Banking and Management Review Vol. 14 No.2

Explainable Artificial Intelligence Uncovers Non-Bank Financial Industry Contagion and Implications for Central Bank Institutional Governance

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ABSTRACT

Introduction/Main Objectives: This paper examines systemic risk interconnections within Indonesia's Non-Bank Financial Industry (NBFI), which displays intricate systemic risk interconnections that alter traditional macroprudential dynamics. As financial ecosystems digitalize, understanding cross-sectoral risk transmission beyond banking is crucial for stability. The study further aims to develop a transparent artificial intelligence framework capable of supporting timely macroprudential policy interventions and institutional decision-making. **Background Problems:** Systemic risk from NBFI interconnections insurance, pension funds, finance companies, guarantee institutions, and P2P lending remains insufficiently mapped, and linear models fail to capture nonlinear contagion, raising the question of how risks transmit across NBFI sectors and what their primary drivers are. **Novelty:** This paper pioneers integrating econometrics with Explainable AI (SHAP-Random Forest) to construct an NBFI systemic risk framework, offering transparent, actionable insights for regulators to strengthen macroprudential governance and safeguard financial stability. **Research Methods:** The study employs correlation analysis, Granger causality, OLS regression, and Random Forest with SHAP decomposition using Indonesian NBFI sectoral data (2016–2024). **Finding/Results:** Results reveal strong cross-sectoral risk linkages and nonlinear transmission, identifying pension fund asset size and foreign funding exposures as dominating cross-sectoral systemic risk, contributing mean SHAP values of 0.576 and 0.326, respectively. During COVID-19, NBFI sectors acted as shock absorbers rather than amplifiers. **Conclusion:** The findings underscore the need for Algorithmic Macroprudential Governance, where explainable AI enhances evidence-based supervision, strengthens institutional autonomy, improves systemic risk monitoring in emerging financial architectures, and provides actionable insights for regulators in safeguarding long-term financial stability.

ARTICLE INFO

Keywords:
Systemic Risk_1, Non-Bank Financial Industry_2, Explainable Artificial Intelligence_3, Macroprudential Policy_4, Algorithmic Governance_5

Submitted: 29 May 2026
Reviewed: 16 July 2026
Accepted: 2 September 2026
Published: 19 November 2026

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1. Introduction

The transformation of the global financial architecture over the past two decades has shifted the structure of financial systems from a predominantly bank-centric model toward an increasingly fragmented and interconnected ecosystem-wide financial architecture (Gancarczyk et al., 2022; Palmié et al., 2020; Broby, 2021; Stefanelli & Manta, 2022). In Indonesia, the expansion of the Non-Bank Financial Industry (NBFI) comprising insurance companies, pension funds, finance companies, guarantee institutions, and peer-to-peer (P2P) lending–based financial technology platforms has generated a complex and multidimensional network of risk interconnections (Darjana et al., 2025; Harjono, 2022; Junarsin et al., 2023).

This phenomenon reflects a paradigmatic shift in financial system stability from a sectoral approach to a network-based systemic stability framework (Li & Zhang, 2024; Hasse, 2021; Gao, 2022). Within the Network Theory of Systemic Risk (Allen & Gale, 2000), financial stability is no longer determined solely by the strength of individual institutions, but rather by the structure of connectivity and the intensity of cross-sectoral exposures. A shock originating from a relatively small node, for instance, a surge in non-performing loan ratios within P2P lending platforms, can propagate through funding dependence channels, portfolio exposure linkages, and market impact channels, ultimately compelling the monetary authority to intervene as lender of last resort (Su et al., 2024; Yeo & Jun, 2020; Jiang et al., 2023; Bardoscia et al., 2021).

In this context, the role of Bank Indonesia has become increasingly strategic yet more challenging. The institutional autonomy of the central bank in safeguarding rupiah stability and financial system soundness can no longer rely exclusively on the regulation of the banking sector. The growing complexity of interactions between banks and non-bank financial institutions (NBFIs) necessitates a novel analytical framework for systemic risk. From 2016–2024, bank assets grew from IDR 4,496T to 8,086T, while NBFI assets rose from IDR 443T to 589T, yet their share declined from 8.96% to 6.79%.

The central issue addressed in this study is the rising potential for systemic risk stemming from non-bank financial interconnections that remain insufficiently mapped in structural and dynamic terms. First, the exponential growth of P2P lending has generated a pattern of Digital Minskyan Instability, characterized by speculative and Ponzi-type financing phases marked by credit accumulation and escalating default risk (Bao et al., 2023; Xu et al., 2021; Ariza-Garzón et al., 2021). A surge in the TWP90 ratio on certain platforms may trigger liquidity pressures on finance companies

dependent on external funding, amplify claims on guarantee institutions, and increase portfolio volatility within insurance companies and pension funds (Raimo et al., 2021; Gabor, 2020; Boermans & Galema, 2019).

Furthermore, the dominance of government bond (SBN) investments by insurance companies and pension funds may give rise to a shadow liquidity trap, whereby the transmission of benchmark interest rate policy becomes distorted due to concentrated ownership of sovereign instruments within the non-bank sector (Li et al., 2024; Bonizzi et al., 2023). Finally, conventional supervisory models based on linear statistical techniques and traditional macroprudential approaches remain limited in their capacity to transparently identify the primary drivers of systemic risk at specific points in time (Ran et al., 2024; Renn, 2020; Renn et al., 2020). Although black-box machine learning models demonstrate strong predictive performance, they are less suitable for public policy governance, which requires accountability and rational justification. The core research problem thus lies in the need for an early warning system and systemic risk transmission mapping framework that is not only predictively accurate but also explainable, thereby supporting the legitimacy of macroprudential policy and preserving central bank autonomy.

The existing literature on Explainable Artificial Intelligence (XAI), macroprudential policy, and central bank institutional governance has demonstrated significant progress; however, it remains conceptually and methodologically fragmented. Within the domain of XAI, Martins et al. (2024) developed an integrated taxonomy of XAI methods and identified their applications in the financial sector. While this study offers a strong conceptual contribution in classifying explainability techniques, it does not explicitly link them to financial system stability or macroprudential policy frameworks. Similarly, Hassija et al. (2023) provide a comprehensive review of black-box models and their interpretability approaches, emphasizing transparency and predictive accuracy, yet without integrating XAI into the broader context of public policy governance.

Furthermore, Weber et al. (2023) demonstrate through a systematic literature review that XAI applications in finance predominantly concentrate on credit risk management, stock price prediction, and fraud detection. In parallel, Černevičienė and Kabašinskas (2024) highlight that techniques such as SHAP, feature importance measures, and rule-based explanations are the most commonly applied methods in financial practice. Nevertheless, both studies emphasize micro-level analysis (firm-level or individual credit risk) rather than macroprudential dimensions or cross-sectoral systemic stability.

At the operational level, Nallakaruppan et al. (2024) developed an XAI-based model for assessing P2P lending credit risk using Random Forest and SHAP, achieving high predictive accuracy. Although highly relevant to digital credit risk assessment, this study did not examine risk transmission to other financial sectors or its implications for central bank policy.

From a forward-looking perspective, Luca et al. (2023) identified 27 open challenges in advancing XAI, including accountability, fairness, and multidisciplinary integration in the" XAI 2.0 Manifesto. Despite proposing a progressive research agenda, this study does not explicitly connect XAI to central bank autonomy or algorithm-based macroprudential policymaking.

On the monetary and macroprudential policy front, (Çoban, 2021) highlights the political-bureaucratic dynamics underlying macroprudential coordination in Turkey, demonstrating how analytically stronger central banks may subordinate other regulators. Although this study enriches the governance literature, it does not incorporate analytical technologies, such as AI or XAI, into decision-making processes.

