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Liquidity and Capital Thresholds as Buffers against Macroeconomic Uncertainty: Evidence from Panel Threshold and Causal Machine Learning in ASEAN

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Abstract: This study examines the nonlinear and heterogeneous effects of macroeconomic uncertainty on bank stability in ASEAN emerging markets, with particular emphasis on the moderating roles of capital and liquidity buffers. Using panel data of 62 banks over 2010–2023, the analysis integrates panel threshold regression (PTR) with double machine learning (DML) and causal forests. PTR results reveal a statistically significant capital adequacy threshold of approximately 8%, above which the adverse effect of uncertainty is significantly attenuated, while liquidity shows consistent mitigating effects in machine learning (ML) estimates but lacks robust threshold evidence. In contrast, ML evidence uncovers conditional heterogeneity: higher liquidity systematically reduces the destabilising impact of uncertainty, whereas elevated capital ratios in some cases amplify vulnerability, reflecting structural frictions and risk-taking incentives in emerging markets. Robustness checks across alternative stability measures, subsamples (pre- vs. post-COVID, small vs. large banks), and uncertainty regimes confirm that uncertainty shocks are most damaging during high-uncertainty episodes and for smaller banks. The findings highlight that while both buffers matter, capital provides strong protection only once a critical threshold is reached, whereas liquidity consistently supports resilience. These insights underscore the need for tailored macroprudential strategies that integrate buffer design with institutional quality.

Keywords: ASEAN, bank stability, capital adequacy, liquidity buffer, macroeconomic uncertainty
JEL classification: C33, C55, E44, G21, G28

1. Introduction

Over the past two decades, the global financial system has faced repeated shocks testing banking resilience and regulatory effectiveness. The global financial crisis (GFC) of 2007–2009 exposed structural weaknesses, including excessive leverage, weak capitalisation and liquidity mismatches. In response, Basel III was introduced to strengthen capital and liquidity requirements, aiming to enhance resilience and reduce systemic risk (Patel et al., 2022; Petrović & Trifunović, 2024).

Despite these reforms, uncertainty remains pervasive. The COVID-19 pandemic generated a simultaneous supply-demand shock, triggering severe volatility and

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economic contraction. Evidence shows that banks with stronger capital and liquidity buffers were more resilient, mitigating spillovers to the real economy (Ding et al., 2025; Zhang, 2023). More recently, geopolitical tensions, supply chain disruptions, and interest rate volatility have continued to challenge banking stability (Danisman & Tarazi, 2024; Merrino & Harris, 2025). These developments highlight the enduring role of prudential regulation and raise a critical question: under what conditions do capital and liquidity effectively function as "stability shields"?

These concerns are particularly acute in ASEAN emerging economies. Although Indonesia, Vietnam, Malaysia, the Philippines and Thailand have achieved substantial financial development, they remain vulnerable due to high openness, reliance on external capital and shallow domestic markets (Shonhadji & Irwandi, 2023). Banks play a central role in regional growth but face persistent liquidity constraints, weak capitalisation and governance limitations (Wahyudi et al., 2024). The pandemic further intensified these vulnerabilities (Thi Tran, 2024), while systematic evidence on banking stability under uncertainty in ASEAN remains limited.

Existing literature emphasises the importance of capital and liquidity buffers for financial stability. While Basel III enhances resilience, its effects vary across institutions and contexts (Sharma & Chauhan, 2023; Veeramoothoo & Hammoudeh, 2022). Moreover, growing evidence suggests nonlinear effects, with buffers becoming effective only beyond critical thresholds (Patel et al., 2022; Sharma & Chauhan, 2023). This raises an important policy issue: whether regulatory minima are sufficient or should be adjusted to reflect country-specific conditions.

At the same time, macroeconomic uncertainty has become increasingly multi-dimensional. Reliance on a single indicator such as the economic policy uncertainty (EPU) index fails to capture the full spectrum of risks. Banks are simultaneously exposed to geopolitical risk (GPR), pandemic-related uncertainty (WPUI – World Pandemic Uncertainty Index), and sentiment-driven fluctuations (WSI – World Sentiment Index). Integrating these dimensions into a composite index using principal component analysis (PCA) provides a more comprehensive measure of systemic uncertainty and allows for testing how capital and liquidity buffers moderate its effects.

