Available online at www.ijournalse.org

Emerging Science Journal

(ISSN: 2610-9182)

Vol. 10, No. 1, February, 2026

Regulatory Thresholds as Disciplinary Signals: Evidence from Bank Nonperforming Loan Supervision

Thi Lan Nhi Phung [1*], Chi Dat Le [1], Van Kien Pham [2*]

[1] *School of Finance, University of Economics Ho Chi Minh City, Viet Nam.*

[2] *Smart Green Transformation Center and College of Business and Management, VinUniversity, Hanoi, Vietnam.*

Abstract

Persistent high levels of nonperforming loans (NPLs) remain a key threat to banking stability, yet limited evidence exists on how regulatory thresholds influence bank discipline and risk behavior. This study investigates whether supervisory NPL ceilings serve as effective disciplinary mechanisms that balance profitability and credit risk in commercial banking systems. Using a balanced panel dataset from multiple emerging-market banks between 2013 and 2023, we employ Hansen's (1999) panel threshold regression to identify critical points at which bank behavior changes significantly. The findings indicate that when NPL ratios exceed an optimal threshold, banks exhibit heightened self-discipline by tightening credit growth and accepting lower short-term returns, demonstrating a strong regulatory disciplining effect rather than moral hazard. Conversely, when NPLs remain below the threshold, the traditional risk–return trade-off weakens, suggesting stability and prudence. The results highlight the importance of threshold-based supervision as a prudential instrument that enhances banking stability through behavioral signaling. The study contributes to signaling theory by conceptualizing regulatory thresholds as negative signals that trigger pre-emptive risk management and to policy design by offering empirical insights into optimizing supervisory frameworks.

Keywords:

Nonperforming Loans (NPLs);
Bank Discipline; Threshold Regression;
Regulatory Supervision;
State Bank of Vietnam (SBV);
Credit Risk Management.

Article History:

Received:	26	September	2025
Revised:	21	December	2025
Accepted:	30	December	2025
Published:	01	February	2026

1- Introduction

The provision of credit lies at the heart of banking activity, yet it inevitably exposes institutions to credit risk that can manifest in nonperforming loans (NPLs). Persistent high NPL ratios can erode bank profitability, restrict credit supply, and threaten the overall stability of financial systems [1, 2]. In recent years, regulatory authorities in emerging economies have increasingly adopted supervisory thresholds for NPL ratios as preventive mechanisms to contain systemic risk and promote prudent lending. However, whether such regulatory thresholds act as effective disciplinary tools or induce unintended risk-taking behavior remains insufficiently understood.

Existing research has examined NPLs from multiple perspectives. Bank-specific factors such as capital adequacy, liquidity, and corporate governance affect loan quality [3-5] while macroeconomic conditions such as GDP growth, interest rates, and inflation significantly influence NPL performance [6, 7]. For instance, Gashi et al. [8] identified that GDP growth, government consumption, real interest rates, and gross domestic savings jointly shape NPL ratios in Western Balkan countries, highlighting the importance of both macroeconomic and structural determinants. These findings underscore that NPL behavior is multifaceted, influenced by both internal bank dynamics and external economic pressures.

* **CONTACT**: lannhyphung@gmail.com; kien.pv@vinuni.edu.vn

DOI: http://dx.doi.org/10.28991/ESJ-2026-010-01-07

Beyond macroeconomic factors, the growing role of technology and data analytics in banking supervision has also been highlighted in recent studies. For example, Doğuç [9] emphasized that data mining applications and advanced analytical tools can enhance the monitoring of credit portfolios and risk exposure while safeguarding customer privacy, illustrating how digital transformation can strengthen prudential oversight. These technological perspectives suggest that the effectiveness of regulatory thresholds increasingly depends on the ability of institutions to measure, monitor, and interpret NPL trends accurately.

Although prior literature has advanced understanding of the determinants of NPLs, there remains a major conceptual and empirical gap regarding how banks react when supervisory thresholds are reached or breached. Regulatory thresholds are designed to serve as *disciplinary signals*, encouraging self-correction and prudent behavior. Yet, if banks perceive potential regulatory forbearance or implicit guarantees, thresholds may inadvertently foster *moral hazard* by motivating excessive risk-taking [10, 11]. This dichotomy between discipline and moral hazard forms the theoretical foundation of this study.

While studies such as [12, 13] have empirically identified statistical breakpoints or behavioral thresholds in bank performance data, few have linked these thresholds explicitly to regulatory frameworks or examined their signaling function within supervised banking environments. Moreover, the literature offers limited insights into whether such thresholds remain static or evolve over time with institutional strengthening, technological adoption, and market maturity. This lack of empirical evidence limits policymakers' ability to design optimal prudential thresholds that balance profitability and risk containment.

To address these gaps, this study investigates whether regulatory NPL thresholds act as behavioral inflection points that discipline bank management or promote moral hazard. Using a balanced panel dataset of commercial banks across an emerging market from 2013 to 2023, the study applies panel threshold regression approach to identify the point at which bank behavior changes significantly when NPL ratios cross supervisory ceilings [14]. This method allows for non-linear relationships and provides statistical validation of threshold effects within the data. The empirical design also accounts for institutional quality, bank size, capitalization, and credit growth heterogeneity to ensure robustness and generalizability.

The theoretical framework of this study integrates regulatory economics and signaling theory. Regulatory thresholds are conceptualized as *negative signals* that convey information to bank managers and investors regarding the acceptable boundary of credit risk. When banks approach this boundary, they may exhibit self-discipline by tightening lending standards and improving monitoring processes. Conversely, weak enforcement may dilute the credibility of these signals, encouraging moral hazard and excessive lending. This framework emphasis on interdisciplinary research that bridges economics, management, and applied technology in understanding systemic challenges.

This study makes several key contributions to the existing body of knowledge**.** First, it provides empirical evidence on how supervisory NPL ceilings shape bank behavior, thereby addressing the limited understanding of behavioral dynamics under prudential regulation**.** Second, it introduces a conceptual interpretation of regulatory thresholds as disciplinary signals within the broader context of signaling theory, extending theoretical discussions beyond simple risk-return frameworks. Third, it contributes to policy design by identifying how threshold-based regulation can promote financial stability while maintaining credit efficiency. In doing so, it answers the broader call for interdisciplinary approaches in financial risk research, integrating insights from economics, technology, and management to address real-world challenges**.**

The remainder of the paper is structured as follows. Section 2 reviews prior literature and theoretical perspectives on NPLs, regulatory thresholds, and banking discipline. Section 3 outlines the data, variables, and methodological framework, including the threshold regression model. Section 4 presents the results and discusses their implications. Section 5 concludes by summarizing findings and highlighting policy implications for supervisory authorities and financial institutions.

2- Literature Review

2-1- NPLs and Bank Behavior

Although extending credit is the central business activity of commercial banks and credit growth is often a key driver of profit expansion, rapid or excessive loan growth does not always lead to higher profitability [15]. When loan portfolios expand too quickly, the likelihood of moral hazard increases, and banks face a greater risk of accumulating non-performing loans (NPLs) [12, 16]. The rise in NPL levels can significantly undermine bank profitability [17-21] and has a direct influence on lending behavior [1].

Bernanke & Gertler [6] demonstrated that the level of NPLs in one period shapes bank decisions in the subsequent period. The nature of the adjustment depends on the bank's appetite for risk. Banks that are inclined to accept more risk and exhibit moral-hazard tendencies may respond to higher NPLs by engaging in risk-shifting activities, such as rolling over existing loans in the hope of eventual recovery [22]. This can also involve temporarily expanding lending to reduce the reported NPL ratio, a phenomenon referred to as the *dilution effect* [12].

By contrast, prudent banks tend to respond to higher NPLs by tightening their lending strategies. Some reduce overall credit growth in order to protect loan quality [23]. Others selectively adjust their borrower base, focusing on large, financially sound firms that are considered more creditworthy than small and medium-sized enterprises [24]. These contrasting behavioral responses illustrate that the relationship between NPLs and bank conduct is complex and mediated by internal risk preferences.

Recent empirical studies reinforce these behavioral differences. Salas et al. [25] used a dynamic global panel (2007–2021) and found that institutional quality and macroprudential environments strongly mediate how banks respond to rising NPL ratios. Their findings suggest that prudential “trip-wire” thresholds may operate differently across countries, motivating context-specific analyses such as ours. Similarly, Chun & Ardaaragchaa [26] revealed that credit expansion slows sharply once the NPL signal becomes adverse, supporting the disciplinary-channel (λ) mechanism in our conceptual framework.

Governance and institutional quality also influence how banks internalize risk. Nurkhin et al. [27] documented that robust governance and effective screening systems lower NPL ratios, consistent with our μ parameter representing internal monitoring quality. Gashi et al. [8] further showed that macroeconomic shocks amplify credit risk in emerging economies where governance is weak, underscoring that institutional discipline strengthens the effectiveness of prudential thresholds.

In addition, several recent studies have contributed evidence using advanced analytical techniques. Hamada et al. [28] applied machine-learning models to predict early warning signals in retail and corporate credit portfolios, showing that data-driven “decision thresholds” can anticipate shifts in bank risk behavior. Similarly, Tu et al. [29] employed parameter-optimized machine-learning frameworks to forecast banking stability in ASEAN markets, demonstrating that hybrid models can identify non-linear regime changes in financial resilience analogous to prudential threshold effects. Together, these studies highlight a growing trend toward quantitative identification of risk thresholds, aligning closely with this paper’s focus on NPL ratios as disciplinary signals in emerging market supervision.

The behavioral dynamics can also be understood through the *Charter Value Hypothesis* [30], which posits that banks with higher franchise value are less likely to take excessive risks. Conversely, the *Risk-Shifting Hypothesis* [31] argues that banks with deteriorating asset quality may take on additional risk in pursuit of recovery. Together with the new empirical evidence [25, 26], these theories reinforce that risk behavior under rising NPLs is shaped by both internal governance and external supervisory discipline.

2-2- Optimal NPL Ratio Thresholds

Since NPL levels strongly influence bank decision-making, it is important to determine the point at which they trigger behavioral changes. This level, often called the *NPL threshold,* serves as a reference point for bank managers to monitor performance and for regulators to design policies that preserve stability. Without a defined threshold, the effectiveness of loan monitoring can decline as NPL levels rise [32].

One methodological approach to identifying such a threshold is threshold regression analysis**,** which reveals specific points where bank behavior changes significantly. Zhang et al. [12] applied this method to Chinese banks and identified a behavioral threshold of 4.81 percent, suggesting it could serve as a supervisory benchmark to limit moral hazard. However, identifying the statistical point of change does not necessarily define an optimal *regulatory* threshold. An effective ceiling must balance risk control with profitability [23, 33].

A number of studies have sought to define *optimal* NPL levels. Bolarinwa et al. [13] estimated a 5 percent threshold for Nigerian banks that maintained stability without eroding profits, while Alnabulsi et al. [34] found that a 4 percent ceiling in the MENA region preserved earnings potential. Despite such evidence, there is no universal consensus on an optimal level.

More recent work has extended the search for prudential thresholds using updated datasets and new modelling tools. Salas et al. [25] demonstrated that NPL sensitivities vary by institutional setting, implying that thresholds are context-dependent rather than universal. Hamada et al. [28] showed that machine-learning techniques can identify early turning points in asset quality, complementing econometric threshold models. Additionally, recent studies provide a methodological bridge between threshold regression and non-linear forecasting, indicating that NPL ceilings may evolve dynamically over time [28, 29].

In the Vietnamese context, Quang [35] proposed a 5.5 percent *warning level* as a risk signal, notably higher than the State Bank of Vietnam’s (SBV) formal 3 percent ceiling. Given evolving macroeconomic and institutional conditions, it remains uncertain whether the SBV’s fixed threshold remains optimal in disciplining banks. The absence of empirical studies testing behavioral thresholds in Vietnam reinforces the need for our present analysis.

