploying ROA as an early-warning indicator in volatile, capacity-constrained financial systems.

2. Theoretical Framework and Literature Review

2.1. Profitability and Bank Stability

Traditional financial theory posits that profitability is a key determinant of bank stability through mechanisms such as internal capital accumulation and risk buffer formation (Berger & Bouwman, 2013). Specifically, Return on Assets (ROA) reflects a bank's ability to generate returns from its assets, thus indicating its inherent capacity to sustain operations and meet liquidity obligations.

However, empirical evidence suggests that this relationship is not always linear. In periods of economic turbulence, ROA may also reflect heightened risk-taking behaviors, as banks pursue short-term returns through aggressive asset allocation. Fu et al. (2014) found that under conditions of rising macroeconomic uncertainty, the link between profitability and stability becomes nonlinear and sensitive to capital structure and risk management strategies.

2.2. Liquidity Risk and Pandemic Shocks

Liquidity maintenance is vital for bank survival, particularly during times of systemic crisis. The liquidity gap (FGAP) - the mismatch between short-term liquid assets and liabilities - serves as a key indicator of liquidity pressure (Vodová, 2011). During the COVID-19 pandemic, study by Demirgüç-Kunt et al. (2021) emphasized that this shock not only eroded profitability but also substantially heightened liquidity risk and systemic contagion.

Liquidity fragility remains a central source of systemic vulnerability among banks in emerging ASEAN economies, where heavy reliance on short-term funding and limited access to interbank markets heighten exposure to liquidity shocks. Empirical evidence by Huong et al. (2021) demonstrates that liquidity risk substantially weakens bank performance and amplifies the transmission of macro-financial shocks, underscoring the importance of adaptive liquidity management and context-sensitive regulatory frameworks to safeguard financial stability.

Moreover, Kumar & Prasanna (2019) revealed that liquidity risk tends to be procyclical during global financial disruptions, especially for banks with short-term funding profiles. These patterns - first observed during the 2008 global financial crisis - were amplified during the COVID-19 pandemic, raising the need to re-examine the interactions between ROA, FGAP, and external shocks.

2.3. Causal and Machine Learning Frameworks in Finance

The relationship between ROA, liquidity, and bank stability is inherently complex and often influenced by unobserved confounders. Conventional methods such as linear regression and GMM may fall short in accurately identifying causal effects in such settings (Chernozhukov et al., 2018). DML combines modern causal inference with ML, allows for robust control of confounding variables and unbiased estimation of average and conditional treatment effects (ATE and CATE).

Meanwhile, there is growing demand for model transparency in financial ML applications. SHAP have emerged as a powerful tool for interpreting model predictions through cooperative game theory, quantifying the marginal contribution of each input variable (Lundberg & Lee, 2017). XAI enhances transparency and fulfills ethical and compliance requirements in complex financial systems (Černevičienė & Kabašinskas, 2024). The integration of causal inference and interpretable modeling thus represents an emerging paradigm in financial risk management.

2.4. Research Gap and Contributions

While previous studies have addressed the individual effects of ROA, FGAP, and COVID-19 on bank stability, few have proposed a unified framework that integrates these elements under a modern, explainable causal learning approach. Specifically, to the best of our knowledge, no existing work simultaneously combines three core elements of next-generation financial AI: (i) ML for predictive accuracy, (ii) global optimization via PSO, and (iii) explainability via SHAP for transparent, logic-traceable outputs.

In addition, this research makes a notable contribution in the preprocessing and variable engineering phase - often overlooked in ML-based financial studies. By systematically applying Lasso, Ridge, and Elastic Net regressions, we not only improve variable selection but also identify latent predictors with nonlinear interactions. The inclusion of interaction terms and nonlinear transformations among ROA, FGAP, and COVID-19 enhances the model's ability to uncover hidden causal patterns.

What sets this study apart is its multi-layered integration of DML (for causal identification and CATE estimation), PSO (for predictive model optimization), and SHAP (for interpretability). This approach enables us to answer not just whether ROA affects bank stability, but also how, under what conditions, and for which types of banks the effect occurs. By adopting this comprehensive analytical structure, the study not only delivers more robust empirical insights, but also constructs an explainable causal map - one that regulators, supervisors, and bank managers can utilize to support strategic decision-making in increasingly volatile financial environments.