In the Indonesian context, Handayani & Setiastuti (2024) identify synergies between monetary and macroprudential policies through the bank lending channel, with asymmetric effects depending on bank characteristics. Meanwhile, Adenan et al. (2024) employ a VAR framework to analyze the impact of macroprudential instruments on conventional bank performance, finding that most instruments do not exert a statistically significant effect on return on assets (ROA). Both studies remain focused on the banking sector and rely on traditional econometric approaches.

More broadly, Gaganis et al. (2020) demonstrate that the interaction between corporate governance and macroprudential policy influences bank risk-taking across countries. However, the scope of analysis remains confined to banking institutions and does not extend to the non-bank financial industry (NBFI).

Finally, within the realm of mathematical modeling, Ansori et al. (2025) developed a bank balance sheet model incorporating macroprudential instruments based on the loan-to-deposit ratio. Although this model contributes structurally to the analysis of bank stability, it does not incorporate cross-sectoral interconnections or machine learning-based approaches.

From a governance and legal reform perspective, Dwi et al. (2025) analyze financial sector legal reforms and their implications for the institutional relationship between the Bank of Indonesia and the government. Their study highlights a new perspective on central bank independence within the policy-mix framework. However, this approach remains predominantly normative-legal in nature and is not grounded in predictive quantitative modeling.

In the domain of technology governance, Wadipalapa et al. (2024) examined artificial intelligence policy in Indonesia within a decentralized governmental system and identified power asymmetries between central and regional authorities. Meanwhile, Perdana et al. (2025) proposed a governance and algorithmic regulatory blueprint for Bank Indonesia, emphasizing ethical, legal, and social aspects (GELSI). Nevertheless, both studies stop short of developing empirical models based on systemic risk data.

Within the sphere of Islamic banking, Wisandani et al. (2025) integrate RGEC indicators with the Islamicity Performance Index to evaluate the performance of Islamic banks in Indonesia. Similarly, Taufiqurrahman & Alwie (2024) investigated the effect of governance on the performance of regional development banks in the post-pandemic period. Although these studies enrich the literature on bank performance and governance, they do not address the issue of cross-sectoral systemic risk interconnections.

Based on this review, several research gaps emerge as the primary foundation of the present study. First, at the conceptual level, the literature on Explainable Artificial intelligence (XAI) in the financial sector, such as that advanced by Martins et al. (2024), Weber et al. (2023), and Černevičienė & Kabašinskas (2024), has not yet linked explainability to macro-level financial system stability or to the institutional autonomy of central banks. XAI remains largely positioned as a micro-level risk management instrument and has yet to evolve into an analytical tool within macroprudential policy frameworks.

Second, from a sectoral perspective, most macroprudential studies, including those by Handayani & Setiastuti (2024), Adenan et al. (2024), and Gaganis et al. (2020), continue to focus predominantly on the banking sector. Risk interconnections among non-bank financial institutions (NBFI), including insurance companies, pension funds, finance companies, guarantee institutions, and peer-to-peer lending platforms, have not been systematically analyzed using network-based contagion approaches capable of comprehensively capturing cross-sectoral risk transmission.

Third, methodologically, dominant approaches remain Vector Autoregression (VAR), panel regression, or deterministic mathematical models, as illustrated by Ansori et al. (2025). To date, no ensemble machine learning model grounded in XAI has been developed that can simultaneously map cross-sectoral shock transmission while providing both global and local explainability suitable for public policy formulation.

Fourth, in terms of governance and institutional autonomy, studies on governance and legal reform such as those by Dwi et al. (2025), Çoban (2021), and Perdana et al. (2025) have yet to integrate predictive data-driven quantitative models into the formulation of an algorithmic governance framework for central banks. The relationship between algorithmic transparency and the safeguarding of macroprudential autonomy remains empirically unexplored.

Fifth, from a theoretical standpoint, empirical testing of the Financial Accelerator Hypothesis and the dynamics of Digital Minskyan Instability within the context of Indonesia's shadow banking sector has not been conducted using non-bank financial industry (NBFI) data. The existing literature tends to treat systemic risk network theory, financial accelerator mechanisms, and fintech-driven instability as separate strands, without adequate computational integration.

In light of these gaps, this study occupies a distinctive position by integrating network-based systemic risk theory, empirical testing of the Financial Accelerator Hypothesis and Digital Minskyan Instability, an Explainable Artificial Intelligence (XAI) approach, and an analysis of governance implications for the macroprudential autonomy of Bank Indonesia. This integrative framework is expected to generate a novel analytical architecture that not only maps and predicts cross-sectoral systemic risk within the Non-Bank Financial Industry (NBFI) with greater precision, but also provides normative and operational foundations for strengthening algorithmic governance in Indonesia's evolving financial architecture.

This study proposes a solution through the development of an early warning model and systemic risk interconnection mapping based on Explainable Artificial Intelligence (XAI). Ensemble machine learning models, such as XGBoost and Random Forest, will be employed to predict the Financial System Stability Index using NBFI indicators over the 2016–2024 period. Subsequently, XAI algorithms, specifically SHAP (Shapley Additive exPlanations) and LIME, will be implemented to: first, generate global explainability by identifying the most dominant structural variables shaping systemic risk; and second, produce local explainability by elucidating specific crisis episodes and isolating primary transmission channels (credit risk channel, funding vulnerability channel, or market impact channel). This approach not only enhances predictive accuracy but also provides data-driven justification for the formulation of a transparent and politically unbiased Macroprudential Policy Index (MPI).

The principal motivation for this research stems from the strategic necessity to safeguard the effectiveness and autonomy of macroprudential policy amid the ongoing transformation of financial architecture. In the context of mounting fiscal pressures, accelerating financial digitalization, and deepening global market integration, central banks face the risk of eroding independence if policy interventions are not supported by robust and transparent analytical justifications. This study is grounded in the premise that algorithmic governance, defined as policy governance supported by XAI-based models, can serve as a novel instrument to reinforce public policy legitimacy while preserving institutional independence from short-term political pressure.

The overarching objective of this research is to construct an XAI-based early warning and systemic risk mapping model to analyze vulnerability interconnections within the Non-Bank Financial Industry (NBFI), and to formulate a renewed macroprudential response framework for Bank Indonesia aimed at maintaining financial system stability and strengthening institutional autonomy within a continuously transforming financial architecture.

More specifically, this study seeks to conduct a network contagion analysis by examining shock transmission patterns across five NBFI subsectors using historical data from 2016 to 2024, thereby identifying key risk nodes and cross-sectoral vulnerability propagation pathways. In addition, the

research aims to decode systemic risk triggers through the implementation of XAI algorithms to quantify the contribution of specific variables to increases in the systemic vulnerability index, while ensuring algorithmic transparency and accountability in the analytical process.

Furthermore, the study tests the applicability of emerging risk transmission theories, particularly Digital Minskyan Instability and the Financial Accelerator Hypothesis, within the context of Indonesia's shadow banking ecosystem, thereby extending the empirical validity of these theoretical frameworks to the NBFI sector. In its final stage, the research formulates governance and central bank autonomy enhancement strategies by developing recommendations for an adaptive institutional governance and macroprudential policy framework grounded in XAI-derived metrics and findings. This framework is intended to serve as a responsive policy foundation capable of addressing increasingly complex systemic risk dynamics.