2-3- Regulation and Bank Behavior

Prudential regulation plays a pivotal role in shaping bank behavior when NPLs approach or exceed critical levels. Exceeding a regulatory ceiling may lead to supervisory interventions such as credit-growth restrictions, which act as strong signals for banks to impose self-discipline. In addition, higher provisioning requirements linked to elevated NPLs can reduce both profitability and funds available for new lending [36]. These forces compel managers to weigh the benefits of additional risk-taking against the cost of supervisory sanctions.

However, if banks anticipate that regulators or governments will rescue distressed institutions, they may increase risk exposure in expectation of bailouts, which is a classic moral-hazard effect [10]. In weak institutional environments, stringent regulations may even worsen outcomes, as corruption or political interference distort loan-quality reporting [37].

Empirical evidence confirms that regulatory signals influence lending. Gropp et al. [10] observed that the removal of state guarantees for German savings banks encouraged safer lending. Degryse et al. [38] found that the adoption of *Supervisory Technology* in Brazil reduced lending to less creditworthy clients, showing a tangible disciplinary effect.

In emerging markets, prudential reforms have improved both stability and efficiency. Özkan-Günay et al. [39] reported that post-crisis reforms in Turkey enhanced banking efficiency. Audi & Al-Masri [11] analyzed 100 banks across emerging economies (2004–2023) and concluded that strong regulation reduced NPLs and raised Z-scores by limiting excessive risk-taking. Amin et al. [40] observed similar effects in Bangladesh, where robust supervision lowered NPL ratios.

Recent ESJ research provides complementary insights. Gashi et al. [8] linked macroeconomic volatility to rising NPLs in weakly regulated Balkan markets, while Hamada et al. [28] demonstrated how AI-based early-warning models can support regulators by identifying risk thresholds in advance. Together, these studies highlight the growing integration of data-driven tools into prudential oversight and the continuing need to calibrate supervisory thresholds empirically.

Vietnam's banking system has undergone significant reform since the early 2010s, including the creation of the Vietnam Asset Management Company (VAMC) in 2013 to address mounting NPLs [5]. While these initiatives lowered reported ratios, concerns remain regarding off-balance-sheet debt and the true effectiveness of the SBV's 3 percent ceiling in shaping behavior. To date, no study has systematically tested whether this regulatory ceiling functions as a behavioral threshold, which is a gap that the present research directly addresses.

2-4- Conceptual Framework Linking NPLs, Regulatory Thresholds, and Bank Behavior

Figure 1 illustrates the integrated conceptual relationships among non-performing loans (NPLs), regulatory thresholds, and bank behavior in the Vietnamese banking context. The framework links four main theoretical and empirical strands of literature.

First, credit growth influences NPL levels, which in turn affect profitability and trigger behavioral adjustments, either through moral hazard (risk shifting and dilution) or through prudence (reduced lending and tighter credit standards). This behavioral asymmetry reflects the "disciplinary versus opportunistic" tension in banking decision making [6, 12, 26].

Second, the optimal NPL ratio threshold represents the point at which banks alter their conduct significantly, with potential implications for profitability, stability, and regulatory compliance. In this study, the NPL threshold is interpreted as a regulatory signal that communicates supervisory expectations to banks. When the NPL ratio approaches the ceiling, it triggers a signal consistent with signaling theory [41], prompting banks either to self-discipline or to engage in strategic risk taking.

Third, regulatory interventions such as the State Bank of Vietnam's formal 3 percent NPL ceiling function as prudential tripwires that can reinforce discipline by imposing supervisory constraints or encourage moral hazard if banks anticipate state support. This dual possibility aligns with the Charter Value Hypothesis [30], which suggests that institutions with greater franchise value behave prudently to preserve long-term profitability, and the Risk-Shifting Hypothesis [31] which predicts greater risk appetite when capital buffers weaken.

Fourth, the institutional-governance dimension moderates these relationships. Following [8, 27] strong governance systems (high μ) enhance the credibility and effectiveness of supervisory signals, whereas weak institutional quality dilutes them. In emerging markets such as Vietnam, where discretionary interventions remain common, governance quality determines whether the same NPL threshold acts as a *disciplinary mechanism* or a *moral-hazard trigger*.

Figure 1 therefore synthesizes these theoretical linkages – credit expansion, threshold signaling, regulatory intervention, and institutional governance – into a unified framework. It highlights the central research gap: empirical evidence remains scarce on whether the SBV's 3 percent ceiling operates as an effective disciplinary threshold under Vietnam's evolving institutional conditions. This study addresses that gap by testing the behavioral response of commercial banks to the supervisory NPL signal.

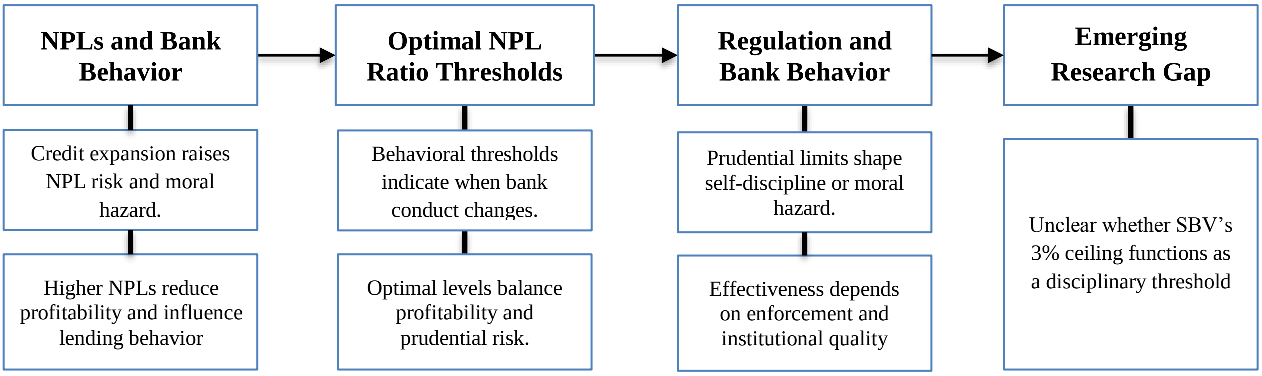


Figure 1. Conceptual framework linking credit expansion, NPL thresholds, regulatory signaling, and governance influences on bank behavior in Vietnam

Building upon the conceptual framework that links NPLs, regulatory thresholds, and bank behavior, the following section develops a formal theoretical model to explain how the NPL threshold operates as a public negative signal within an asymmetric information environment. This framework formalizes the mechanisms of regulatory and market discipline, as well as the potential for moral hazard, thereby providing a rigorous foundation for the empirical analysis that follows.

2-5- Conceptual and Theoretical Framework: NPL Threshold as a Negative Signal

The foundation for our analysis is rooted in Agency Theory, which points to the inherent conflict of interest between managers and shareholders that can lead to two opposing behavioural tendencies when a bank's asset quality deteriorates. The Risk-Shifting Hypothesis predicts that managers will tend to take on greater risk, whereas the Charter Value Hypothesis posits that banks with high franchise value will behave more prudently to protect long-term profitability.

The question that arises is: When faced with a regulatory benchmark such as an NPL supervisory threshold, which behaviour will dominate? This is where Signalling Theory, in a context of asymmetric information, serves as the key mechanism. Drawing on seminal works such as [42], we argue that in an environment of informational asymmetry between the bank (the informed party) and outside stakeholders, the NPL threshold functions not just as an administrative rule but as a powerful public negative signal. This signal influences bank behaviour through three primary channels:

First, through Market Discipline. Breaching the threshold sends a clear negative signal, helping to resolve the asymmetric information problem by revealing banks with potentially weak risk management in credit appraisal, portfolio management, or those pursuing overly risky growth strategies. The signal also suggests that future profitability may be adversely affected by higher provisioning costs and lower debt recovery prospects. This prompts the market to negatively update its beliefs, leading to market discipline, as demonstrated in the classic work of Flannery & Sorescu [43], whereby investors and depositors demand higher risk premia, increasing the bank's cost of funding. Therefore, once the NPL signal turns adverse, deteriorating asset quality serves as a negative signal that leads to tighter funding conditions and a subsequent adjustment in credit supply [26], compelling banks to adopt more prudent behaviour.

Second, through Regulatory Discipline. The negative signal from a breach triggers supervisory interventions by the central bank, such as inspections and credit growth restrictions. These measures create tangible costs that produce a deterrence effect, compelling banks to self-discipline to avoid penalties. The essential role of supervision in curbing moral hazard is a central theme in the financial intermediation literature [38, 44, 45].

Finally, through Bailout Expectations. The signal's effectiveness can be weakened if banks believe they will be bailed out. The expectation of an implicit guarantee or regulatory forbearance lowers the cost of risk, encouraging moral hazard. This moral hazard mechanism builds upon the foundational work of Merton [46].

To formalize these theoretical intuitions and derive testable predictions, we develop a theoretical model of a bank in an asymmetric information environment.

We consider a bank i with a risk type $\theta \in$ {prudent, aggressive}. The bank chooses a loan growth rate $g \geq 0$. The probability of its Non-Performing Loan (NPL) ratio exceeding the supervisory threshold γ in period t is given by[*]

$$p(g,\theta) = \Pr(NPL_t > \gamma \mid g,\theta) = \Phi(\alpha(\theta)\, g - \mu + \varepsilon_t) \tag{1}$$

where, γ is the supervisory NPL threshold, $\alpha(\text{aggressive}) > \alpha(\text{prudent}) > 0$ reflects the risk sensitivity of NPLs to loan growth, μ represents the quality of the bank's internal screening and monitoring[†], and ε_t is macro shocks[‡]

[*] We model threshold breach probability with a standard laten-index probit specification [47].

[†] Ozili [48] identifies governance, fintech, internal monitoring quality as internalized discipline aligns with the lastest frontier in NPL research.

[‡] Salas et al. [25] showed that advers macro-shocks are correlated with higher NPL levels.

The bank's short-term profit function, which is increasing and concave in g, is:*

$$\pi(g)=Ag - \frac{B}{2}g^2 \text{ với } A, B > 0$$

where, A is the marginal benefit of loan growth at low levels, and B captures the diminishing marginal returns (or increasing marginal costs) as growth accelerates. The marginal profit is therefore $\pi'(g) = A-Bg$

Following signalling theory in an asymmetric information context, a bank's asset quality and risk-management effort are its private information, whereas outside stakeholders (depositors, funders, investors, and supervisors) observe only noisy signals. Therefore, if $NPL_t > \gamma$, the bank issues a public signal†, incurring an expected cost ‡. This cost comprises three main components:

(i) Regulatory Discipline Cost (P): The negative signal triggers stricter on-site and off-site monitoring and invites binding prudential actions, such as tighter credit growth quotas or higher provisioning requirements. This increases the expected cost of expanding risky assets.

(ii) Funding Cost (λC): The signal prompts the market to update its beliefs negatively about the bank's quality, leading to market discipline. This raises the risk premia required by depositors and wholesale lenders. We denote this incremental marginal funding cost as λC. Here, $C > 0$ denotes the baseline marginal funding cost increment (per unit of credit growth) associated with a fully adverse market update; $\lambda \in [0,1]$ scales that increment by the signal's intensity.

(iii) Bailout Expectations (b): The disciplinary effect can be dampened by bailout expectations. Let $b \in [0,1]$ be the perceived probability of a bailout.

The total expected cost of issuing a negative signal is thus

$K=(1-b)(P+\lambda C)$.

The bank's one-period static optimization problem is to choose g to maximize its expected payoff:

$$\max_{g \geq 0} \Pi(g,\theta) = \pi(g) - \Pr(NPL > \gamma | g,\theta)\cdot(1-b)(P+\lambda C) = Ag - \frac{B}{2}g^2 - Kp(g,\theta)$$

The first-order condition (FOC) for an optimal growth rate g^* requires the bank to equate the marginal benefit of growth with its marginal expected signalling cost:

$$A - Bg^* = K\frac{\partial p(g,\theta)}{\partial g}\Big|_{g=g^*}$$

where, $p(g,\theta) = \Phi(\alpha(\theta)g - \mu + \varepsilon_t) \Rightarrow \frac{\partial p}{\partial g} = \alpha(\theta)\,\phi(\alpha(\theta)g - \mu + \varepsilon_t) > 0$

Second-order condition (SOC) and uniqueness: the objective $\Pi(g,\theta) = \pi(g) - Kp(g,\theta)$ is strictly concave in g; since $\pi''(g) = -B < 0$ and, for the probit $p(g,\theta)$, a sufficient condition for uniqueness is $B > K \max_g |p''(g,\theta)|$; it follows that $\Pi''(g,\theta)= \pi''(g)-Kp''(g,\theta)<0$; hence the FOC yields a unique maximizer g^*.