3. Methodology

3.1 Data Description and Preprocessing

This study utilizes a balanced panel dataset comprising 63 commercial banks across six ASEAN economies - Indonesia, Malaysia, Philippines, Singapore, Thailand, and Vietnam - from 2010 to 2023. The dataset includes micro-level financial indicators (e.g., ROA, Z-score, FGAP, ETA, SIZE), macroeconomic variables (GDP, inflation), and a COVID-19 dummy to represent pandemic-induced shocks. Outlier treatment is performed using IQR and Z-score methods. Min - Max normalization is applied to rescale input variables, followed by the generation of nonlinear and interaction terms (e.g., ROA^2, $FGAP^2$, ROA×COVID, ROA×FGAP, FGAP×COVID).

Feature expansion through nonlinear transformation and interaction terms enables machine learning and causal inference models to uncover latent relationships that traditional linear frameworks often miss.

3.2. Dependent Variable: Bank Stability

The Z-score, a widely accepted proxy for bank insolvency risk, is employed as the primary dependent variable:

$$Z_{score\ it} = \frac{ETA_{it} + ROA_{it}}{\sigma_{ROA\ i}} \qquad (1)$$

Where ETA is the equity-to-assets ratio, and σ(ROA) is the standard deviation of ROA. A higher Z-score indicates greater bank stability and a lower probability of default (Berger & Bouwman, 2013; Tu et al., 2025).

3.3. Feature Selection via Regularized Regression

To address multicollinearity and reduce dimensionality in high-noise environments, we apply three penalized regression techniques: Lasso, Ridge, and Elastic Net. These methods are effective in controlling overfitting and variable selection in financial datasets with highly correlated features (Tibshirani, 1996). Among the three, Ridge regression outperforms in terms of stability and predictive power, especially in emerging markets (Sun et al., 2024; Tu et al., 2025). Model performance is assessed using R^2, Root Mean Squared Error (RMSE), and 5-fold cross-validation (CV).

3.4. Causal Estimation Using Double Machine Learning

To estimate the causal effect of ROA on Z-score while accounting for numerous confounding factors, this study employs the Double Machine Learning (DML) framework proposed by Chernozhukov et al. (2018). DML is particularly suited to financial applications involving nonlinearities and high-dimensional data, as it produces unbiased treatment estimates even when predictive models are imperfect.

The central innovation of DML lies in its orthogonalization strategy, which mitigates bias from overfitting and model misspecification. This is achieved by first using machine learning algorithms (e.g., Random Forest, XGBoost) to predict both the treatment variable (ROA) and the outcome variable (Z-score) from the full set of covariates. The residuals from these predictions are then regressed against one another to estimate the causal effect of ROA on stability. This residual-on-residual approach ensures the causal parameter is orthogonal to nuisance components, yielding consistent inference under flexible model specifications.

Beyond estimating the average treatment effect, the framework is extended to capture treatment heterogeneity by interacting residualized ROA with key moderators, specifically, the liquidity gap (FGAP) and a COVID-19 crisis dummy. This allows for the estimation of conditional average treatment effects (CATE), revealing how the profitability–stability relationship varies across liquidity and crisis conditions. Leveraging the flexibility of ensemble learners such as Random Forest and XGBoost, DML isolates context-dependent causal patterns that traditional linear models (e.g., OLS or GMM) cannot uncover, enabling a deeper understanding of when and for whom profitability enhances stability.

3.5. Training and Optimization of Machine Learning Models

To maximize predictive accuracy and prevent overfitting in complex financial data, the study applies Particle Swarm Optimization (PSO) as a global metaheuristic algorithm for hyperparameter tuning. Inspired by collective behavior in nature (Kennedy & Eberhart, 1995), PSO optimizes model parameters by iteratively searching for global minima in non-convex, multidimensional loss surfaces.

Eight supervised learning algorithms are trained, include CatBoost, XGBoost, LightGBM, Gradient Boosting, Random Forest, Support Vector Regression, K-Nearest Neighbors, and Decision Tree. PSO enhances performance by dynamically adjusting key parameters (e.g., learning rate, depth, estimators) based on cross-validated RMSE, improving computational efficiency and convergence stability. The optimized models achieve substantial gains in predictive precision, with CatBoost and XGBoost yielding post-optimization R^2 values exceeding 93%, confirming PSO's effectiveness in calibrating nonlinear learners in volatile financial settings.