This study offers contributions across three principal dimensions. First, at the theoretical level, it extends the Network Theory of Systemic Risk to the context of NBFI and fintech in developing economies, while introducing the concept of a shadow liquidity trap as a novel distortion mechanism in monetary policy transmission. Second, at the methodological level, it integrates machine learning and explainable AI into macroprudential policy frameworks, thereby bridging the gap between algorithmic prediction and public policy accountability. Third, at the policy level, it advances a paradigm shift from a bank-centric macroprudential framework toward ecosystem-wide macroprudential governance. In doing so, the study situates Bank Indonesia within the broader context of central banking in transition, where institutional autonomy is sustained not only by formal regulation but also by transparent, explainable, and adaptive data-driven analytical capacity in response to the complexity of modern financial system interconnections.

2. Literature Review

This study is grounded in two principal theoretical pillars that critically elucidate the anatomy of crises beyond the realm of traditional banking. First, the Financial Accelerator Hypothesis posits that fluctuations in asset prices within the financial sector can amplify macroeconomic cycles in a procyclical manner. Second, Minsky's Financial Instability Hypothesis, adapted in this study into the concept of Digital Minskyan Instability, argues that prolonged periods of economic stability paradoxically induce financial institutions to assume progressively higher levels of risk. In the contemporary digital era, this dynamic manifests in the exponential growth of Peer-to-Peer (P2P) lending platforms, often accompanied by asymmetric risk management practices.

Based on the empirical findings of this research, the interaction of these two theoretical frameworks appears to generate a disrupted dynamic that gives rise to what we term a "Shadow Liquidity Trap." This phenomenon suggests that the accumulation of safe-haven assets such as

government bonds (Surat Berharga Negara/SBN) by insurance companies and pension funds does not linearly transmit macro credit cycles. Instead, it creates new liquidity frictions that may dampen shocks (as evidenced during the 2020 pandemic), while simultaneously reshaping the transmission landscape of monetary policy.

2.1 Central Bank Autonomy Transition and Macroprudential Policy

In response to an increasingly complex financial architecture, the mandate of central banks worldwide has undergone a fundamental transition. Dwi et al. (2025) highlight financial sector legal reforms in Indonesia, particularly through Law No. 4/2023 on Financial Sector Development and Strengthening (UU P2SK), which underscore that the independence of Bank Indonesia (BI) now requires a coherent policy mix capable of accommodating financial system stability without subordinating monetary policy objectives. Such macroprudential governance frequently intersects with bureaucratic and political dynamics; Çoban (2021) emphasizes the necessity of institutional coordination to prevent regulators from functioning merely as regulatory intermediaries for political and business interests.

Previous studies have predominantly concentrated on the effectiveness of macroprudential instruments such as the countercyclical capital buffer and minimum statutory reserves within conventional banking (Adenan et al., 2024; Handayani & Setiastuti, 2024), as well as on mathematical modeling of bank balance sheets (Ansori et al., 2025). Gaganis et al. (2020) further demonstrate that the effectiveness of such macroprudential policies is highly contingent upon corporate governance structures within financial institutions. Nevertheless, this body of literature remains confined to a bank-centric paradigm and has not comprehensively assessed the impact of these policies on the resilience and governance of non-bank entities, whose performance is likewise shaped by governance factors such as risk committees and board size (Taufiqurrahman & Alwie, 2024; Iwan et al., 2025).

2.2 Risk Interconnections and Non-Bank Financial Institutions (NBFI)

Systemic interactions between banks and Non-Bank Financial Institutions (NBFI) constitute a critical blind spot in traditional macroprudential supervision. Wadipalapa et al. (2024) note that information asymmetry and decentralized governance structures in Indonesia often hinder cross-sectoral policy harmonization. In the context of digital credit risk, Nallakaruppan et al. (2024) find that peer-to-peer (P2P) lending platforms harbor latent default risks that require AI-based assessment to mitigate spillover effects on other financial service institutions. If P2P-related risks propagate through funding vulnerability channels to finance companies (multifinance institutions) that remain dependent on bank borrowing, the transmission of shocks to the central banking system becomes unavoidable.

2.3 Algorithmic Governance and Explainable AI (XAI) in the Financial Ecosystem

With the growing adoption of machine learning in the financial sector, there is increasing urgency to address the “black-box” problem inherent in complex AI models (Hassija et al., 2023; Longo et al.,

2023). Explainable Artificial Intelligence (XAI) has emerged as a critical solution to ensuring transparency and accountability in algorithmic decision-making (Martins et al., 2024). Systematic reviews by Weber et al. (2023) and Černevičienė and Kabašinskas (2024) demonstrate that XAI techniques such as SHAP and LIME, when combined with Random Forest and XGBoost models, have been successfully implemented in credit risk management and stock price prediction.

Within the domain of public policy and central banking, the adoption of AI requires a robust governance, ethical, and regulatory framework. Perdana et al. (2025) proposed a GELSI (Governance, Ethics, Legal, and Social Implications) blueprint for algorithmic governance at Bank Indonesia. This framework emphasizes that algorithms deployed in financial systems must be free from historical bias and capable of fostering trust. The implementation of both local and global explainability through SHAP values, as applied in this study (in line with the approach of Nallakaruppan et al., 2024), empirically addresses these governance challenges by transforming raw data into accountable macroprudential insights.

2.4 Literature Synthesis and Research Novelty (State of the Art)

Based on the foregoing review, clear theoretical and methodological gaps remain. First, most macroprudential studies concerning Bank Indonesia focus on transmission effectiveness within conventional and Islamic banking sectors (Handayani & Setiastuti, 2024; Adenan et al., 2024), while overlooking cross-border exposure interconnections and market impact channels within the broader NBFI ecosystem. Second, research on XAI in finance continues to be dominated by micro-level applications, such as customer credit scoring and fraud detection (Černevičienė & Kabašinskas, 2024; Weber et al., 2023). Although Perdana et al. (2025) theoretically underscore the importance of algorithmic governance for Bank Indonesia, no empirical quantitative study has directly applied XAI to deconstruct a macroprudential Systemic Risk Index at the level of shadow banking institutions.

Accordingly, this study seeks to fill these research gaps by: (1) comprehensively reconstructing risk interconnections across the five pillars of the NBFI; (2) testing the disruption of conventional theories within a transitional financial landscape; and (3) formulating macroprudential policy thresholds (an early warning system) grounded in algorithmic governance through the application of global and local explainability approaches. In doing so, the study not only advances the modern econometric and computational finance literature but also formulates a concrete strategy to safeguard the institutional autonomy of Bank Indonesia against non-linear crisis shocks.

3. Method, Data, and Analysis

This study employs an empirical quantitative design integrating machine learning and econometric approaches. The primary focus is to analyze systemic risk interconnections within Indonesia's Non-

Bank Financial Industry (NBFI). The data utilized consist of historical time-series secondary data spanning the period from 2016 to 2024. These data represent aggregate measures of five NBFI subsectors: insurance companies, finance companies (multifinance institutions), pension funds, guarantee institutions, and fintech peer-to-peer (P2P) lending platforms. The dataset is derived from official databases of Bank Indonesia and Otoritas Jasa Keuangan (OJK).

The study categorized variables into two principal groups. First, the dependent variable (target) is the Systemic Risk Index (SRI), which is independently constructed using key ecosystem vulnerability proxies, namely the claims ratio, external borrowing of multifinance institutions, and non-performing loans (NPL) in P2P lending. Second, the independent variables (predictor features) consist of eight NBFI risk transmission indicators: insurance assets, insurance government bond (SBN) portfolio holdings, investment-to-technical reserve ratio, conventional financing receivables, multifinance foreign borrowing, pension fund assets, pension fund investment-to-asset ratio (RITA), and guarantee claims ratio.