K is expected cost of issuing a negative signal and $\frac{\partial p}{\partial g} > 0$ because higher growth increases the probability of breaching the threshold.

By the Implicit Function Theorem, we can analyze the sensitivity of the optimal growth rate g^* to the signalling cost K. The theorem delivers $\frac{\partial g^*}{\partial K} \leq 0$.

Intuitively, the left-hand side, $A-Bg$, is decreasing in g, while the right-hand side, $K\frac{\partial p}{\partial g}$ is increasing in K. For the equality to hold when K increases, g^* must decrease. This leads to the following comparative statics:

$$\frac{\partial g^*}{\partial P} < 0,\ \frac{\partial g^*}{\partial \lambda} < 0,\ \frac{\partial g^*}{\partial b} > 0,\ K= (1-b)(P+\lambda C) \tag{2}$$

A higher expected penalty (P), greater market sensitivity (λ), or lower bailout expectation (b) all increase K, inducing the bank to choose a lower optimal growth rate g^* (i.e., to self-discipline). Conversely, a higher bailout expectation attenuates the disciplinary effect by reducing K.

This framework yields two competing propositions:

Proposition 1 (Discipline Region): For a sufficiently high signalling cost K (i.e., strong regulatory enforcement P and/or high market sensitivity λ, and low bailout expectation b), all bank types will optimally choose a g^* that keeps the probability of breaching the threshold, $\Pr(NPL > \gamma)$, low. This leads to self-disciplinary behavior, such as reducing credit growth as NPLs approach or cross the threshold γ.

* We assume a convave short-run profit in loan growth, any concave form would deliver the same comparative statics [49].

† The public signal is a classic insight in finance, pioneered by a semiworks such as [42].

‡ Expected penalty is modeled addictively as regulatory discipline [44, 45] plus market discipline [43] and bailout beliefs as explicit guarantees [46].

Proposition 2 (Moral Hazard Region): For a sufficiently low signalling cost K (i.e., weak supervision P, insensitive markets λ, or high bailout expectation b), an aggressive bank may find it optimal to choose a high g, accepting the high probability of breaching the threshold to maximize short-term profits. This corresponds to the risk-shifting effect.

Following the theoretical framework above generates clear empirical predictions. Below the threshold (NPL$< \gamma$), the signalling cost is not activated. The bank's decision is dominated by the marginal profit of growth, so loan growth is expected to support performance. At or above the threshold (NPL $\geq \gamma$), the negative signal is activated, raising expected regulatory and funding costs. Consequently, the marginal return to loan growth is expected to weaken or turn negative as heightened risk and provisioning costs take effect.

Mapping to Empirics:

Our empirical design is the reduced-form counterpart of this theoretical model. We implement a panel threshold model using the lagged NPL ratio (NPL_{t-1}) as the threshold variable to distinguish between the discipline and moral-hazard regions. Since supervisors and the market observe the bank's state at t-1 to update their beliefs and set subsequent credit constraints for period t, the bank adjusts its loan growth g_t accordingly, which in turn affects its performance Y_t

The sign and statistical significance of the coefficient on loan growth g_t in the regimes below and above the estimated threshold γ provide a direct test of Propositions 1 and 2. A positive and significant coefficient when $NPL_{t-1}< \gamma$ and a negative or insignificant coefficient when $NPL_{t-1} \geq \gamma$ would be consistent with the disciplinary effect outlined in Proposition 1.

3- Research Methodology

3-1- Data Collection and Sample

This study uses annual data from 27 Vietnamese commercial banks for the period 2013 to 2023, producing a balanced panel of 297 observations. The sample period was chosen because it coincides with the State Bank of Vietnam (SBV) implementing prudential guidelines for supervising non-performing loans (NPLs). Although the study does not directly measure a “regulatory pressure” variable, these years represent a context in which banks were aware of and obliged to comply with the SBV’s NPL regulations.

All financial data were collected from the annual reports of each bank. Prior to 2013, disclosure of operational and performance information was inconsistent, making the construction of a balanced panel infeasible. In accordance with Hansen [14] requirements for threshold regression analysis, banks or years with incomplete data were excluded from the sample.

To ensure consistency and comparability, all monetary values were deflated to constant Vietnamese Dong using the Consumer Price Index (CPI), extreme outliers were winsorized at the 1st and 99th percentiles, and only complete observations were retained with no data imputation performed.

3-2- Empirical Approach

3-2-1- Model Specification

This study uses threshold regression model to test for a threshold at which bank behavior changes significantly. This threshold regression model has been used recently to study bank behaviors [48, 49]. This model allows the sample to be divided into two or more regimes based on whether a threshold variable crosses an endogenously determined critical value.

Bank profitability may also determine managers’ risk-taking behaviors [50]. Banks with high profitability are less pressured to create revenue and are thus less constrained to engage in risky credit offerings, whereas inefficient banks are more likely to experience high levels of problem loans and weak monitoring mechanisms for operating costs. For our research, we chose the variables return on assets, return on equity and the net interest margin, which are common and preferable banking performance indicators used in many studies [13]. Zhang et al. [12] used the NPL ratio as the threshold variable because NPLs can motivate a change in bank behavior. In addition, we set the threshold variable to be the last NPL period because abnormal loan growth can cause significant subsequent losses with a one-year lag; therefore, banks could behave differently than they did under the previous high NPL ratio [16, 17]. In addition, the risk-related variable loan growth is chosen because it changes according to the threshold set in the model to see how loan growth affects bank profitability under low and high NPL regimes because only loan growth can be potentially influenced by the bank managers' decisions [12]. Following previous studies, such as [13, 34], we chose the deposit growth rate, size, age, and equity ratio as the control variables.

Our study examines whether, when faced with high NPL levels, lending decisions of Vietnamese commercial banks exhibit a disciplinary effect or moral hazard under the pressure of the SBV's NPL threshold. If the banks choose moral hazard, they will take excessive risk by increasing credit growth to compensate for existing losses as well as increasing and fluctuating profits due to interest rate adjustments and customer attraction. However, we hypothesize that in the context of Vietnam, when NPLs increase and exceed the regulatory threshold, banks are often strictly risk monitored and under pressure from the SBV, so banks must immediately reduce credit growth and proactively accept lower profits to improve credit quality.

According to Hansen [14] and the arguments put forth above, our model is proposed as below.

Model 2 (Contemporaneous Effect)

$$Bank\ Performance_{i,t} = \alpha_i + \beta_1 LR_{i,t} .I(NPL_{i,t-1} < \gamma) + \beta_2 LR_{i,t} .I(NPL_{i,t-1} \geq \gamma) + \delta X_{i,t} + \varepsilon_{i,t}$$

Model 3 (Lagged Effect only)

$$Bank\ Performance_{i,t} = \alpha_i + \beta_1 LR_{i,t-1} .I(NPL_{i,t-1} < \gamma) + \beta_2 LR_{i,t-1} .I(NPL_{i,t-1} \geq \gamma) + \delta X_{i,t} + \varepsilon_{i,t}$$

Model 4 (Contemporaneous and Lagged Effects)

$$Bank\ Performance_{i,t} = \alpha_i +(\beta_{10} LR_{i,t-1} +\beta_{11} LR_{i,t-1}).I(NPL_{i,t-1} < \gamma)+(\beta_{20} LR_{i,t-1}+\beta_{21} LR_{i,t-1}).I(NPL_{i,t-1} \geq \gamma)+\delta X_{i,t} +\varepsilon_{i,t}$$

Where Bank performance = ROAA/ ROEA/NIM, LR represents the loan growth rate, vector X represents other explanatory variables, i refers to the banks, and t refers to the year. NPL is the non-performing loan ratio, γ is the estimated threshold, I (·) is the indicator function.

This study uses three threshold models, namely, Models 2–4, while Models 1(a), (b), and (c) are the benchmark linear models for comparison purposes (fixed-effects regression). Model 2 includes no lags of the loan growth rate but simply the contemporaneous loan growth rate. Model 3 includes only the lag of the loan growth rate. Model 4 combines Models 2 and 3.

3-2-2- Estimation Procedure and Inference

The NPL threshold value (γ) is determined through a grid search over the sorted values of $NPL_{i,t-1}$ to identify the point that minimizes the sum of squared residuals. Inference follows Hansen [14] bootstrap procedure with 300 replications to obtain confidence intervals and to test the null hypothesis of no threshold effect. The likelihood ratio (LR) statistic is used to assess the statistical significance of the estimated threshold, and bootstrap p-values are reported to ensure robustness to non-normality. Bootstrap confidence intervals for γ are presented along with the LR test statistics and associated p-values in the empirical results. Model fit is evaluated using adjusted R^2, the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC), allowing direct comparison with the benchmark linear models. Robust standard errors clustered at the bank level are applied to address heteroskedasticity and serial correlation.

3-2-3- Variable Selection and Justification

The dependent variables return on assets (ROAA), return on equity (ROEA), and net interest margin (NIM) are selected to capture both profitability and operational efficiency, and they are widely recognized in banking performance analysis as noted by Bolarinwa et al. [13]. The key explanatory variable is the loan growth rate, which reflects managerial decision-making in credit expansion. The lagged NPL ratio serves as the threshold variable because elevated NPL levels in the previous year can significantly influence current lending behavior, as discussed by [16, 17].

The model also includes several control variables with strong theoretical and empirical relevance. The deposit growth rate measures the bank's funding expansion capacity. Bank size, typically proxied by the logarithm of total assets, accounts for potential scale economies and market influence. Bank age reflects maturity and institutional experience, which can influence risk management practices. The equity ratio measures capital adequacy, which is a key determinant of financial stability and resilience. Together, these variables provide a comprehensive set of controls for isolating the relationship between loan growth and bank performance across NPL regimes.

3-2-4- Hypothesis Development

This study examines whether Vietnamese commercial banks, when confronted with high NPL ratios, display a disciplinary effect or a moral hazard effect. The disciplinary effect occurs when banks respond to heightened credit risk by reducing credit growth to improve asset quality, even if it results in lower short-term profitability. The moral hazard effect occurs when banks respond to high NPLs by expanding credit in an attempt to offset losses and temporarily boost profits, which may increase overall risk. Given the strict monitoring and supervisory enforcement of the SBV, we hypothesize that Vietnamese banks are more likely to exhibit the disciplinary effect, reducing loan growth and accepting lower profitability when NPLs exceed the regulatory threshold.

3-2-5- Diagnostic and Robustness Checks

Before estimation, multicollinearity among the independent variables is tested using the Variance Inflation Factor (VIF), and all values are found to be within acceptable ranges. All variables are also tested for stationarity using the Levin–Lin–Chu panel unit root test to ensure their suitability for regression analysis. Robustness is examined through several approaches. First, the performance of the threshold models is compared with that of the benchmark linear models to confirm the main findings. Second, the models are re-estimated using alternative profitability measures to check the consistency of results across dependent variables. Third, using a dynamic threshold regression model to control for endogeneity. Finally, we divide the sample into two periods to examine whether the threshold effect remains stable. These diagnostic and robustness procedures help to ensure the reliability of the empirical findings.

4- Results

4-1- Descriptive Statistics

Table 1 contains the descriptive statistics of all of the variables that we used in this paper. ROEA, which has a minimum of 0.4% and a maximum of 30%, exhibits significant differences in the banks' capital efficiencies. Although the average ROAA and NIM are quite low (at 0.9% and 3%, respectively), the relatively small standard deviation indicates stable fluctuations. Meanwhile, the average of the NPL ratio is 2.06%, which is lower than the 3% ceiling regulation set by SBV, but the highest NPL ratio is 7.27%, indicating that some banks have very high NPL ratios, reflecting credit risk. The loan growth rate fluctuates greatly, from a minimum of -14% to a maximum of 96%, indicating that some banks have restrained credit growth to control risk and reflecting large differences in credit growth among banks and over time.