Methodologically, linear models are insufficient to capture nonlinear threshold effects and heterogeneous responses. Hansen's (1999) panel threshold regression (PTR) identifies regime-dependent relationships, while causal forests within the double machine learning (DML) framework (Athey & Imbens, 2019; Bach et al., 2024; Chernozhukov et al., 2018) enable the analysis of heterogeneity and conditional effects. However, such integrated approaches remain largely unexplored in ASEAN banking research.

Against this backdrop, this study examines whether capital and liquidity thresholds help ASEAN banks withstand macroeconomic uncertainty. It makes three contributions. First, it constructs a composite macroeconomic uncertainty index (CMUI) integrating multiple risk dimensions. Second, it applies PTR to identify threshold effects of capital (ETA – equity-to-total assets) and liquidity (LIQ). Third, it employs causal forests with DML to capture heterogeneous responses to uncertainty shocks.

The findings carry important policy implications. Identifying effective buffer thresholds supports the design of context-specific macroprudential policies beyond uniform Basel III standards. Moreover, cross-country evidence from ASEAN provides insights into institutional differences, contributing to more resilient financial systems under persistent global uncertainty.

The remainder of this paper is organised as follows. Section 2 reviews the relevant literature. Section 3 presents the theoretical framework and hypotheses. Section 4 describes the data and variables. Section 5 explains the methodology. Section 6 reports the empirical results and robustness checks. Section 7 discusses the findings and their implications. Finally, Section 8 concludes and provides policy implications.

2. Literature Review

2.1 Liquidity, Capital and Bank Stability

Capital and liquidity constitute the fundamental pillars of banking stability. Following the 2008 global financial crisis, the Basel III framework strengthened the capital adequacy ratio (CAR) and introduced liquidity standards, including the liquidity coverage ratio (LCR) and net stable funding ratio (NSFR). According to the "buffer hypothesis," these mechanisms enable banks to absorb unexpected shocks and mitigate systemic risk (Sharma & Chauhan, 2023). However, recent evidence indicates that this stabilising relationship is not linear; the protective effects of buffers emerge only once critical thresholds are reached.

A growing body of research supports the positive influence of capital and liquidity on stability. Patel et al. (2022) found that well-capitalised banks are less exposed to market volatility, while Veeramoothoo and Hammoudeh (2022) showed that Basel III liquidity regulations enhance US bank performance, especially under weak profitability. Similarly, Tran, T.N.T. et al. (2025) demonstrated that increased liquidity creation strengthens bank stability in ASEAN-5, confirming liquidity's centrality in emerging markets.

Nevertheless, findings remain mixed. Sharma and Chauhan (2023) observed that stringent Basel III standards may constrain credit supply, particularly for smaller banks. They also noted that incremental capital increases at low levels yield negligible benefits, while surpassing a threshold significantly enhances resilience, highlighting both the benefits and opportunity costs of capital accumulation. Evidence from Vietnam (Vuong et al., 2023) further suggests that liquidity creation can sometimes reduce stability. Consequently, recent studies emphasise nonlinearity, arguing that stabilising effects materialise only at optimal buffer levels. Results by Boussaada et al. (2022) and Haq et al. (2025), within Hansen's (1999) panel threshold regression (PTR) framework, confirm such threshold dynamics.

While international evidence affirms the existence of buffer thresholds, research in ASEAN remains sparse. Despite the region's banking systems being vital for growth, they remain highly exposed to external shocks. Few studies have jointly employed PTR with advanced causal inference methods, such as causal forests within DML, to examine how capital and liquidity moderate uncertainty transmission. This gap motivates further empirical inquiry into whether these buffers genuinely act as "shields" against macroeconomic instability in ASEAN.

2.2 Uncertainty and Financial Stability

Amid global interconnectedness, macroeconomic and policy uncertainty has become a defining determinant of financial stability. Shocks from political crises, pandemics, or policy shifts create unpredictable risks, making uncertainty central to recent empirical inquiry. Widely used indicators include the EPU index (Baker et al., 2016), the GPR index (Caldara & Iacoviello, 2022), the world uncertainty index (WUI), and sentiment-based measures such as the WSI (Ahir et al., 2022). These metrics capture exogenous disturbances affecting banking activity and have been widely applied in stability analyses (Danisman & Tarazi, 2024; Desalegn et al., 2023; Tran, D.V. et al., 2025; Vuong et al., 2024; Zhang, 2023).