To address the conceptual framework concerning institutional governance and central bank autonomy in the era of a New Financial Architecture, data analysis was conducted in four stages. The first stage involves constructing a Systemic Risk Index (SRI). Given that NBFI indicators are measured in heterogeneous units (percentages, ratios, and nominal rupiah values), all variables are standardized using the Z-score approach. The Systemic Risk Index is then constructed as a weighted average of funding and credit risk vulnerabilities, adjusted by the premium resilience component.

$$SRI_t = Z_{Funding,t} + Z_{NPL,t} - Z_{Premium,t} \quad (1)$$

The second stage involves Risk Interconnection Mapping (Network Contagion Analysis). To detect whether shocks originating in one NBFI subsector asymmetrically precede and influence other subsectors for instance, the transmission of digital credit risk from P2P lending to credit growth in multifinance institutions the Granger causality test model is employed.

$$Y_t = \alpha_0 + \sum_{j=1}^{k} \alpha_j Y_{t-j} + \sum_{j=1}^{k} \beta_j X_{t-j} + \epsilon_t \quad (2)$$

The third stage involves predictive modeling using an ensemble machine learning approach. After constructing the index, the Random Forest Regressor algorithm is employed to model the non-linear relationships between the eight NBFI indicators and the Systemic Risk Index. Random Forest is selected due to its capacity to address multicollinearity and small-sample data constraints by constructing an ensemble of decision trees, thereby enhancing model robustness and predictive stability.

$$Y = \frac{1}{B} \sum_{b=1}^{B} T_b(x) \quad (3)$$

The final stage focuses on algorithmic transparency through Explainable Artificial Intelligence (XAI). To open the "black box" of the Random Forest model and inform the formulation of macroprudential policy at Bank Indonesia, the Shapley Additive exPlanations (SHAP) method is applied. SHAP is grounded in Cooperative Game Theory and computes the fair marginal contribution of each NBFI variable to systemic risk formation, both at the aggregate level (Global Explainability) and at specific time points, such as during the 2020 pandemic crisis (Local Explainability).

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(M-|S|-1)!}{M!} [f_x(S \cup \{i\}) - f_x(S)] \quad (4)$$

As a classical linear causality verification tool to test the Financial Accelerator Hypothesis, a multiple Ordinary Least Squares (OLS) regression model is employed. The objective is to compare the sharpness of linear monetary policy transmission with the non-linear insights derived from the XAI-based model.

$$Y_t = \beta_0 + \beta_1 X_{1,t} + \beta_2 X_{2,t} + \epsilon_t \quad (5)$$

All stages of data processing, econometric testing, and ensemble machine learning modeling in this study are executed using Python-based software. The implementation of the Random Forest Regressor is conducted through the Scikit-Learn library, while algorithmic transparency extraction is facilitated by the SHAP (Shapley Additive exPlanations) library. Classical statistical testing, including OLS regression and Granger causality analysis, is performed using Statsmodels, supported by Pandas for dataframe manipulation. Python is selected due to its advanced computational capabilities and precision in decomposing black-box XAI models.

4. Result and Discussion

4.1 Result

The findings of this study address the fundamental question of the transmission channels of shocks (the "what") within the NBFI ecosystem. Based on the Correlation Matrix, as visualized in Figure 1 on Cross-Sectoral Contagion Risk, empirical evidence reveals strong interconnections among subsectors that were previously assumed to operate in a relatively segmented manner. This finding confirms that the risk structure within the Non-Bank Financial Industry (NBFI) is inherently interconnected rather than operating in isolation.

Empirically, a very strong positive correlation (r = 0.886) is identified between the non-performing loan ratio of peer-to-peer (P2P) lending, measured by loans overdue more than 90 days, and the composition of government bond (SBN) investment portfolios in the insurance sector. Furthermore, the P2P non-performing loan ratio exhibits a strong positive correlation with the

guarantee claims ratio (r = 0.714). This pattern indicates a significant relationship between digital credit risk and asset allocation dynamics, as well as risk exposure across other NBFI subsectors.

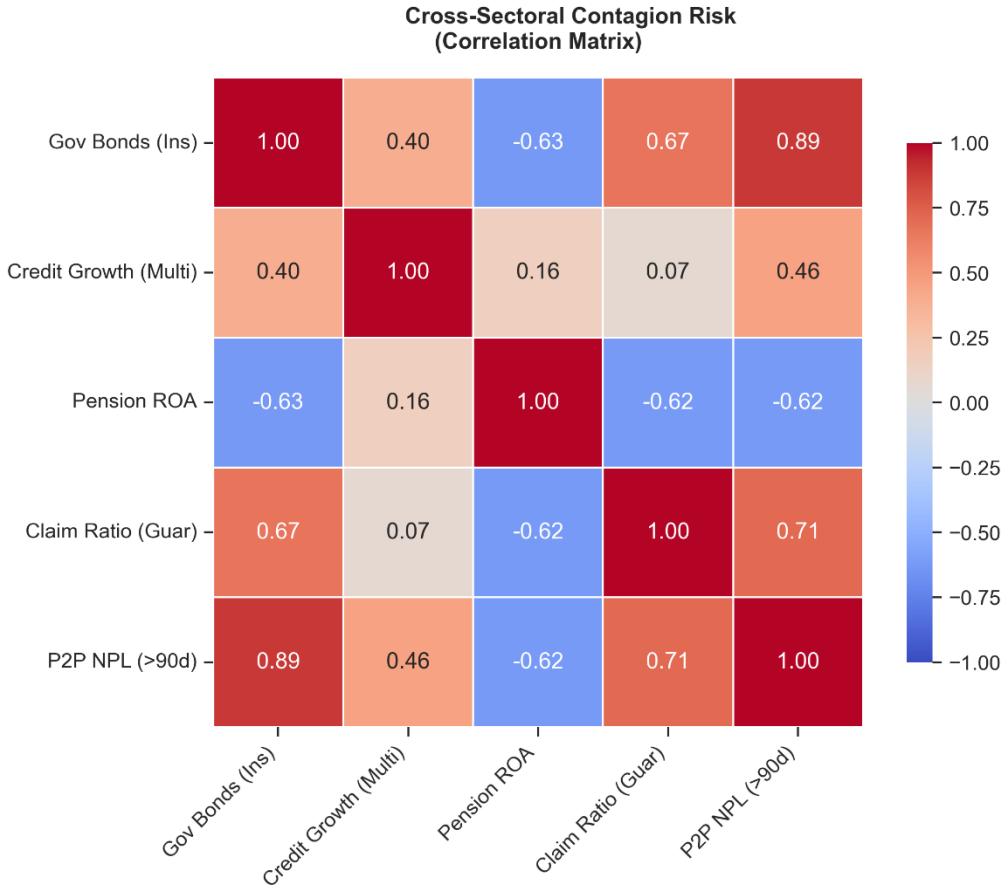


Figure 1. Cross-Sectoral Contagion Risk
Source: Phyton, 2026

From a transmission perspective, these findings point to a phenomenon in which digital credit risk does not remain confined to financial technology platforms. A surge in default rates within the P2P lending sector moves in tandem with increasing pressure on guarantee institutions, which in practice may underwrite portions of digital MSME credit. Simultaneously, the insurance sector exhibits a tendency to reallocate its portfolio more aggressively toward safe-haven instruments such as government bonds (SBN), reflecting a flight-to-quality response amid heightened risk uncertainty.

Interestingly, the results presented in Table 1, which reports the Granger Causality Test, indicate that a linear causality approach fails to provide statistically significant evidence that the P2P non-performing loan ratio directly affects multifinance financing growth at lag-1 (p-value = 0.1815). This lack of statistical significance suggests that risk transmission within the NBFI ecosystem does not operate in a simple and linear manner; rather, it appears to be latent and potentially non-linear. These findings provide methodological justification for employing a machine learning approach in the subsequent stage of analysis to capture more complex and hidden risk dynamics.