Table 1. Summary statistics of the dataset from 2013–2023

Variable	Definition	Observation	Mean	Std. Dev.	Min	Max	Source
Dependent variables							
ROEA	Return on equity = Net income / Average equity	297	10.982	7.128	0.4	30.33	Financial report
ROAA	Return on assets = Net income / Average assets	297	0.924	0.695	0.03	3.58	Financial report
NIM	Net interest margin = Net interest income / Average interest-earning assets	297	3.032	1.275	0.99	9.41	Financial report
Threshold variable							
NPL	NPLs / Total loans	297	2.062	1.129	0.467	7.271	Financial report
Variable changes according to the threshold							
LR	Loan growth rate = (Total Loan$_t$ - Total Loan$_{t-1}$) / Total Loan$_{t-1}$	297	18.712	12.347	−14.23	96.05	Financial report
Control variables							
DR	Deposit growth rate = (Deposit$_t$ - Deposit$_{t-1}$) / Deposit$_{t-1}$	297	16.392	12.311	−8.03	82.7	Financial report
ETA	ETA = Equity / Assets	297	8.721	3.288	4.06	23.84	Financial report
Size	Bank size = logarithm of total assets	297	12.045	1.201	9.595	14.649	Financial report
Age	Bank age = years in operation	297	27.371	12.875	5	67	Financial report

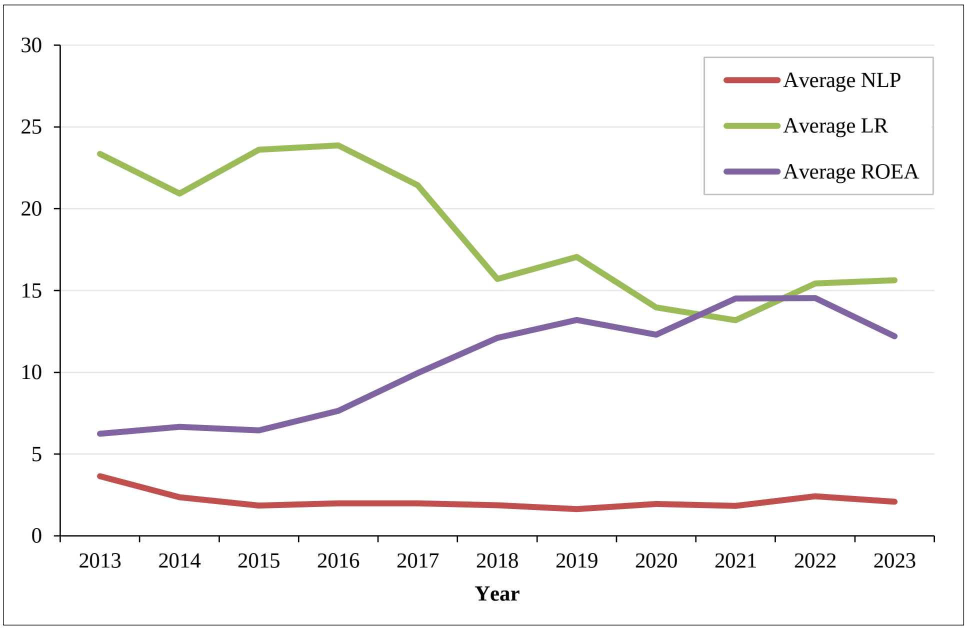


Figure 2. Average NPLs, credit growth rates, and profits for 27 Vietnamese commercial banks from 2013–2023

Figure 2 shows that from 2013–2021, the average NPLs of Vietnamese banks (n = 27) decreased and stabilized at approximately 2%. In contrast, although credit growth was volatile, it significantly decreased during this period. This result indicates that during this period, credit quality improved after the banking system was restructured, and this stability could be the result of stricter debt classification regulations under the SBV's NPL supervisory regulation.

Table 2. Bank type by the SBV regulation's 3% NPL threshold value

Bank type	SOB	JCB	Total
NPL < 3%	42	218	260
NPL ≥ 3%	2	35	37

Note: The numbers reported in this table are bank-year observations. SOB = state-owned bank; JCB = joint-stock commercial bank

Table 2 observes the characteristics of banks that are either above or below the 3% threshold, which is the SBV's prudential guideline. We also sorted the banks above and below the threshold according to two types: state-owned and joint-stock commercial. Most of the banks have NPL ratios that are lower than the 3% SVB threshold value. This result is consistent with our expectation: banks will behave with self-discipline when faced with a regulatory intervention to comply with the government's requests. If banks behave with moral hazard, only a small proportion of them have serious problems.

4-2- Regression Results

4-2-1- Identifying the Optimal NPL Threshold Value

We identify the existence of threshold effects and set the threshold value for each model. Table 3 presents the estimated threshold effects and the corresponding confidence intervals. In addition, we plot the identification of a "nonrejection zone" and construct a confidence interval in Figure 3. The identified thresholds are consistently below 3% and statistically significant in all of the models. Compared to prior studies such as [12, 13, 34, 35], our threshold is significantly lower.

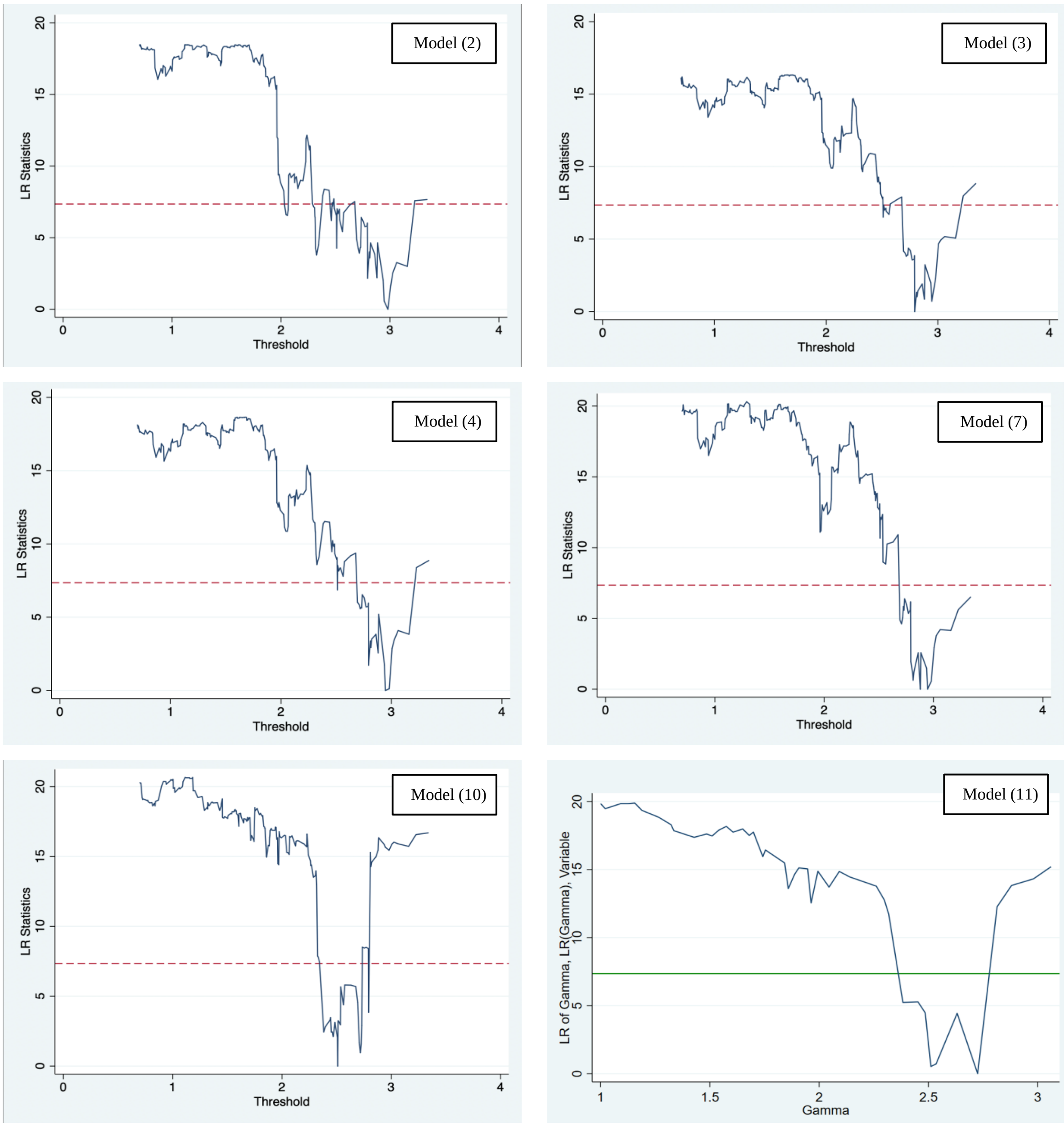
Importantly, our threshold aligns closely with the SBV's regulatory threshold of 3%, reinforcing the view that this benchmark effectively distinguishes between risk and return. This result is justified for the argument of the SBV supervision framework that maintaining NPLs below 3% is adequate for addressing the equilibrium optimal profitability and risk trade-off in banks.

This finding is particularly relevant given the ongoing challenge banks face in balancing profits, regulations, and nonperforming assets [33]. If banks want to decrease NPLs or manage credit risk effectively, ensuring profits is extremely important [5, 20, 23]. Therefore, identifying a threshold at which the risk–return trade-off becomes neutral contributes meaningfully to prudential policy design.

Table 3. Threshold effect estimation

Performance variables	Model	Threshold	Conf. Interval (95%)	P-value
ROAA	2	2.98%	[2.61%, 3%]	0.0233
ROAA	3	2.79%	[2.64%, 2.81%]	0.01
ROAA	4	2.94%	[2.71%, 2.98%]	0.04
ROEA	5	2.88%	[2.70%, 2.89%]	0.02
ROEA	6	2.88%	[2.70%, 2.89%]	0.02
ROEA	7	2.88%	[2.70%, 2.89%]	0.006
NIM	8	2.51%	[2.42%, 2.51%]	0.02
NIM	9	2.72%	[2.48%, 2.73%]	0.24
NIM	10	2.51%	[2.43%, 2.51%]	0.013
NIM	11	2.72%	[2.34%, 2.80%]	0.05

Note: P-values are constructed using 300 bootstraps, and the confidence interval is calculated using the 5% critical value for the nonrejection zone.



Note: Because the LR1 statistics are generally nonstandard, we must calculate the bootstrap p-value. To illustrate the identification of a "nonrejection zone" when constructing a confidence interval, Figure 2 plots the LR2 statistics against all possible threshold values. Given the way LR1 statistics are calculated, the value of LR2 at the estimated threshold value γ will always equal zero. The dashed line depicts the 5% critical value (7.35).

Figure 3. Constructing confidence intervals and the nonrejection zone

4-2-2- Determining the Disciplinary Effect

After confirming the existence of the threshold effect, we evaluate the behavior of banks on both sides of the threshold. Table 4 presents the results from both fixed effects and panel threshold regressions, with ROAA as the measure of bank performance. When NPLs are below the threshold, the coefficient of loan growth (Model 2) is positive and significant at the 5% level, indicating that prudent banks can expand credit and improve profitability without facing excessive risk. Conversely, when NPLs exceed the threshold, the coefficient becomes negative and significant, suggesting that further lending under this regime results in inefficient credit allocation and increased provisioning, thereby harming performance. This result supports the idea that Vietnamese banks behave cautiously under regulatory pressure from the SBV. If the loan growth coefficient remained positive above the threshold, moral hazard behavior would be implied as a result of banks pursuing profits regardless of risks. Furthermore, Models 3 and 4 consider the lagged and contemporaneous combined effects of loan growth. The lagged coefficients below the threshold are positive, larger in value, and highly significant, indicating that banks maintaining controlled NPL levels benefit from previous credit expansion over time. In contrast, for those banks with previous significant losses who might exercise discretion, accept NPL restructuring, and reduce massive credit expansion, we expect that credit growth will not continue to decrease ROAA. This observation is suggested because the coefficient of LR in the contemporaneous period for troubled banks becomes insignificant. These findings reinforce the importance of the SBV's threshold policy for both profitability and stability. Maintaining NPLs below 3% enables banks to benefit in the long term, confirming the disciplinary role of regulatory thresholds in credit risk management.