However, most studies rely on single indicators, overlooking the multidimensional nature of uncertainty and the interaction among its sources. Recent contributions employ CMUI using principal component analysis (PCA), integrating multiple dimensions into a unified systemic measure (Ayinde & Adeyemi, 2024; Mawardi et al., 2025).

Empirical evidence consistently shows that rising uncertainty undermines banking stability, especially for smaller, less-capitalised institutions, while strong capital and liquidity buffers mitigate these effects (Danisman & Tarazi, 2024; Desalegn et al., 2023). In ASEAN, results are heterogeneous: EPU, WPUI and MPU typically weaken stability, whereas GPR may encourage better risk management (Vuong et al., 2024). Moreover, the link between uncertainty and stability is nonlinear: moderate uncertainty may promote prudent risk management, but beyond a threshold it becomes destabilising (Choi & Hadad, 2025; IMF, 2024). This reinforces the suitability of nonlinear models such as PTR or Bayesian VAR to capture threshold and regime-dependent effects.

The literature increasingly recognises the necessity of integrating multidimensional uncertainty measures with advanced quantitative tools to reflect the complex macro-financial environment. Yet, within ASEAN, empirical studies employing CMUI or nonlinear frameworks remain limited, leaving a critical research gap.

2.3 Empirical Studies in ASEAN and Emerging Markets

ASEAN's rapid growth has increased exposure to external shocks, including financial volatility and policy uncertainty, positioning banks as both stabilisers and transmission channels of systemic risk. Recent evidence consistently suggests that the relationship between capital, liquidity, and stability is nonlinear and state-dependent.

Empirical studies in ASEAN confirm this pattern. Liquidity creation generally enhances stability, although its effectiveness varies across countries due to institutional and regulatory differences, indicating the presence of optimal thresholds rather than linear effects (Tran, T.N.T. et al., 2025). Similarly, macroeconomic uncertainty, captured by EPU, WPUI, MPU (monetary policy uncertainty) and GSCP (global supply chain pressure) tends to undermine stability, with heterogeneous impacts reflecting differences in capital strength, liquidity positions and institutional quality (Vuong et al., 2024). These findings imply that the stabilising role of financial buffers depends critically on whether they exceed minimum effective levels.

Evidence from specific banking segments and broader emerging markets reinforces this nonlinear perspective. In ASEAN Islamic banking, capital buffers and governance appear more decisive than liquidity (Wahyudi et al., 2024), while studies in other emerging markets show that capital influences stability both directly and indirectly through liquidity creation and diversification, with effects reversing at higher levels (Vu & Ngo, 2023). Likewise, liquidity contributes more effectively to stability under stronger governance and disclosure frameworks (Gupta & Kashiramka, 2024). These results suggest that buffer effectiveness is conditional on institutional context and may exhibit diminishing or even adverse effects beyond certain levels.

Moreover, cross-period analyses highlight clear regime dependence: capital plays a limited role in normal conditions but becomes critical during crises, significantly enhancing resilience and reducing liquidity risk (Haq et al., 2025). This supports a theoretical view in which financial buffers operate through nonlinear transmission mechanisms, providing limited protection below critical thresholds but becoming significantly more effective once sufficient loss-absorbing capacity and market confidence are established.

Despite this growing evidence, important gaps remain. First, most studies still rely on linear frameworks, failing to formally identify threshold effects where stabilising impacts emerge only beyond specific buffer levels. Second, the measurement of uncertainty is often incomplete, relying on single indices that overlook its multidimensional nature, with limited use of composite measures such as CMUI. Third, empirical research in ASEAN remains methodologically constrained, with little application of advanced approaches capable of jointly capturing nonlinearity and heterogeneity. In particular, no prior study integrates PTR with causal forests within a DML framework to examine how capital and liquidity buffers condition the impact of uncertainty.

Addressing these gaps is essential for both theory and policy. Identifying effective threshold levels of capital and liquidity not only advances understanding of nonlinear financial stability mechanisms but also provides critical guidance for designing adaptive macroprudential policies in emerging markets under persistent uncertainty.

3. Theoretical Framework

The theoretical framework of this study rests on three main pillars: (i) theories of banking stability under macroeconomic uncertainty, (ii) the capital and liquidity buffer theories, and (iii) nonlinear transmission mechanisms between macroeconomic uncertainty and systemic financial risk.