3.6. Explainable AI via SHAP

While predictive accuracy is essential, interpretability is equally critical in banking applications, where regulatory transparency and accountability are required. To this end, SHAP, a cooperative game theory–based framework, is employed to interpret the predictions of the best-performing model (CatBoost). SHAP quantifies each feature's marginal contribution to model output, decomposing complex predictions into additive, intuitive components.

At the global level, SHAP summary plots rank variables by their average impact on bank stability, identifying ROA, FGAP, and their interaction terms as dominant determinants. At the local level, dependence and force plots reveal how variations in individual features affect predicted stability, exposing nonlinear thresholds and context-dependent interactions. Together, these insights transform opaque machine learning models into interpretable tools for financial supervision, allowing policymakers and managers to understand not only what drives stability, but why and under what conditions profitability translates into resilience.

To ensure generalizability and reliability of the findings, we conduct a comprehensive robustness validation process, such as: K-fold cross validation, bootstrap resampling, subgroup analysis by bank size, country, and capital structure, comparison across pre- and post-COVID periods. These checks ensure that the estimated causal effects are not only sample-specific but also hold practical significance for policy and managerial applications.

4. Empirical Results

4.1. Regularization Performance: Lasso, Ridge, and Elastic Net

To select the optimal predictors while minimizing multicollinearity and overfitting, three penalized regression methods were employed. Among them, Ridge regression exhibited the highest performance:

Ridge Regression: $R^2 = 0.6676$; RMSE = 0.3017

Lasso: $R^2 = 0.6216$; RMSE = 0.3219

Elastic Net: $R^2 = 0.6171$; RMSE = 0.3238

These findings reaffirm the robustness of Ridge regression in financial datasets with highly correlated features, consistent with recent empirical validations in high-dimensional macro-finance applications (Sun et al., 2024).

This result compellingly highlights the superior stability and robustness of Ridge regression across a wide range of regularization strengths. While Lasso and Elastic Net exhibit a sharp degradation in performance (R^2) and a steep rise in error (MSE) as the penalty increases, Ridge maintains consistently high explanatory power, underscoring its effectiveness for high-dimensional, correlated financial datasets - especially in emerging market contexts where variable multicollinearity is prevalent.

4.2. Causal Effects Estimation via Double Machine Learning

To estimate the causal impact of profitability on bank stability, we employ the DML framework, which allows for robust treatment effect estimation in the presence of high-dimensional, nonlinear confounders (Chernozhukov et al., 2018). Specifically, we estimate both the ATE and the CATE of ROA on Z-score, while accounting for potential heterogeneity across liquidity conditions and crisis periods.

To control for unobserved heterogeneity, we incorporate bank-level fixed effects in the residualization stage of DML. Covariate functions for both treatment (ROA) and outcome (Z-score) are estimated using Random Forest and XGBoostlearners under a 5-fold cross-fitting scheme. Statistical inference is conducted using 500 bootstrap replications, allowing us to construct 95% confidence intervals and assess p-values.

The estimated ATE of the COVID-19 pandemic (dummy = 1) on Z-score is –578.97, which is statistically significant at the 1% level ($p < 0.01$, 95% CI: [–694.2, –462.3]). This confirms a strong average destabilizing effect of systemic shocks on bank stability. To explore treatment heterogeneity, we estimate CATEs across combinations of FGAP levels (high/low) and time periods (pre-/during COVID). Results are summarized in Table 1.

Table 1. COVID-19 CATE Estimates by FGAP and Time

Group	CATE	95% CI	
High FGAP - During COVID	-854,233	[–962,108 ; –741,947]	<0,001
High FGAP - Pre-COVID	-574,372	[–691,002 ; –455,885]	<0,001
Low FGAP - During COVID	-205,811	[–328,994 ; –91,670]	<0,005
Low FGAP - Pre-COVID	42,753	[–79,219 ; +163,802]	0,421

Source: Author' own work

These results confirm substantial treatment effect heterogeneity. The most severe destabilizing effects are observed in banks with high liquidity gaps during crisis periods, while the effect is negligible or statistically insignificant for low-FGAP banks in stable conditions. These findings suggest that the destabilizing effect of COVID-19 is significantly amplified among banks with higher liquidity gaps. This complements prior evidence in global contexts (Mashamba, 2022), while also extending causal inference with richer interaction structures. The destabilizing effect is significantly stronger for banks with high FGAP during the COVID-19 period.