Table 1. Granger Causality Test (Transmission Direction)

Transmission Direction	Lag	P-Value	Conclusion
P2P Stuck -> Multifinance Growth	1	0.1815	Not Significant

Source: Python, 2026

To address the question of how crisis-triggering variables interact with precision, the Random Forest Regressor model is interpreted using the SHAP (Shapley Additive Explanations) approach, as presented in Figure 2 on XAI Systemic Risk Drivers. This Explainable Artificial Intelligence (XAI) framework effectively resolves the black-box problem inherent in machine learning models by isolating and quantitatively measuring the contribution of each variable to the formation of the Systemic Risk Index (SRI) in a transparent manner.

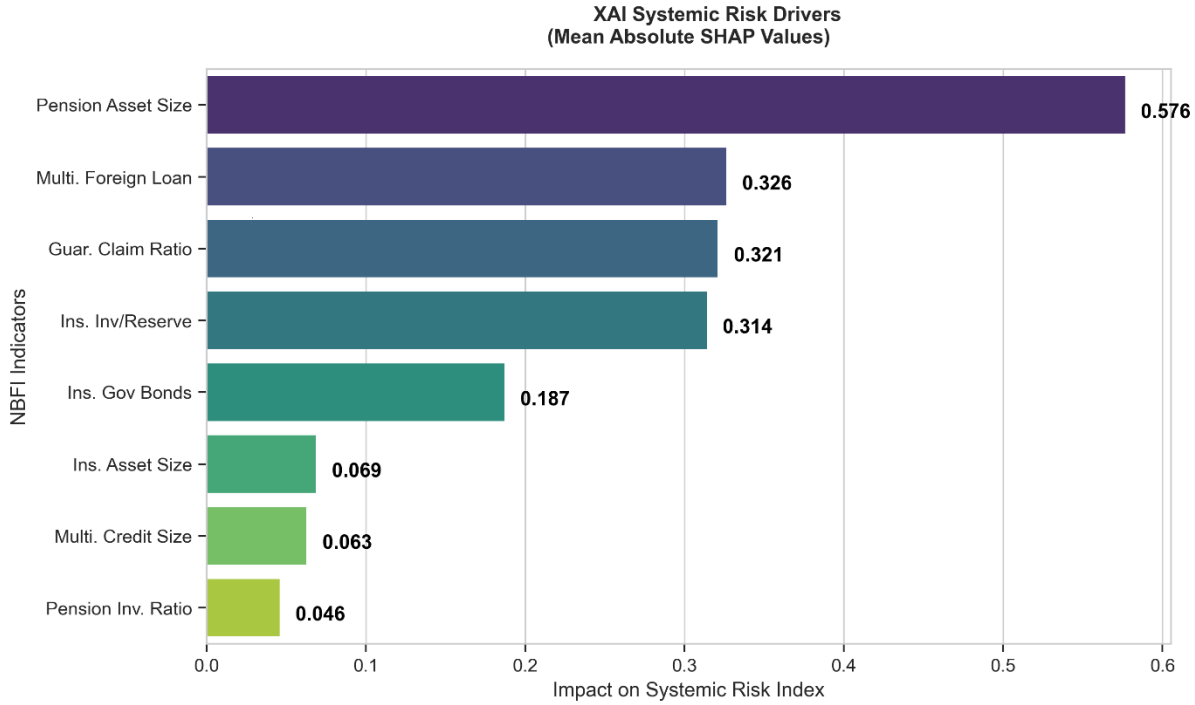


Figure 2. XAI Systemic Risk Drivers
Source: Python, 2026

The estimation results indicate that the ratio of Pension Fund Assets to Total Financial Sector Assets constitutes the largest contributor to systemic risk, with a mean absolute SHAP value (Mean |SHAP|) of 0.5765. This finding validates the presence of a market impact channel, whereby liquidity shocks in the pension fund subsector possess the strongest spillover capacity and the most significant potential impact on aggregate financial system stability. In other words, pressures on pension fund portfolios and cash flows may generate multiplier effects that amplify systemic vulnerability.

The second-largest risk contributor is the proportion of bank and foreign borrowings in the multifinance sector, with a Mean |SHAP| of 0.3263. This result underscores that funding vulnerability

arising from cross-border exposure represents a critical channel for crisis transmission from global markets to the domestic financial system. Dependence on external funding sources heightens sensitivity to international interest rate volatility, shifts in global investor sentiment, and external liquidity pressures.

Furthermore, SHAP-based risk contribution quantification carries important implications for the transparency and effectiveness of macroprudential policy. Supported by explainability metrics, Bank Indonesia no longer needs to conduct broad and unfocused surveillance across all indicators simultaneously. Instead, supervisory resources can be prioritized toward the three to four indicators with the highest Mean |SHAP| values. This approach enables the formulation of more precise, adaptive, and evidence-based policies to safeguard financial system stability.

Beyond identifying long-term risk drivers (Global Explainability), the Explainable AI (XAI) algorithm also possesses forensic capabilities to dissect specific time points (Local Explainability). In this study, the analysis focuses on the 2020 observation to examine the anatomy of the COVID-19 pandemic shock on the stability of the Non-Bank Financial Industry (NBFI).

Based on the comprehensive visualization in Figure 3, a highly significant theoretical anomaly emerges: in the first year of the pandemic, the NBFI Systemic Risk Index (SRI) declined to -1.4595, substantially below its historical expected mean (Base Value = 0.2658). In aggregate, all variables within the NBFI ecosystem exhibited a net risk-mitigating contribution, as reflected in a Total SHAP Impact of -1.7252. This figure indicates that, during the observation period, the fundamental configuration of the non-bank financial sector functioned more as a shock absorber than as an amplifier of stress. The Local SHAP Values further reveal, with full transparency, the internal mechanisms through which each indicator contributed to either dampening or intensifying systemic risk.

The empirical findings demonstrate that the NBFI ecosystem functioned as a shock absorber rather than an amplifier. The real-sector economic shock triggered by the pandemic did not transmit into a systemic crisis within the non-bank financial sector due to the buffering effect of several key indicators exhibiting negative SHAP values. The ratio of Pension Fund Assets to Total Financial Sector Assets recorded a SHAP value of −0.7891, making it the largest mitigating variable in 2020. The long-term and relatively closed liability structure of pension funds rendered this subsector more resilient to short-term liquidity panic. This structural stability played a significant role in containing the pace of crisis contagion to other subsectors.

Moreover, the Insurance Investment-to-Technical Reserves Ratio (SHAP = −0.2557) and the composition of Government Bonds (SBN) in insurance portfolios (SHAP = −0.2072) indicate that the insurance sector's response through strengthening technical reserves and reallocating portfolios

toward safer instruments constituted an effective stabilization strategy. The shift of assets toward SBN as safe-haven instruments reflects a flight-to-quality mechanism that served as an anchor of stability amid heightened volatility.

Within the multifinance sector, the Foreign Borrowing variable exhibited a SHAP value of −0.2366, suggesting that the reduction in the proportion of bank and external loans, including the widespread credit restructuring implemented in 2020, effectively curtailed funding vulnerability channels. These measures, undertaken in coordination with relevant authorities including Bank Indonesia, contributed to preventing potential capital flight that could have amplified systemic risk.