To further strengthen the conclusion that Vietnamese banks behave prudently, we first compared credit behavior and operating efficiency based on the NPL threshold. Specifically, benchmark Models 1(a) and 1(b) in Table 4 show that when NPL is below the regulatory threshold, credit growth has a significant positive impact on bank efficiency; conversely, when banks have high NPL levels, this impact is negative (although not statistically significant).

Table 4. **Fixed-Effects and Threshold Panel Regression Results (Dependent Variable: ROAA)**

Variable	FE 1a (NPL < 3%)	FE 1b (NPL ≥ 3%)	FE 1c (All)	Threshold 2	Threshold 3	Threshold 4
LR	0.0070*** (0.0025)	−0.0034 (0.0091)	0.0072*** (0.0023)	–	–	–
LR (l.NPL < thr.				0.0064** (0.0026)	–	0.0030 (0.0028)
LR (l.NPL ≥ thr.)	–	–	–	−0.0091** (0.0044)	–	−0.0058 (0.0056)
l.LR (l.NPL < thr.)	–	–	–	–	0.0112*** (0.0022)	0.0090*** (0.0025)
l.LR (l.NPL ≥ thr.)	–	–	–	–	−0.0001 (0.0030)	−0.0030 (0.0043)
DR	0.0053** (0.0024)	0.0032 (0.0097)	0.0020 (0.0023)	0.0011 (0.0023)	−0.0001 (0.0022)	−0.0004 (0.0023)
ETA	0.1286*** (0.0123)	−0.0178 (0.0566)	0.1128*** (0.0010)	0.1108*** (0.0117)	0.1096*** (0.0113)	0.1143*** (0.0115)
Size	0.6182*** (0.1330)	−0.8598 (0.7365)	0.4656*** (0.1302)	0.4189*** (0.1468)	0.4541*** (0.1436)	0.4666*** (0.1443)
Age	0.2602 (0.3219)	−1.6816 (1.3761)	0.3651 (0.2685)	0.3365 (0.3274)	0.3610 (0.3185)	0.3974 (0.3213)
Constant	−8.7448*** (1.5052)	14.9399* (7.5452)	−7.1126*** (1.4589)	−6.2428*** (1.8760)	−6.8117*** (1.8344)	−7.1423*** (1.8540)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	260	37	297	297	297	297
R^2	0.6214	0.6035	0.5968	0.5864	0.6062	0.6069

Notes: *Models 1a–1c are fixed-effects regressions; Models 2–4 are [14] threshold regressions. LR and l.LR = loan growth rates (current and lagged). Threshold models allow marginal effects to vary above/below estimated NPL threshold. Robust SEs in parentheses. ***, **, * = significance at 1%, 5%, and 10%.*

Furthermore, Table 5 shows that banks with NPL ratios below the threshold have significantly higher ROAA than do banks in the high NPL group, reflecting better asset quality and more stable profitability. This result, together with the low standard deviation of ROAA between the two groups, demonstrates that banks maintain a stable business strategy, not pursuing credit growth or interest rates recklessly.

Table 5. **Bank Performance (ROAA) in Low vs. High NPL Regimes**

Group	Mean	Std. Dev.	95% Confidence Interval
Low NPL (< 3%)	0.9894	0.6834	[0.9016, 1.077]
High NPL (≥ 3%)	0.6782	0.6884	[0.5034, 0.8530]
Combined	0.9245	0.6950	[0.8451, 1.004]

T-test Results:

- Ha: diff < 0 → p = 0.9992
- Ha: diff ≠ 0 → p = 0.0016**
- Ha: diff > 0 → p = 0.0008***

Note: Two-sample t-test compares ROAA means under low and high NPL regimes (3% threshold from Model 2).

Finally, Table 6 demonstrates that banks with NPLs > 3% reduced their credit growth by approximately 3.67 percentage points, which was statistically significant at the 5% level compared to the group below the threshold. All of these findings suggest that banks behave with self-discipline by reducing credit growth and accepting lower efficiency to restructure NPLs safely.

Table 6. Regression: High NPL Regime (NPL ≥ 3%) and Credit Growth

Variable	Coef.	Robust SE	t	p-value	95% Conf. Interval
Regime (NPL ≥ 3%)	−3.6655**	1.6700	−2.20	0.029	[−6.9522, −0.3789]
ETA	−0.2922	0.2009	−1.45	0.147	[−0.6877, 0.1032]
Size	0.5666	0.6102	0.93	0.354	[−0.6344, 1.7676]
Age	−0.2280***	0.0519	−4.39	0.000	[−0.3301, −0.1258]
DR	0.5527***	0.0747	7.40	0.000	[0.4058, 0.6997]
Constant	12.3804	7.7970	1.59	0.113	[−2.9654, 27.7262]
Model R^2 = 0.3828					

*Note: Dependent variable = credit growth (LG). Regime dummy = 1 if NPL ≥ 3%, else 0. Controls: ETA, size (log assets), age (years), and DR. Robust SEs used. ***, **, * = significance at 1%, 5%, 10%.*

In the Chinese market, Zhang et al. [12] found moral hazard in banks; specifically, when faced with high NPL levels (> 4.8%), the banks increased lending to hide their NPLs. In contrast, our study of a sample of Vietnamese banks from 2013–2023 under the SBV’s 3% NPL threshold policy found no clear evidence of banks trying to increase profits by lending riskily to boost short-term profits when NPL levels were high; instead, the results reflect a disciplinary effect. This behavior aligns with [6] theoretical proposition that high NPL levels can elicit either discipline or moral hazard. Our evidence is consistent with findings in emerging markets (e.g., [1, 11, 39, 40]), supporting the role of regulation in fostering prudence. Compared to the results from developed countries in which strong institutional environments and market discipline enhance regulatory enforcement [10, 38], our result shows that SBV regulations are effective in shaping cautious bank behavior in emerging markets such as Vietnam, which often lack mature regulatory frameworks.

The effective mechanism behind the cautious behavior of Vietnamese banks may stem from the SBV's supervisory tools: inspections, sanctions, and restraining credit growth. Banks maintaining NPLs below 3% may access higher credit growth ceilings; those with weak asset quality face restrictions. Additionally, even sales of NPLs to the Vietnam Asset Management Company (VAMC) require compliance with the 3% cap. This requirement acts as an external red line, limiting excessive risk-taking. Therefore, Vietnamese banks are not highly motivated to engage in moral hazard.

From a signaling theory perspective, breaching the 3% threshold sends a negative signal to investors, depositors, and regulators that poor asset quality, mismanagement, or ineffective supervision exists. As a result, this threshold serves not only as a regulatory tool but also as a danger threshold, encouraging proactive adjustments to maintain public trust and stability.

4-2-3- Robustness Checks

To ensure the robustness of the results, we conducted tests in which we replaced the dependent variable with other performance indicators (ROEA or NIM), performed a dynamic panel threshold regression, and divided the sample into two periods (2013–2018 and 2019–2023). The credit growth rate may be endogenous due to the bidirectional relationship with bank performance, and the previous period's performance affects this period [51, 52]. Because the static threshold model does not address endogeneity and dynamic issues, we applied the dynamic threshold model of [53].

The results of the alternative indicators and dynamic panel threshold regression are presented in Table 7, whereas the results of the period test are presented in Table 8. In particular, the NPL threshold estimates from Models 5–11 (Table 3) further confirms the existence of a < 3% threshold. All of the regression results from the robustness tests (Tables 7 and 8) are consistent with the main findings, firmly affirming our conclusions.

Table 7. Robustness Checks: Alternative Performance Indicators and Dynamic Threshold Models

Variable	ROEA 5	ROEA 6	ROEA 7	NIM 8	NIM 9	NIM 10	NIM 11 (Dynamic)
l.Y	–	–	–	–	–	–	−0.0794 (0.1759)
LR (l.NPL < thr.)	0.0595* (0.0328)	–	0.1150*** (0.0314)	0.0085* (0.0044)	–	0.0117** (0.0050)	0.0061 (0.0079)
LR (l.NPL ≥ thr.)	−0.1037** (0.0476)	–	−0.0250 (0.0510)	−0.0097* (0.0050)	–	−0.0139** (0.0062)	−0.0190* (0.0109)
l.LR (l.NPL < thr.)	–	0.1230*** (0.0270)	0.0050 (0.0353)	–	0.0033 (0.0036)	0.0050 (0.0044)	–
l.LR (l.NPL ≥ thr.)	–	−0.0430 (0.0408)	−0.0301 (0.0580)	–	−0.0092* (0.0050)	−0.0039 (0.0058)	–
DR	−0.0319 (0.0284)	−0.0469* (0.0269)	−0.0460 (0.0281)	−0.0042 (0.0036)	−0.0029 (0.0036)	−0.0036 (0.0037)	−0.0106 (0.0065)
ETA	0.1868 (0.1445)	0.2253 (0.1340)	0.2282 (0.1413)	0.1264*** (0.0183)	0.1321 (0.0186)	0.1270*** (0.0184)	0.1020** (0.0464)
Size	4.4647** (1.8090)	5.3600*** (1.7590)	5.2470*** (1.7760)	0.2650 (0.2322)	0.3827 (0.2360)	0.2270 (0.2340)	1.3090** (0.6600)
Age	−1.7878 (4.0341)	−1.0670 (3.9080)	−1.0292 (3.9390)	0.2491 (0.5174)	0.0684 (0.5240)	0.2161 (0.5180)	−3.0520 (1.9730)
Constant	−37.9679 (23.0487)	−52.7971 (22.5010)	−51.4652 (22.7647)	−2.0924 (2.9411)	−2.9920 (3.0100)	−1.4881 (2.9820)	−3.5040** (1.8290)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	–
Sargan Test	–	–	–	–	–	–	$\chi^2(48) = 53.40$, $p = 0.274$
Obs.	297	297	297	297	297	297	297
R^2	0.4445	0.4758	0.4766	0.3167	0.2883	0.3222	–

Notes: *Models 5–10 are [14] panel threshold regressions. Model 11 uses [53] dynamic threshold model with lagged dependent variable. Granger noncausality tests confirm NPL exogeneity. ***, **, * = significance at 1%, 5%, 10%.*

Table 8. Threshold Regression Results by Period

Period	Estimated Threshold (95% CI)	LR (l.NPL < thr.)	LR (l.NPL ≥ thr.)	DR	ETA	Size	Age	Constant	Obs.	R^2
2013–2018	2.9800**	0.001 (0.003)	−0.009** (0.004)	0.004* (0.002)	0.150*** (0.018)	0.632** (0.245)	0.701 (0.540)	−10.213*** (2.841)	135	0.5843
2019–2023	2.8140**	0.001 (0.005)	−0.017*** (0.006)	−0.002 (0.004)	0.043 (0.029)	−0.110 (0.327)	−0.069 (1.122)	2.343 (4.780)	135	0.3087

Notes: *Subsample regressions compare 2013–2018 vs. 2019–2023 using [14] threshold model.*

4-3- Institutional Context and the Signalling Effectiveness of the NPL Threshold

Our theoretical framework provides a clear channel through which institutional factors shape bank behaviour. The effectiveness of the NPL threshold as a disciplinary signal is determined by the expected cost of breaching it, $K = (1-b)(P + \lambda C)$. Institutional quality directly influences each parameter of this cost function. Stronger institutions raise P (credible enforcement and supervisory capacity) and raise λ (greater market transparency and creditor rights), while a history of forbearance or expected bailouts (a key feature of the institutional landscape) increases b, thereby dampening the total expected cost K. The model's comparative statics (2) imply that stronger institutions (higher P, higher λ, lower b) expand the discipline region, making self-disciplinary behaviour more likely. Conversely, weaker institutions tilt the outcome toward moral hazard.