4.3. Predictive Performance of Machine Learning Models

Eight machine learning algorithms were trained and evaluated before and after hyperparameter optimization using PSO. Post-optimization results show marked improvement, especially in CatBoost and XGBoost.

Table 2. Predictive performance of ML models before and after PSO-based optimization

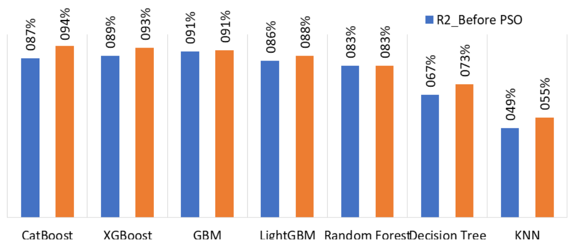
Models	RMSE_Before PSO	R2_Before PSO	RMSE_After PSO	R2_After PSO
CatBoost	0,2036	86,97%	0,1388	93,95%
XGBoost	0,1909	88,54%	0,1499	92,94%
GBM	0,1706	90,85%	0,1649	91,45%
LightGBM	0,2122	85,85%	0,1925	88,36%
Random Forest	0,2327	82,98%	0,2383	82,15%
Decision Tree	0,3236	67,09%	0,2939	72,85%
KNN	0,4027	49,03%	0,3795	54,72%
SVR	0,4088	0,4748	0,3857	0,5324

Source: Authors' own work

Table 2 provides a detailed presentation of the training results obtained from machine learning algorithms, both before and after the application of PSO. This table reports RMSE and R^2 metrics for eight machine learning algorithms, evaluated before and after hyperparameter tuning via PSO. Post-optimization results demonstrate significant improvements in CatBoost, XGBoost, and GBM, highlighting the effectiveness of PSO in enhancing model accuracy.

Traditional models such as OLS and GMM underperformed ($R^2 < 0.55$), underscoring the value of nonparametric machine learning, especially in nonlinear, noisy datasets. Figure 1 displays the comparative R^2 before and after PSO optimization.

Figure 1. Model performance comparison before and after hyperparameter optimization via PSO (R^2 Scores)



Source: Author' own work

The bar chart presents the R^2 for various machine learning models before and after applying PSO. Overall, PSO consistently improved model accuracy, with CatBoost, XGBoost, and GBM achieving the highest post-optimization performance.

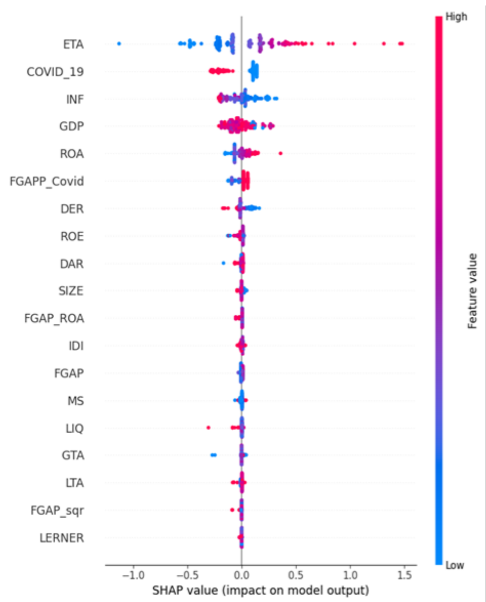
4.4. SHAP-Based Explainability

To enhance interpretability and uncover the mechanisms behind the model's predictive structure, SHAP analysis was applied to the best-performing CatBoost model (R^2 = 93.95%, RMSE = 0.1388). SHAP enables both global and local interpretability by quantifying each feature's marginal contribution to the predicted Z-score, transforming the model from a "black box" into a transparent "glass box."