Conversely, among all analyzed indicators, the XAI algorithm precisely identified only one variable exerting a positive contribution to increased risk: the ratio of Insurance Assets to Total Financial Sector Assets (SHAP = +0.0676). Although its contribution was relatively small, this finding reflects mark-to-market asset valuation pressures in capital markets during the first quarter of 2020, which temporarily reduced the investment asset values of the insurance sector before being neutralized by shock-absorbing mechanisms in other subsectors. Overall, this configuration confirms that during the crisis period, the structural resilience capacity of the NBFI outweighed its potential for risk amplification.

These Local Explainability findings provide strong empirical justification for Bank Indonesia. The analysis demonstrates that the large-scale relaxation and restructuring programs implemented at the onset of the pandemic (2020) successfully transformed the NBFI ecosystem, particularly pension funds and insurance reserves, into a stabilizing buffer rather than an epicenter of further crisis propagation. Therefore, the future macroprudential framework of Bank Indonesia should ensure that the buffering capacity of the pension fund subsector is maintained above a prudent safety threshold.

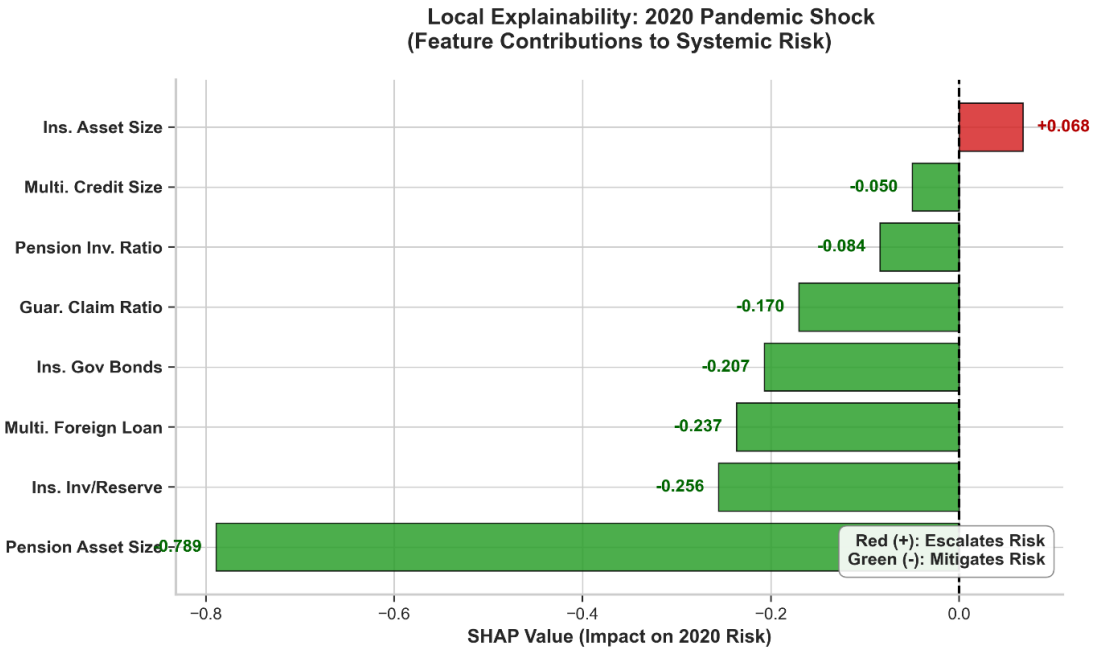


Figure 3. Local Explainability: 2020 Pandemic Shock
Source: Phyton, 2026

This analysis explores why interconnections among variables within the NBFI ecosystem generate new theoretical insights in the architecture of contemporary finance. Based on the OLS regression results visualized in Figure 4 on the Financial Accelerator Nexus, the validity of the Financial Accelerator Hypothesis is examined in the context of Indonesia's non-bank financial sector.

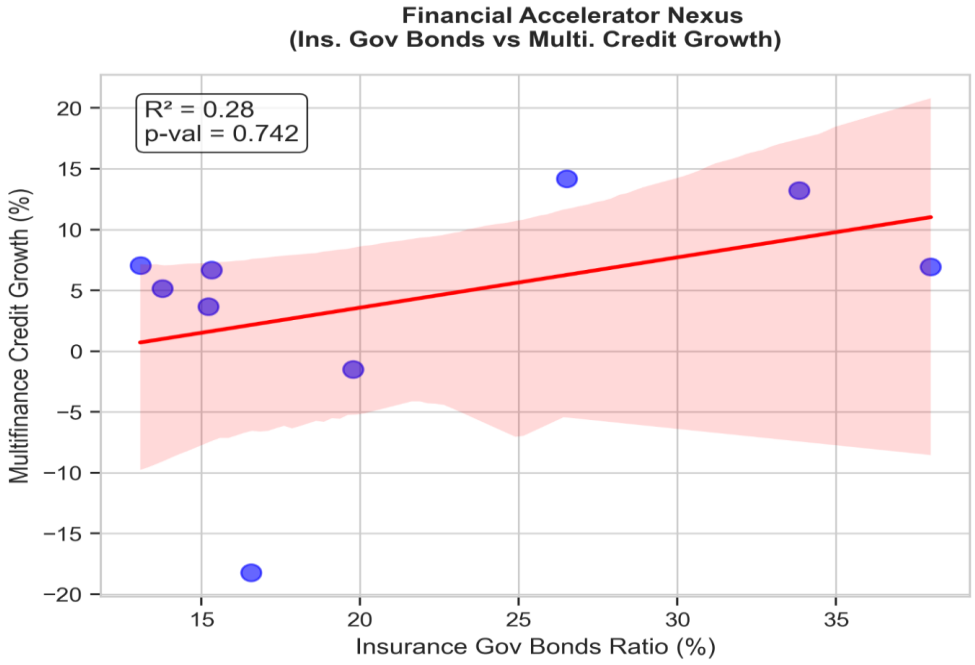


Figure 4. Financial Accelerator Nexus
Source: Phyton, 2026

From an econometric perspective, the regression results indicate that the composition of Government Bonds (SBN) in the insurance sector and external borrowing in the multifinance sector jointly explain approximately 28% of the variation in financing growth, as reflected in the coefficient of determination ($R^2 = 0.280$). However, both variables are statistically insignificant at the $\alpha = 0.05$ significance level, with p-values of 0.742 and 0.354, respectively. Furthermore, the extremely large Condition Number (2.46×10^6) signals the presence of strong structural multicollinearity within the NBFI dataset, implying that the relationships among variables are intricately interwoven and not easily separable within a classical linear regression framework.

The insignificance of the linear model, paradoxically, opens space for the formulation of new theoretical insights, which may be described as a shadow liquidity trap phenomenon. Within an increasingly differentiated financial architecture, the accumulation of SBN by non-bank institutions, particularly within the insurance sector, no longer linearly transmits credit cycles as assumed by the classical Financial Accelerator framework. Rather than reinforcing financing expansion through balance sheet mechanisms, the concentration of assets in relatively safe instruments may generate latent liquidity frictions that remain undetected by conventional indicators.

Simultaneously, the evolution of financial technology introduces new dynamics that may be conceptualized as Digital Minskyan Instability, namely, the expansion of high-risk credit in domains operating beyond traditional banking supervision. In this context, the interaction between the consolidation of safe assets in the insurance sector and the expansion of riskier digital credit creates a risk configuration that cannot be fully explained by earlier theoretical frameworks, thereby necessitating a more integrative and adaptive analytical approach.

The final section addresses the “So What” question and formulates strategic implications for Bank Indonesia. Based on the 75th percentile threshold formulation (Table 2) and its visualization through the early warning mechanism in Figure 5, a new policy architecture is designed.