As a parsimonious institutional check, we use state ownership (SOE) as a proxy for a distinct micro-institutional environment. We assumed that SOE status captures three institutional channels simultaneously: higher bailout expectations (b), lower effective enforcement (P), and lower market sensitivity (λ). While the bailout itself is a government policy, the expectation that this policy will be selectively applied to SOEs is an unwritten institutional feature. Both the market and the banks themselves believe that the probability of receiving government assistance during financial distress is significantly higher for SOEs than for their private counterparts. This captures the essence of the "soft budget constraint" concept, where state-owned banks are shielded from harsh market discipline due to implicit government guarantees [54, 55]. Therefore, SOE plausibly captures these channels jointly to test whether this belief in an "institutional safety net" weakens discipline.

Furthermore, state-owned banks may receive more lenient treatment from regulators due to political connections, which can influence lending decisions and supervisory actions, implying a lower perceived enforcement cost P [56]. Finally, the market may perceive SOE risk as being implicitly underwritten by the government, making their funding costs less sensitive to negative signals about NPLs and thus subject to weaker market discipline [55]. We therefore hypothesize that the institutional environment of SOEs lowers the expected cost *K*, leading to a weaker disciplinary response.

Our empirical findings strongly support this hypothesis. As shown in Table 9, bank behaviour diverges sharply across ownership types when the NPL threshold is breached.

Table 9. Institutional heterogeneity (SOE and JCB) around the NPL threshold

Variable	Estimated threshold (95% CI)	Lr_Private (NPL < thr)	Lr_Private (NPL ≥ thr)	Lr_SOE (NPL < thr)	Lr_SOE (NPL ≥ thr)	R^2
Value	2.98%**	0.006**	−0.010*	0.028**	0.040*	0.3473

*Notes: Model re-estimated at the identified threshold with fixed effects and SOE interactions. Robust SEs (clustered by bank) in parentheses. ***, **, * denote significance at 1%, 5%, and 10%. ROAA is the dependent variable. Few SOE observations above the threshold, so heterogeneity results are indicative only.*

The result shows that private banks exhibit a self-disciplinary tendency, reflected in the negative coefficient on loan growth (-0.010). In contrast, SOEs show evidence of moral hazard, with a positive and statistically significant coefficient on loan growth (0.040). A Wald test rejects the equality of the two coefficients in the high-NPL regime (F=6.57, p=0.0165). Furthermore, a slope difference-in-differences test confirms that the threshold's disciplinary impact is significantly stronger for private banks than for SOEs (coefficient of the difference = 0.0285, p=0.012). This result indicates that the threshold not only has a different impact on the two groups but also triggers opposite behavioural responses. This finding suggests that the institutional safety net enjoyed by SOEs creates an environment where they bear less of the full cost of issuing a negative signal, thus incentivizing riskier behaviour. Therefore, the institutional factor, as captured by state ownership, is a key determinant of the policy's effectiveness.

4-3-1- Comparative Institutional Contexts and Regulatory Effectiveness

The global analysis by Salas et al. [25] shows that adverse macroeconomic shocks and weak institutional quality are correlated with persistently higher NPL levels. As our theoretical framework predicts, in environments with weak enforcement and limited market discipline (low *P*, low λ, and high bailout or forbearance beliefs *b*), the NPL signal becomes uninformative. With a small effective penalty *K*, the behavioral response to breaching the threshold becomes muted, and banks have little incentive to reduce loan growth. Empirically, the slope gap ($\beta_1 - \beta_2$) therefore narrows, allowing loan growth to remain performance-enhancing even above the regulatory limit, particularly under risk-shifting conditions.

This pattern aligns with evidence from China (2006–2012) in Zhang et al. [12], where a context of regulatory forbearance and opportunities to window-dress NPLs through evergreening and shadow exposures rendered official NPL metrics less informative and weakened the disciplinary role of thresholds. Similarly, Islam & Nishiyama [57] documented that in India and Bangladesh, despite the existence of NPL regulations, political interference and weak enforcement mechanisms prevented effective implementation. The experience of Japan during the 1990s [58] also illustrates how delayed resolution of bad loans and supervisory forbearance created "zombie lending," undermining the credibility of prudential tripwires.

In contrast, our findings for Vietnam provide a rare example from an emerging market where a simple and transparent regulatory threshold, supported by a credible enforcement mechanism, has proven effective in shaping prudent bank behavior. This contrast reinforces that the effectiveness of financial regulation is not automatic but depends critically on the institutional environment, particularly on enforcement credibility and market discipline.

4-4- The Disciplinary Behavior Mechanism: Internalization versus External Enforcement

While our theoretical framework primarily formalizes external enforcement via the effective penalty $K=(1-b).(P+\lambda C)$ and the empirical patterns we document fit the external-discipline channel, internalized discipline would operate through the bank's internal primitives, namely its screening and monitoring quality (μ) in the probability function (1)

In mechanism terms, better internal governance can be interpreted as a higher screening quality μ, which reduces the breach sensitivity $\frac{\partial p}{\partial g}$ at a given g (lowers the probability of high NPLs). Holding the external penalty K fixed, the FOC: $A - Bg^* = K\frac{\partial p}{\partial g}$ then implies a lower optimal loan growth $g*$ once near/above the threshold, yielding a more negative above-threshold slope on g in the empirical specification. Consistent with internalized prudence, well-governed banks reduce loan growth once in the high-NPL regime, yielding a negative and significant above-threshold slope. By contrast, weakly governed banks show no significant adjustment, indicating muted discipline rather than moral hazard. To distinguish between these two mechanisms, we present empirical analysis. First, we test whether the disciplinary effect is amplified by internal governance quality. We use board meeting attendance as a proxy for monitoring quality (μ), a standard practice in the governance literature [27]. We interact with this proxy with loan growth in our threshold model.

The results in Table 10 are consistent with internalized prudence, well-governed banks reduce loan growth once in the high-NPL regime, yielding a negative and significant above-threshold slope. By contrast, weakly governed banks show no significant adjustment, indicating muted discipline rather than moral hazard. A Wald test confirms this difference is highly significant (p=0.001), indicating that stronger internal governance (proxied by board meeting attendance as a standard measure of monitoring quality) amplifies the disciplinary effect.

Table 10. Heterogeneity in Disciplinary Effects

Variable	Coef
Estimated threshold (95%CI)	2.88%***
l.Lr_.lowgov (l.NPL < thr)	0.011***
l.Lr_lowgov (l.NPL ≥ thr)	0.022
l.Lr_highgov (l.NPL < thr)	0.010***
l.Lr_highgov (l.NPL ≥ thr)	-0.020***
R-square	0.624

*Notes: Model re-estimated at the threshold with fixed effects and HighGov1 interactions. HighGov1 = 1 indicates good governance (no board absence), lagged (t–1) to reduce endogeneity. Robust SEs (bank-clustered) in parentheses. ***, **, * = 1%, 5%, 10%. Bank/year FE included. T-test: F = 20.32, p = 0.000. ROAA is the dependent variable.*

Furthermore, to support this argument, we use a histogram of the NPL distribution as visual evidence. The idea behind this method is to search for the "behavioural footprint" that each mechanism leaves on the data. The analysis of economic agents' bunching at policy thresholds is a standard tool in public economics for detecting strategic behavioural responses [59]. If the histogram were to show a sharp bunching just below the 3% threshold, this behaviour would reflect the minimum effort necessary to comply with the regulation and avoid penalties. Conversely, if banks had truly internalized the principles of risk management, their NPL distribution would be smoother and more spread out in the safe region (1.5% - 2.5%).

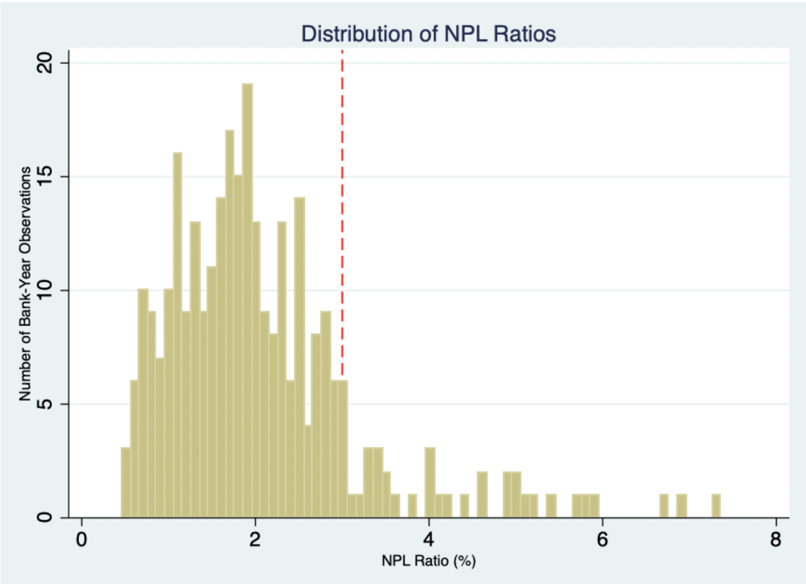


Figure 4. NPL Distribution and the 3 Percent Regulatory Threshold

The histogram presented in Figure 4 illustrates the distribution of nonperforming loan (NPL) ratios across the sample and shows a broad safety buffer around 1.5–2.5 percent. The figure provides no clear evidence of bunching in the classic sense, that is, a sharp peak and a cliff immediately before the supervisory threshold. Instead, the overall shape of the distribution supports the self-discipline hypothesis, indicating that banks proactively maintain low NPL ratios not merely for compliance purposes but as part of prudent internal governance. The McCrary [60] density test around the 3 percent cut-off further confirms this pattern, finding no statistically significant discontinuity in the NPL distribution (T = –1.47, p = 0.142). Therefore, as illustrated in Figure 4, the State Bank of Vietnam's regulation has effectively established a "red line" that functions both as an external deterrent and as a behavioral signal encouraging sound risk management practices. This alignment between external supervision and internal discipline demonstrates that banks have internalized regulatory expectations, maintaining stability through self-imposed prudence.

Therefore, it can be concluded that the SBV's regulation has succeeded in creating an effective "red line" that acts as an external deterrent, while also encouraging prudent internal governance. This results in bank behaviour consistent with sound risk management, which can be seen as an expression of internalized discipline.

4-5- Endogeneity Robustness Tests

While the model by Kremer et al. [53] accounts for the dynamics and endogeneity of regressors, potential endogeneity concerns—such as the bidirectional relationship between performance and NPLs or omitted variable bias—may not be fully resolved. To address these issues, two additional and more stringent tests are conducted.

First, the methodology of Seo & Shin [61] is applied. This advanced dynamic threshold model explicitly allows the threshold variable (NPL) to be endogenous, using deeper lags as instruments within a GMM framework. Across these estimators, the estimated cut-off and the below- and above-regime slopes remain qualitatively unchanged, alleviating concerns regarding endogeneity. Specifically, the estimated threshold is 2.92%, closely matching the threshold reported in Hansen [14]. Furthermore, the loan-growth slope is near zero below the threshold and becomes negative and statistically significant above it. A Wald test confirms a significant change in slopes across regimes, consistent with the disciplinary behavior hypothesis.

Second, a pre-determined regime is employed using NPL_{t-2} as the threshold variable. The use of a more distant lag creates temporal separation that strengthens the credibility of the exogeneity assumption, as NPL_{t-2} is determined by earlier information and is less likely to be influenced by factors affecting contemporaneous performance. Results from the model using NPL_{t-2} continue to indicate a stable threshold around 3%. More importantly, this specification also confirms the disciplinary effect, with the coefficient on loan growth in the above-threshold regime remaining negative and statistically significant. Since the main conclusions hold across these alternative specifications, the findings demonstrate robustness against concerns of endogeneity in the threshold variable.