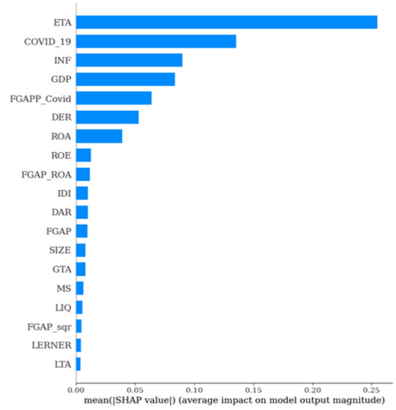
At Figure 2, Panel (a) ranks all input variables by their mean absolute SHAP values, showing that capital strength (ETA) and systemic shocks (COVID-19) are the most influential determinants of bank stability, followed by macroeconomic variables (INF, GDP) and interaction terms such as FGAP × COVID. ROA demonstrates moderate standalone importance but interacts strongly with liquidity and systemic factors, confirming the conditional profitability–stability hypothesis.

Figure 2. SHAP Summary Plot

Panel (a). Feature contributions to predicted Z-score



Panel (a). Global feature importance in predicting Z-score



Source: Author' own work

Panel (b) visualizes SHAP value distributions across all observations, revealing both the direction and intensity of each feature's effect on the Z-score. ETA and COVID-19 exhibit the most consistent contributions, while ROA displays asymmetric behavior, its stabilizing influence increases under moderate conditions but weakens markedly with higher FGAP or during pandemic stress. The color gradient highlights nonlinear dependencies and cross-feature interactions that traditional linear regressions cannot capture.

SHAP-based diagnostics confirm that ROA is a critical but conditional driver of bank resilience. The combination of high liquidity stress (FGAP > 0.15) and low profitability (ROA < 0.5%) can even reverse its stabilizing effect. These insights validate the theory of conditional profitability–stability transmission and demonstrate the value of explainable AI for supervisory practice. By revealing when and why ROA influences financial stability, SHAP enhances transparency and enables data-driven, context-aware early-warning systems, advancing the shift toward interpretable AI in prudential regulation (Černevičienė & Kabašinskas, 2024).

The SHAP-based analysis further reveals that the stabilizing impact of profitability on bank stability is inherently nonlinear and contingent upon contextual stressors such as liquidity pressure and systemic crises. Specifically, the effect of ROA on Z-score strengthens when liquidity gaps are low but weakens markedly as FGAP exceeds 0.15 or during pandemic periods, indicating that profitability's resilience-enhancing role diminishes under adverse liquidity and crisis conditions. This pattern underscores a threshold dynamic, wherein ROA above approximately 1.2% yields disproportionately stronger stabilizing effects, primarily through internal capital accumulation and improved equity buffers, while below this level, profitability loses its protective capacity. Moreover, the interaction between ROA, FGAP, and COVID-19 demonstrates a second-order moderation effect: systemic shocks not only directly erode stability but also attenuate the marginal utility of earnings as a buffer mechanism.

These findings confirm that profitability alone cannot ensure resilience without adequate liquidity management. By integrating DML and SHAP, this study uncovers these conditional, nonlinear mechanisms, shifting the interpretation of ROA's influence from a static indicator to a dynamic, context-sensitive determinant of financial stability in volatile banking environments.

5. Conclusion and Policy Implications

This study develops a comprehensive analytical framework integrating causal inference through DML, predictive optimization using ML with PSO, and model interpretability via SHAP to examine the causal effect of bank profitability ROA on institutional stability, proxied by the Z-score, under liquidity stress and systemic shocks. Using data from 63 commercial banks across six ASEAN economies (2010–2023), the findings reveal that profitability enhances stability; however, this relationship is nonlinear, context-dependent, and shaped by macro-financial conditions. The stabilizing effect of ROA is stronger when liquidity gaps are low but diminishes markedly during crises such as COVID-19. SHAP interaction plots expose hidden mechanisms and nonlinear thresholds often invisible to conventional econometric models, offering interpretable and policy-relevant insights into banking resilience in emerging markets.