Table 2. Critical Threshold for Macroprudential Policy

Special Attention Indicators	**Critical Threshold (75th Percentile)**	**Policy Response Recommendations**
Multifinance Bank / Foreign Loans	91796.00	Tightening of the foreign debt ratio limit for non-bank financial institutions
P2P Non-Performing Loan Ratio (>90 days)	2.78	Activation of anti-cyclical capital buffer instruments
Guarantee Claim Ratio	0.84	Mandatory stress test with the Financial Services Authority (OJK)

Source: Phyton, 2026

The institutional governance of Bank Indonesia, particularly in safeguarding its autonomy amid the mandate transition under the Financial Sector Development and Strengthening Law (UU P2SK), requires an Algorithmic Governance framework. Drawing upon Explainable Artificial Intelligence (XAI) indicators, Bank Indonesia should monitor three critical thresholds. First, multifinance foreign borrowing at 91,796.00; exceeding this threshold warrants policy measures equivalent to Loan-to-Value adjustments or the tightening of NBFI external debt ratios to mitigate imported risk. Second, a P2P lending non-performing loan (NPL) ratio of 2.78%, which signals an escalation of Digital Minskyan Instability and thus necessitates the sectoral activation of a Countercyclical Capital Buffer in coordination with the Financial Services Authority. Third, a guarantee claims ratio of 0.84%, which requires the mandatory implementation of fundamental stress testing to assess contingent liability risk.

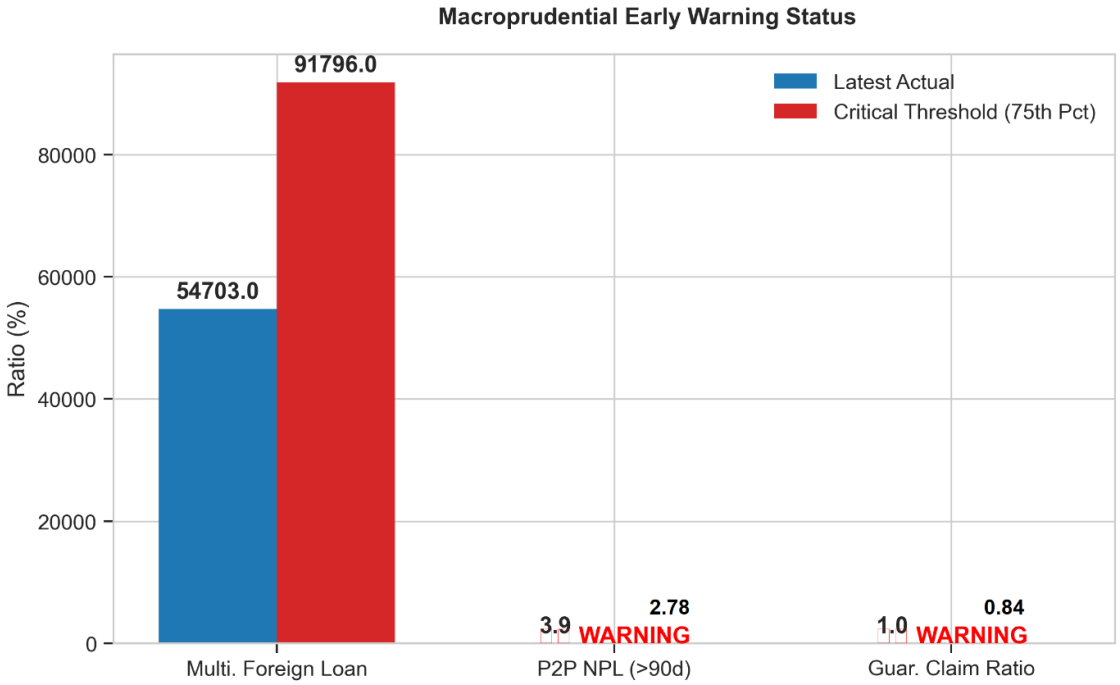


Figure 5. Macroprudential Early Warning Status
Source: Phyton, 2026

By adopting this XAI-based threshold formula, Bank Indonesia can safeguard its institutional autonomy. Policy interventions would no longer be driven primarily by political pressures (from parliament or the government) or market sentiment; instead, they would rest upon transparent, accountable (explainable), and adaptive analytical legitimacy aligned with the evolving New Financial Architecture.

4.2 Discussion

The finding of a very strong correlation between P2P Lending NPLs and the composition of government bond (SBN) investment in the insurance sector (r = 0.886), as well as with the guarantee claims ratio (r

= 0.714), confirms that the non-bank financial institution ecosystem (NBFI) is no longer fragmented but has evolved into an interconnected risk network. This result is consistent with the findings of Allen & Gale (2000), who demonstrate that financial network integration can enhance efficiency while simultaneously amplifying contagion risk in the presence of asymmetric shocks.

In the Indonesian context, this evidence extends the liquidity spirals argument developed by Markus Brunnermeier & Pedersen (2009), whereby stress in one market segment may induce simultaneous portfolio rebalancing across other institutions. A surge in defaults on P2P lending platforms does not remain confined to the digital domain; rather, it propagates through two principal transmission channels. First, the Credit Guarantee Channel, reflected in rising guarantee claims attributable to heightened credit risk among digital MSMEs. Second, the Portfolio Reallocation Channel, whereby insurance institutions respond through a flight-to-quality toward government securities (SBN) as a haven.

These findings broaden a literature that has thus far been predominantly bank-centric. For instance, Handayani and Setiastuti (2024) document monetary–macroprudential policy synergies through the bank lending channel; however, their analysis remains confined to the banking sector. Similarly, Adenan et al. (2024) employ a VAR framework to examine the impact of macroprudential instruments on bank ROA without incorporating non-bank intermediaries. By contrast, the present study closes this gap by demonstrating that NBFI possesses its own risk network structure with the potential to generate systemic spillovers. Accordingly, it advances the macroprudential discourse from bank-centric supervision toward ecosystem-based supervision.

The absence of statistically significant linear Granger causality at lag-1 further reinforces the view that risk transmission within the non-bank sector is inherently nonlinear and latent. This observation aligns with the complex adaptive systems perspective in financial stability advanced by Haldane & May (2011), which emphasizes that modern financial systems operate within complex network topologies that do not necessarily conform to short-term linear cause-and-effect relationships. Moreover, this finding highlights the limitations of traditional econometric approaches, such as the model developed by Ansori et al. (2025), which constructs a bank balance sheet framework based on the Loan-to-Deposit Ratio yet does not accommodate cross-sectoral interconnections and nonlinearity.

Overall, this research confirms a paradigm shift from silo-based supervision toward network-based macroprudential surveillance. From a policy perspective, Bank Indonesia should integrate cross-sectoral correlation analysis into its financial stability dashboard rather than monitoring sectoral indicators in isolation.

The application of Random Forest and SHAP values enhances transparency in identifying contributors to systemic risk. The finding that the ratio of pension fund assets to total financial sector assets emerges as the largest contributor (Mean |SHAP| = 0.5765) offers a novel perspective on the market impact channel within the context of emerging economies. This result extends the findings of Adrian & Shin (2010) regarding the role of non-bank financial institutions in transmitting global leverage cycles. Whereas the global literature frequently positions shadow banking as a risk amplifier, this study demonstrates that, in the Indonesian context, pension funds function instead as structural stabilizers.

Methodologically, the use of SHAP corroborates the argument advanced by Lundberg & Lee (2017) that Explainable Artificial Intelligence can bridge the trade-off between predictive accuracy and policy interpretability. In the realm of public policy, algorithmic transparency constitutes a prerequisite for regulatory legitimacy. Within the XAI literature, Martins et al. (2024) develop a taxonomy of explainability methods, while Hassija et al. (2023) examine transparency issues in black-box models. However, both studies remain conceptual and do not explicitly link XAI to financial system stability. Furthermore, Weber et al. (2023) demonstrate that XAI applications are predominantly concentrated in micro-level credit risk management. Similarly, Černevičienė and Kabašinskas (2024) emphasize the use of SHAP and feature importance at the firm level.