Table 11. Robustness Checks for Threshold Variable Endogeneity

Variables	Estimated threshold (95% CI)(1)	Lr (below threshold l.NPL)	Lr (above threshold l.NPL)	Estimated threshold (95% CI)(2)	Lr (l2.NPL < thr)	Lr (l2.NPL ≥ thr)
Values	2.92 %**	0.001	−0.052*	3.00 %**	0.004	−0.010**

*Notes: (1) and (2) use the [61] and lagged NPL_{t-2} approaches, respectively. Threshold models allow marginal effects to differ above and below the estimated NPL threshold. Robust SEs clustered by bank. ***, **, * denote significance at 1%, 5%, and 10%. Wald test rejects slope equality across regimes (p = 0.053).*

4-6- Threshold Stability and Dynamic Adjustment

While the baseline analysis assumes a fixed NPL threshold, the framework allows it to vary with macro-financial conditions through in the probability function (1).

An adverse macroeconomic shock ($\varepsilon_t < 0$), such as an economic crisis or a pandemic, increases the probability of breaching the NPL threshold at any given level of loan growth, *g*. To maintain an acceptable probability of a breach, banks would be forced to choose an even lower optimal growth rate, *g**. From a policy perspective, this implies that regulators may need to recalibrate the threshold dynamically in line with the economic cycle, for instance, by temporarily relaxing it to 4% or 5% to avoid an unnecessary credit crunch during difficult times. Although estimating a formal time-varying threshold model is beyond the scope of this paper, it is a promising avenue for future research. Empirically, we test for the threshold's stability by splitting our sample into two distinct economic periods: 2013–2018 and 2019–2023. The results in Table 8 show a mild downward drift in the estimated threshold, from 2.98% to 2.81%. While this difference is small and the threshold remains stable around the 3% mark, the downward shift during the 2019–2023 period is highly consistent with our theoretical framework. This period coincided with adverse macroeconomic shocks such as COVID-19, the corporate bond crisis, and tighter prudential standards on provisioning and loan classification. As systemic risk increases, the probability of a breach at any given growth rate *g* also rises. Consequently, banks tend to react sooner by reining in loan growth at a lower NPL level than they would in normal times. This downward shift in the behavioural breakpoint reflects banks' endogenous adjustment to a riskier environment.

5- Discussion and implications

5-1- Summary of Findings

This study set out to resolve a critical regulatory dilemma in emerging economies: how to determine a non-performing loan (NPL) threshold that maintains financial stability without impeding bank profitability and operational efficiency. Using panel threshold regression on a decade of data from 27 Vietnamese commercial banks, we find that the optimal NPL ratio is approximately three percent. This figure aligns precisely with the State Bank of Vietnam’s (SBV) formal regulatory ceiling. The results indicate that when banks operate below this threshold, credit expansion contributes positively to efficiency in both the short and long term, supporting sustainable lending practices. However, when banks exceed the three percent level, credit growth no longer enhances efficiency and instead forces managers to navigate a difficult trade-off between profitability and elevated risk. Importantly, the evidence points to a strong regulatory disciplining effect: the presence of a clear supervisory ceiling prompts banks to adjust lending strategies in anticipation of potential sanctions or reputational damage, even in the absence of highly punitive enforcement mechanisms. Robustness tests confirm the stability of these findings across model specifications.

5-2- Contributions to the Literature

The research makes several significant contributions to the banking and regulatory literature. First, it addresses an underexplored gap by directly linking a specific supervisory threshold to measurable shifts in bank lending behavior. Most prior studies focus broadly on the quality of regulation or institutional strength without examining whether a particular quantitative benchmark can act as an inflection point in managerial decision-making. By doing so, this study moves beyond normative debates and offers empirical precision. Second, it extends signaling theory into the domain of prudential regulation, framing the NPL threshold as a form of public signal that conveys potential distress to investors, depositors, and supervisors. This signaling effect appears to alter lending strategies before problems escalate, serving as a preventive rather than purely corrective mechanism. Third, the study contributes rare evidence from Vietnam, a bank-dominated financial system in which capital markets play a limited role and regulatory capacity is still developing. In such contexts, the effectiveness of a simple, transparent rule carries broader implications for other emerging markets where similar institutional constraints exist.

5-3- Policy Implications

The findings carry meaningful policy lessons for regulators, bank executives, and financial sector stakeholders. For the SBV and other regulatory authorities, the Vietnamese experience demonstrates that a clearly defined and consistently communicated NPL ceiling can operate as a cost-effective risk management tool. It requires fewer resources than continuous micro-level supervision while still influencing strategic choices at the bank level. Nevertheless, the optimal threshold is unlikely to be static. Shifts in macroeconomic conditions, credit cycles, or sectoral exposures could necessitate periodic recalibration to maintain effectiveness. For bank managers, the evidence underscores the importance of integrating NPL monitoring directly into strategic planning. Banks approaching the threshold should prioritize portfolio quality, strengthening loan underwriting standards and recovery processes before considering aggressive credit expansion. This strategic discipline not only enhances regulatory compliance but also preserves long-term profitability and resilience. For other emerging economies, the Vietnamese case offers a regulatory design that is both straightforward to implement and demonstrably effective in shaping behavior, even in markets where formal enforcement mechanisms are less comprehensive.

5-4- Limitations and Directions for Future Research

The analysis is subject to several limitations that provide opportunities for further study. One limitation concerns the reliability of reported NPL figures. In Vietnam, a considerable proportion of distressed assets have been transferred to the Vietnam Asset Management Company (VAMC), which may obscure the true scale of problem loans on bank balance sheets. Future research could adjust for these transfers or use alternative asset quality measures. Another limitation lies in the assumption of a stable threshold over the study period. Economic shocks, regulatory reforms, or structural changes in the banking sector could shift the balance point between risk and profitability. Extending the model to allow for time-varying thresholds would provide valuable insight into the adaptability of the regulatory ceiling. Furthermore, the study did not differentiate between types of loans contributing to the NPL ratio. Disaggregating the data by sector, borrower type, or loan size could reveal whether certain categories are more sensitive to threshold effects, thereby helping regulators target interventions more effectively.

6- Conclusion

This study provides empirical evidence that the State Bank's three percent nonperforming loan (NPL) ceiling functions as an effective behavioral threshold that disciplines banks and promotes financial stability. Using panel threshold regression across emerging-market banks from 2013 to 2023, the analysis confirms that when NPL ratios surpass this regulatory benchmark, banks respond through self-corrective actions such as tightening credit growth, improving risk monitoring, and accepting lower short-term profits. These behavioral adjustments indicate that the NPL ceiling operates as a credible disciplinary signal rather than a simple compliance requirement. The findings demonstrate that stability and profitability can be mutually reinforcing when regulatory thresholds are designed on the basis of empirical evidence and consistently applied.

The implications of this research extend beyond Vietnam to other emerging markets that seek to strengthen supervisory capacity and align bank incentives with prudential objectives. In environments where market discipline is weak and enforcement resources are limited, clear and measurable thresholds can help bridge the gap between regulatory design and actual banking practice. Incorporating institutional factors such as governance quality, transparency, and enforcement consistency could further enhance the effectiveness of threshold-based supervision. This study also contributes to signaling theory by conceptualizing regulatory thresholds as negative behavioral signals that encourage managerial prudence and proactive risk management. Overall, the results highlight that well-calibrated and data-informed thresholds can promote both financial stability and sustainable profitability, offering a practical framework for strengthening the resilience of banking systems in emerging economies.

7- Declarations

7-1- Author Contributions

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

7-2- Data Availability Statement

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

7-3- Funding

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

7-4- Acknowledgments

We would like to thank the University of Economics Ho Chi Minh City for their continued support and resources provided throughout the research process.

7-5- Institutional Review Board Statement

Not applicable.

7-6- Informed Consent Statement

Not applicable.

7-7- Conflicts of Interest

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

8- References

[1] Ahmed, S. A., Sayed, O. A., & Ahmed, I. E. (2024). The bank lending behaviour: Does non-performing loans matter? Evidence from the top-ten banks in the Arab world. Asian Development Policy Review, 12(2), 100–110. doi:10.55493/5008.v12i2.4997.

[2] Kulu, E., & Osei, B. (2024). Drivers of financial stability gap: evidence from sub-Saharan Africa. Journal of Financial Economic Policy, 16(1), 19–33. doi:10.1108/JFEP-07-2023-0184.

[3] Klein, N. (2013). Non-Performing Loans in CESEE: Determinants and Impact on Macroeconomic Performance. IMF Working Papers, 13(72), 1. doi:10.5089/9781484318522.001.

[4] Dimitrios, A., Helen, L., & Mike, T. (2016). Determinants of non-performing loans: Evidence from Euro-area countries. Finance Research Letters, 18, 116–119. doi:10.1016/j.frl.2016.04.008.

[5] Nguyen, P. D. (2025). Non-performing loans and bank profitability: evidence from Vietnam. Macroeconomics and Finance in Emerging Market Economies, 18(2), 399–419. doi:10.1080/17520843.2024.2318927.

[6] Bernanke, B., & Gertler, M. Agency costs, net worth, and business fluctuations. Am. Econ. Rev, 79, 14–31. doi:10.3386/w2015.

[7] Erdas, M. L., & Ezanoglu, Z. (2022). How Do Bank-Specific Factors Impact Non-Performing Loans: Evidence from G20 Countries. Journal of Central Banking Theory and Practice, 11(2), 97–122. doi:10.2478/jcbtp-2022-0015.

[8] Gashi, A., Tafa, S., & Bajrami, R. (2022). The Impact of Macroeconomic Factors on Non-performing Loans in the Western Balkans. Emerging Science Journal, 6(5), 1032–1045. doi:10.28991/ESJ-2022-06-05-08.

[9] Doğuç, Ö. (2022). Data Mining Applications in Banking Sector While Preserving Customer Privacy. Emerging Science Journal, 6(6), 1444–1454. doi:10.28991/ESJ-2022-06-06-014.

[10] Gropp, R., Gruendl, C., & Guettler, A. (2014). The impact of public guarantees on bank risk-taking: Evidence from a natural experiment. Review of Finance, 18(2), 457–488. doi:10.1093/rof/rft014.

[11] Audi, M., & Al Masri, R. (2024). Examining the impacts of regulatory framework on risk in commercial banks in emerging economies. Journal of Business and Economic Options, 7(2), 10-19.

[12] Zhang, D., Cai, J., Dickinson, D. G., & Kutan, A. M. (2016). Non-performing loans, moral hazard and regulation of the Chinese commercial banking system. Journal of Banking and Finance, 63, 48–60. doi:10.1016/j.jbankfin.2015.11.010.

[13] Bolarinwa, S. T., Olayeni, R. O., & Vo, X. V. (2021). Is there a nonlinear relationship between nonperforming loans and bank profitability? Evidence from dynamic panel threshold. Managerial and Decision Economics, 42(3), 649–661. doi:10.1002/mde.3262.

[14] Hansen, B. E. (1999). Threshold effects in non-dynamic panels: Estimation, testing, and inference. Journal of Econometrics, 93(2), 345–368. doi:10.1016/S0304-4076(99)00025-1.

[15] Ma'aji, M. M., Barnett, C., Bin-Nashwan, S. A., Roslan, N. H., & Ali, R. A. (2026). Risk-driven profitability: the role of bank capital, liquidity and credit in frontier banking markets. Journal of Financial Regulation and Compliance, 34(1), 60-80. doi:10.1108/JFRC-01-2025-0008.

[16] Dermirgue-Kunt, A. (1989). Deposit-institution failures: a review of empirical literature. Economic Review, 25(4), 2–18.

[17] Foos, D., Norden, L., & Weber, M. (2010). Loan growth and riskiness of banks. Journal of Banking and Finance, 34(12), 2929–2940. doi:10.1016/j.jbankfin.2010.06.007.

[18] Aiyar, S., Bergthaler, W., Garrido, J., Ilyina, A., Jobst, A., Kang, K., Kovtun, D., Liu, Y., Monaghan, D., & Moretti, M. (2015). A Strategy for Resolving Europe's Problem Loans. Staff Discussion Notes, 15(19), 1. doi:10.5089/9781513591278.006.