The results carry important policy and managerial implications. For central banks and financial supervisors, ROA should be integrated as a forward-looking indicator in systemic early-warning systems, complemented by liquidity risk measures such as FGAP. The SHAP evidence highlights that profitability's stabilizing role weakens under liquidity stress, underscoring the need for dynamic, context-aware supervisory models. Basel prudential frameworks should incorporate countercyclical capital buffer guidelines that adjust based on profitability–liquidity interactions. Embedding DML–SHAP analytics into supervisory pipelines allows real-time causal detection and transparent interpretability, enhancing regulatory responsiveness and trust.

For bank management, profitability should be viewed not only as a performance metric but also as a strategic stability buffer. Banks achieving high ROA during normal periods should proactively reinforce capital reserves, anticipating the erosion of profitability's stabilizing power during downturns. The identified threshold of approximately 1.2% ROA can guide decisions on capital retention and dividend policy.

For investors and rating agencies, incorporating SHAP-based interpretability into credit risk models enables dynamic, event-contingent risk pricing and portfolio management.

Future research could extend this causal–explainable AI framework to other financial systems, integrate time-varying causal structures, and employ unstructured data (e.g., news sentiment or disclosures) via NLP techniques to enhance predictive precision. Embedding this hybrid model into real-time macroprudential stress testing could further strengthen regulatory and supervisory capacity in volatile financial environments.

References:

Berger, A. N., & Bouwman, C. H. (2013). How does capital affect bank performance during financial crises? Journal of Financial Economics, 109(1), 146–176. https://doi.org/10.1016/j.jfineco.2013.02.008

Černevičienė, J., & Kabašinskas, A. (2024). Explainable artificial intelligence (XAI) in finance: A systematic literature review. Artificial Intelligence Review, 57, 216. https://doi.org/10.1007/s10462-024-10619-9

Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., & Newey, W. (2018). Double/debiased machine learning for treatment and structural parameters. The Econometrics Journal, 21(1), 1–68. https://doi.org/10.1111/ectj.12097

Demirgüç-Kunt, A., Pedraza, A., & Ruiz-Ortega, C. (2021). Banking sector performance during the COVID-19 crisis. Journal of Banking & Finance, 133, 106305. https://doi.org/10.1016/j.jbankfin.2021.106305

Huong, T. T. X., Nga, T. T. T., & Oanh, T. T. K. (2021). Liquidity risk and bank performance in Southeast Asian countries: a dynamic panel approach. Quantitative Finance and Economics, 5(1), 111–133. https://doi.org/10.3934/QFE.2021006

Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. Proceedings of ICNN'95 - International Conference on Neural Networks, 1942–1948. https://doi.org/10.1109/ICNN.1995.488968

Kumar, S., & Prasanna, K. (2019). Global financial crisis: Dynamics of liquidity risk in emerging Asia. Finance: The Journal of the Institute for Financial Management and Research, 18(3), 224–238. https://doi.org/10.1177/0972652719846323

Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. Advances in Neural Information Processing Systems, 30, 1–10. https://doi.org/10.48550/arXiv.1705.07874

Mashamba, T. (2022). Liquidity dynamics of banks in emerging market economies. Journal of Central Banking Theory and Practice, 11(1), 179–206. https://doi.org/10.2478/jcbtp-2022-0008

Muntaqiah, K., & Akhmadi, A. (2024). Banking Financial Performance as Influenced by Credit Risk, Liquidity and Bank Size In Conventional Banks Listed On The Indonesian Stock Exchange For The Period 2014 - 2023. Indonesian Journal of Innovation Multidisipliner Research, 2(4), 149–160.

Sun, X., Yuan, P., Yao, F., Qin, Z., Yang, S., & Wang, X. (2024). Financial fragility in emerging markets: Examining the innovative applications of machine learning design methods. Journal of the Knowledge Economy. https://doi.org/10.1007/s13132-023-01731

Tu, P. T., Nga, H. P., & Van, L. T. (2025). Factors Affecting Banking Financial Stability in Vietnam's Emerging Economy: A Lasso, Ridge, and Elasticnet Regression Analysis. Ianna Journal of Interdisciplinary Studies, 7(1), 452–463.

Vodová, P. (2011). Liquidity of Czech commercial banks and its determinants. International Journal of Mathematical Models and Methods in Applied Sciences, 5(6), 1060–1067.