This study moves beyond such micro-level approaches by applying SHAP to a cross-sectoral Systemic Risk Index (SRI). Its principal contribution lies in transforming XAI from a micro-predictive tool into a macroprudential policy instrument. The findings concerning P2P lending risk also complement the work of Nallakaruppan et al. (2024), who employ Random Forest and SHAP for P2P credit risk assessment. In contrast to their study, the present research demonstrates that digital credit risk carries cross-sectoral systemic implications.

Accordingly, this study introduces the concept of Algorithmic Macroprudential Surveillance, defined as the integration of explainable machine learning into the macroprudential policy framework. From a policy perspective, authorities no longer need to monitor all indicators symmetrically. Mean |SHAP|-based prioritization enables more efficient allocation of supervisory resources and enhances the precision of policy interventions.

The finding that the Systemic Risk Index (SRI) in 2020 declined to −1.4595 constitutes a significant anomaly. Theoretically, a global pandemic would be expected to heighten systemic risk, as predicted by the financial accelerator framework developed by Bernanke et al. (1999). However, the Local SHAP results indicate that pension funds and strengthened insurance reserves functioned as effective shock absorbers. This evidence is consistent with the post–global financial crisis literature on

the countercyclical capital buffer (CCyB) pioneered by the Bank for International Settlements (Settlements, 2010).

Previous governance-oriented studies, such as Dwi et al. (2025), emphasize normative legal reforms in the financial sector, while Çoban (2021) highlights the political–bureaucratic dynamics of policy coordination. Nevertheless, neither provides quantitative validation grounded in predictive modeling. The present study offers empirical evidence that the restructuring and relaxation policies implemented in 2020 effectively strengthened the buffering capacity of pension funds and the insurance sector. In doing so, it bridges normative governance perspectives with data-driven validation.

This finding also enriches sectoral performance studies such as Wisandani et al. (2025) and Taufiqurrahman and Alwie (2024), which focus primarily on banking performance without examining cross-NBFI systemic stability. The results demonstrate that credit relaxation and restructuring policies during the pandemic were not merely short-term microprudential measures; rather, they systematically altered the structure of the risk network, thereby reducing crisis amplification. In contrast to numerous international studies documenting heightened systemic stress during the COVID-19 period, this research provides empirical evidence that well-designed domestic policies can transform the non-bank sector into a stabilizing buffer for the financial system.

The OLS regression results, which are individually insignificant yet jointly significant, indicate the presence of structural frictions and high multicollinearity. This pattern underscores the limitations of linear models in capturing the dynamics of modern financial architecture. The Financial Accelerator framework developed by Bernanke et al. (1999) assumes a relatively linear credit transmission mechanism. However, in the context of government bond (SBN) accumulation by insurance institutions and the rapid penetration of fintech, such transmission becomes distorted.

This study introduces two novel theoretical constructs. The first, Shadow Liquidity Trap, posits that the accumulation of liquid assets by non-bank financial institutions does not automatically translate into productive credit expansion; instead, it generates liquidity distribution frictions. The second, Digital Minskyan Instability, extends the instability hypothesis of Hyman Minsky (Minsky, 1986) into the digital domain, operating beyond the traditional perimeter of banking regulation.

These conceptual contributions complement the XAI 2.0 framework advanced by Longo et al. (2023), which emphasizes multidisciplinary integration and AI accountability but does not explicitly connect explainability to macroprudential stability. By situating these concepts within the broader financial stability discourse, this research extends the Financial Accelerator framework into the context of shadow banking and the fintech ecosystem, thereby providing a theoretical foundation for understanding risk transmission in the digital era.

To establish this framework as a replicable standard for macroprudential supervision, the technical implementation follows a structured, end-to-end pipeline. First, the Systemic Risk Index (SRI) is constructed using standardized Z-scores of NBFI vulnerability proxies (funding dependence, credit risk, and premium resilience), ensuring cross-sectoral comparability. Second, the Random Forest Regressor is trained on eight NBFI transmission indicators, with hyperparameter tuning optimized via grid search and cross-validation to enhance predictive stability. Third, SHAP (Shapley Additive exPlanations) is applied to decompose model outputs into global feature importance (identifying persistent systemic drivers) and local explanations (forensically analyzing crisis episodes), enabling transparent, auditable risk attribution. Fourth, the 75th-percentile thresholds derived from SHAP values are operationalized as trigger points for policy intervention, creating an Early Warning System that is objective, measurable, and adaptive. This entire workflow is coded in Python using open-source libraries (Scikit-Learn, SHAP, Pandas), ensuring reproducibility and ease of adoption by other central banks.

The governance and institutional autonomy implications for Bank Indonesia are reflected in the adoption of this threshold-based approach, which becomes increasingly relevant following Law No. 4 of 2023 on Financial Sector Development and Strengthening. Grounded in Algorithmic Governance, each policy intervention, including the tightening of multifinance external borrowing ratios and the activation of a sectoral Countercyclical Capital Buffer (CCyB) for fintech, acquires transparent and empirically accountable legitimacy. The broader public policy implications encompass the reinforcement of data-driven policy independence, the reduction of discretionary bias arising from political pressures, and the enhancement of accountability and explainability in macroprudential policymaking.

This study offers four principal contributions. Empirically, it provides quantitative evidence of NBFI risk interconnectedness based on a network contagion framework in an emerging market context. Methodologically, it integrates classical econometrics with Explainable Artificial Intelligence within a unified macroprudential framework. Theoretically, it introduces the concepts of Shadow Liquidity Trap and Digital Minskyan Instability as extensions of financial transmission theory. From a policy perspective, it develops an Algorithmic Governance model with a fully specified technical pipeline that can be replicated as a template for AI-based macroprudential supervision in emerging markets.

5. Conclusion and Suggestion

This study aims to map risk interconnections within the Non-Bank Financial Industry (NBFI), identify systemic risk drivers using Explainable Artificial Intelligence (XAI), examine the relevance of financial transmission theories within the digital financial architecture, and formulate macroprudential

governance implications for Bank Indonesia. The findings indicate that digital risk in the P2P lending sector exhibits strong linkages with the insurance and credit guarantee sectors, thereby forming a nonlinear cross-sectoral contagion network. The Random Forest and SHAP approaches successfully identify the pension fund asset ratio and multifinance external borrowing exposure as the principal determinants of the Systemic Risk Index (SRI). Local evidence from 2020 further demonstrates that NBFI functioned as a shock absorber during the pandemic, underscoring the effectiveness of relaxation and restructuring policies in preserving financial stability. Theoretically, this research introduces the concepts of Shadow Liquidity Trap and Digital Minskyan Instability as extensions of classical transmission theory within the context of the non-bank and digital financial ecosystem.

Nevertheless, this study is subject to several limitations. These include the restricted observation period and data granularity constraints, particularly within the fintech and guarantee subsectors, which remain in developmental stages. Moreover, the machine learning models employed depend on the quality and completeness of historical data, implying that future structural shifts may affect predictive stability. Future research is therefore encouraged to extend the temporal horizon, incorporate high-frequency data, and integrate network-based approaches—such as dynamic graph analysis or agent-based modeling—to capture real-time risk evolution. Comparative cross-country studies across emerging markets would also be valuable to assess the generalizability of the Macroprudential Algorithmic Governance framework across diverse institutional settings.

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