[19] Phung, Q. T., Van Vu, H., & Tran, H. P. (2022). Do non-performing loans impact bank efficiency? Finance Research Letters, 46, 102393. doi:10.1016/j.frl.2021.102393.

[20] Duong, K. D., Tran, P. M. D., Nguyen, P. Y. N., & Pham, H. (2023). How do funding diversity and non-performing loans affect bank performance in different economic cycles? Cogent Business and Management, 10(2), 2215076. doi:10.1080/23311975.2023.2215076.

[21] Lawrence, B., Doorasamy, M., & Sarpong, P. (2024). The Impact of Credit Risk on Performance: A Case of South African Commercial Banks. Global Business Review, 25(2_Suppl), S151–S164. doi:10.1177/0972150920969927.

[22] Bruche, M., & Llobet, G. (2011). Walking wounded or living dead? Making banks foreclose bad loans. Financial Markets Group Discussion Papers 675, The London School of Economics and Political Science, London, United Kingdom.

[23] Thornton, J., & Di Tommaso, C. (2021). The effect of non-performing loans on credit expansion: Do capital and profitability matter? Evidence from European banks. International Journal of Finance and Economics, 26(3), 4822–4839. doi:10.1002/ijfe.2042.

[24] Tsagkanos, A., & Andriakopoulos, K. (2025). Ex-post credit risk and the cyclicality of banks' self-discipline: empirical evidence from US banks. Journal of Economic Studies, 52(4), 824–839. doi:10.1108/JES-02-2024-0119.

[25] Salas, Mb., Lamothe, P., Delgado, E., Fernández-Miguélez, A. L., & Valcarce, L. (2024). Determinants of Nonperforming Loans: A Global Data Analysis. Computational Economics, 64(5), 2695–2716. doi:10.1007/s10614-023-10543-8.

[26] Chun, S. H., & Ardaaragchaa, N. (2024). Analysis of Factors Affecting the Loan Growth of Banks with a Focus on Non-Performing Loans. Journal of Risk and Financial Management, 17(5), 203. doi:10.3390/jrfm17050203.

[27] Nurkhin, A., Fachrurrozie, F., Widiatami, A. K., Baswara, S. Y., & Wolor, C. W. (2024). Does Governance Affect Non-Performing Loans? Empirical Evidence of Indonesian Banks. Banks and Bank Systems, 19(4), 58–69. doi:10.21511/bbs.19(4).2024.05.

[28] Hamada, M. A., Farag, K., & Abiche, A. E. (2025). Early Prediction Detection of Retail and Corporate Credit Risks Using Machine Learning Algorithms. Emerging Science Journal, 9(2), 995–1012. doi:10.28991/ESJ-2025-09-02-025.

[29] Tu, P. T., Oanh, D. L. K., & Trang, D. D. (2025). Machine Learning and Parameter Optimization for Banking Stability Prediction and Determinants Identification in ASEAN. Emerging Science Journal, 9(3), 1189–1208. doi:10.28991/ESJ-2025-09-03-04.

[30] Keeley, M. C. (1990). Deposit insurance, risk, and market power in banking. American Economic Review, 80(5), 1183–1200.

[31] Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. Journal of Financial Economics, 3(4), 305–360. doi:10.1016/0304-405X(76)90026-X.

[32] Piatti, D., & Cincinelli, P. (2019). Does the threshold matter? The impact of the monitoring activity on non-performing loans: Evidence from the Italian banking system. Managerial Finance, 45(2), 190–221. doi:10.1108/MF-02-2018-0077.

[33] Kanoujiya, J., Bhimavarapu, V. M., & Rastogi, S. (2023). Banks in India: A Balancing Act between Profitability, Regulation and NPA. Vision, 27(5), 650–660. doi:10.1177/09722629211034417.

[34] Alnabulsi, K., Kozarević, E., & Hakimi, A. (2023). Non-Performing Loans and Net Interest Margin in the MENA Region: Linear and Non-Linear Analyses. International Journal of Financial Studies, 11(2), 1–17. doi:10.3390/ijfs11020064.

[35] Quang, L. D. (2020). Determinants of banking crisis: The case of Vietnam. Hcmcoujs - Economics and Business Administration, 5(2), 64–81. doi:10.46223/hcmcoujs.econ.en.5.2.66.2015.

[36] Balgova, M., Nies, M., & Plekhanov, A. (2018). The Economic Impact of Reducing Non-Performing Loans. SSRN Electronic Journal, 193. doi:10.2139/ssrn.3119677.

[37] Barth, J. R., Lin, C., Ma, Y., Seade, J., & Song, F. M. (2013). Do bank regulation, supervision and monitoring enhance or impede bank efficiency? Journal of Banking and Finance, 37(8), 2879–2892. doi:10.1016/j.jbankfin.2013.04.030.

[38] Degryse, H., Huylebroek, C., & Doornik, B. Van. (2025). The disciplining effect of bank supervision: evidence from SupTech. BIS Working Papers, Bank of Finland, Helsinki, Finland.

[39] Özkan-Günay, E., Günay, Z., & Günay, G. (2013). The impact of regulatory policies on risk taking and scale efficiency of commercial banks in an emerging banking sector. Emerging Markets Finance and Trade, 49(SUPPL. 5), 80–98. doi:10.2753/REE1540-496X4905S505.

[40] Amin, A. S., Imam, M. O., & Malik, M. (2019). Regulations, Governance, and Resolution of Non-Performing Loan: Evidence from an Emerging Economy. Emerging Markets Finance and Trade, 55(10), 2275–2297. doi:10.1080/1540496X.2018.1523788.

[41] Spence, M. (1973). Job market signaling. Quarterly Journal of Economics, 87(3), 355–374. doi:10.2307/1882010.

[42] Leland, H. E., & Pyle, D. H. Informational asymmetries, financial structure, and financial intermediation. The Journal of Finance, 32(2), 371–387.

[43] Flannery, M. J., & Sorescu, S. M. (1996). Evidence of bank market discipline in subordinated debenture yields: 1983-1991. Journal of Finance, 51(4), 1347–1377. doi:10.1111/j.1540-6261.1996.tb04072.x.

[44] Diamond, D. W. (1984). Financial intermediation and delegated monitoring. Review of Economic Studies, 51(3), 393–414. doi:10.2307/2297430.

[45] Hellmann, T. F., Murdock, K. C., & Stiglitz, J. E. (2000). Liberalization, moral hazard in banking, and prudential regulation: Are capital requirements enough? American Economic Review, 90(1), 147–165. doi:10.1257/aer.90.1.147.

[46] Merton, R. C. (1977). An analytic derivation of the cost of deposit insurance and loan guarantees an application of modern option pricing theory. Journal of Banking and Finance, 1(1), 3–11. doi:10.1016/0378-4266(77)90015-2.

[47] Fadden, D. M. (1974). Conditional logit analysis of qualitative choice behavior. Frontiers in Econometrics, 33(8), 105–142.

[48] Ozili, P. K. (2025). Bank non-performing loans research around the world. Asian Journal of Economics and Banking, 9(3), 437–462. doi:10.1108/ajeb-09-2024-0103.

[49] Simon, C. P., & Blume, L. (1994). Mathematics for economists. Norton, New York, United States.

[50] Boudriga, A., Boulila Taktak, N., & Jellouli, S. (2009). Banking supervision and nonperforming loans: a cross- country analysis. Journal of Financial Economic Policy, 1(4), 286–318. doi:10.1108/17576380911050043.

[51] Swamy, D. V. (2012). Impact of Macroeconomic and Endogenous Factors on Non Performing Bank Assets. SSRN Electronic Journal, 9, 26–47. doi:10.2139/ssrn.2060753.

[52] García-Marco, T., & Robles-Fernández, M. D. (2008). Risk-taking behaviour and ownership in the banking industry: The Spanish evidence. Journal of Economics and Business, 60(4), 332–354. doi:10.1016/j.jeconbus.2007.04.008.

[53] Kremer, S., Bick, A., & Nautz, D. (2013). Inflation and growth: New evidence from a dynamic panel threshold analysis. Empirical Economics, 44(2), 861–878. doi:10.1007/s00181-012-0553-9.

[54] KORNAI, J. (1986). The Soft Budget Constraint. Kyklos, 39(1), 3–30. doi:10.1111/j.1467-6435.1986.tb01252.x.

[55] La Porta, R., Lopez-De-Silanes, F., & Shleifer, A. (2002). Government ownership of banks. Journal of Finance, 57(1), 265–301. doi:10.1111/1540-6261.00422.

[56] Khwaja, A. I., & Mian, A. (2005). Do lenders favor politically connected firms? Rent provision in an emerging financial market. Quarterly Journal of Economics, 120(4), 1371–1411. doi:10.1162/003355305775097524.

[57] Islam, M. S., & Nishiyama, S. I. (2016). The determinants of bank net interest margins: A panel evidence from South Asian countries. Research in International Business and Finance, 37(3), 501–514. doi:10.1016/j.ribaf.2016.01.024.

[58] Caballero, R. J., Hoshi, T., & Kashyap, A. K. (2008). Zombie lending and depressed restructuring in Japan. American Economic Review, 98(5), 1943–1977. doi:10.1257/aer.98.5.1943.

[59] Saez, E. (2010). Do taxpayers bunch at kink points? American Economic Journal: Economic Policy, 2(3), 180–212. doi:10.1257/pol.2.3.180.

[60] McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. Journal of Econometrics, 142(2), 698–714. doi:10.1016/j.jeconom.2007.05.005.

[61] Seo, M. H., & Shin, Y. (2016). Dynamic panels with threshold effect and endogeneity. Journal of Econometrics, 195(2), 169–186. doi:10.1016/j.jeconom.2016.03.005.

Appendix I

Table A1. Sampled Banks (2013–2023)

Number	ID	Bank name	Type
1	ABB	An Binh Commercial Joint Stock Bank	JCB
2	ACB	Asia Commercial Joint Stock Bank	JCB
3	BAB	Bac A Commercial Joint Stock Bank	JCB
4	BID	Joint Stock Commercial Bank for Investment and Development of Vietnam	SOB
5	BVB	Viet Capital Commercial Joint Stock Bank	JCB
6	CTG	Vietnam Joint Stock Commercial Bank for Industry and Trade	SOB
7	EIB	Vietnam Commercial Joint Stock Export–Import Bank	JCB
8	HDB	Ho Chi Minh City Development Joint Stock Commercial Bank	JCB
9	KLB	Kien Long Commercial Joint Stock Bank	JCB
10	LPB	Fortune Vietnam Joint Stock Commercial Bank	JCB
11	MBB	Military Commercial Joint Stock Bank	JCB
12	MSB	Vietnam Maritime Commercial Joint Stock Bank	JCB
13	NAB	Vietnam Maritime Commercial Joint Stock Bank	JCB
14	OCB	Orient Commercial Joint Stock Bank	JCB
15	PGB	Prosperity and Growth Commercial Joint Stock Bank	JCB
16	SHB	Saigon Hanoi Commercial Joint Stock Bank	JCB
17	SSB	Southeast Asia Commercial Joint Stock Bank	JCB
18	STB	Sai Gon Thuong Tin Commercial Joint Stock Bank	JCB
19	TCB	Vietnam Technological and Commercial Joint Stock Bank	JCB
20	TPB	Tien Phong Commercial Joint Stock Bank	JCB
21	VAB	Vietnam–Asia Commercial Joint Stock Bank	JCB
22	VCB	Bank for Foreign Trade of Vietnam	SOB
23	VIB	Vietnam International Commercial Joint Stock Bank	JCB
24	VPB	Vietnam Prosperity Joint Stock Commercial Bank	JCB
25	AGR	Vietnam Bank for Agriculture and Rural Development	SOB
26	Baovietbank	Bao Viet Joint Stock Commercial Bank	JCB
27	SGB	Saigon Bank for Industry and Trade	JCB

Note: SOB: State-owned bank; JCB: Joint-stock commercial bank