3.1 Banking Stability under Macroeconomic Uncertainty

The classical model of Diamond and Dybvig (1983) laid the foundation for understanding the vulnerability of banking systems to expectation and liquidity shocks, particularly the phenomenon of bank runs. In the modern context, macroeconomic uncertainty, including policy risk, geopolitical instability and global financial volatility, is viewed as a critical trigger of shifts in investor and depositor expectations, thereby undermining overall system stability (Acharya et al., 2010; Adrian & Shin, 2009). In this setting, banking stability depends not only on the external macroeconomic environment but also on banks' internal capacity to absorb shocks, particularly the quality of capital and liquidity positions.

3.2 Capital and Liquidity Buffer Theories

The capital buffer theory, advanced by Milne and Whalley (2001), posits that banks maintain capital above regulatory minima to reduce the probability of breaching requirements when income is volatile. Similarly, the liquidity buffer theory suggests that high-quality liquid assets (HQLA) serve as a protective cushion against liquidity shocks and erosion of confidence in the interbank market.

However, the protective effects of these buffers are not uniform across all conditions but depend on risk exposure and market regimes. In normal periods, modest buffers may be sufficient to ensure stability, but under turbulent conditions, banks must surpass an "effective safety threshold" to absorb shocks effectively (Gupta et al., 2023; Rendón et al., 2024; Sharma & Chauhan, 2023). This leads to the central research question of this study: *Do optimal capital and liquidity thresholds exist that safeguard banks against macroeconomic uncertainty*?

3.3 Nonlinear Transmission Mechanisms between Uncertainty and Financial Risk

Empirical research in financial econometrics has documented that the impact of macroeconomic uncertainty on banking stability is nonlinear and contingent upon internal structural conditions (Cecchetti et al., 2004; Rey, 2015). Under high uncertainty, even small shocks may propagate rapidly through expectation channels, financial imbalances, or policy constraints. Furthermore, banks' resilience is shaped by their size, capitalisation, liquidity position and the institutional quality of their respective countries (Delis et al., 2017).

This study builds on that perspective by assuming that uncertainty does not affect all banks uniformly but interacts with moderating variables such as capital and liquidity to generate heterogeneous effects. This provides the rationale for applying PTR to identify effective thresholds, as well as DML to analyse the dynamic transmission of shocks within the banking system.

The theoretical framework of the study is built upon three core assumptions: (i) Banking stability is vulnerable to macroeconomic uncertainty, particularly in emerging economies; (ii) Capital and liquidity buffers serve moderating roles but exert their effects only once critical thresholds are surpassed; and (iii) The transmission of uncertainty to banking risk is nonlinear, dynamic and state-dependent.

This theoretical approach not only reflects the link between micro-level banking conditions and macro-level financial stability but also establishes a solid foundation for the dual empirical framework employing PTR and DML in subsequent sections.

Building on the theoretical foundations of capital and liquidity buffers and consistent with empirical evidence on the nonlinear effects of macroeconomic uncertainty, this study proposes four hypotheses.

Liquidity is essential to solvency and market confidence in banking systems (Diamond & Dybvig, 1983). Basel III reinforces this through the LCR and NSFR to ensure resilience under stress. However, liquidity's stabilising role is nonlinear: when insufficient, banks remain exposed to funding shocks, but once it exceeds a threshold, liquidity substantially mitigates systemic risk.

H1: Liquidity exerts a nonlinear (threshold) effect on bank stability (ZSCORE).

According to the buffer capital theory (Milne & Whalley, 2001) and Basel III, capital absorbs losses and limits insolvency risk. Yet, similar to liquidity, its impact is nonlinear, minimum compliance capital offers limited protection, while higher capitalisation beyond a threshold strengthens resilience and confidence.

H2: Capital adequacy (ETA) exerts a nonlinear (threshold) effect on bank stability.

Macroeconomic uncertainty, measured by indices such as the EPU, GPR, WPUI and WSI, is linked to higher credit risk, funding costs and declining market confidence (Danisman & Tarazi, 2024; Vuong et al., 2024). These dynamics weaken banking stability, particularly in emerging markets with limited capital market depth.

H3: Higher composite macroeconomic uncertainty (CMUI) reduces bank stability.

Beyond direct effects, liquidity and capital buffers moderate the adverse impact of uncertainty. Well-capitalised and liquid banks can better absorb macro-financial shocks, reducing the negative influence of uncertainty on stability (Haq et al., 2025; Tran, D.V. et al., 2025).

H4: The negative effect of CMUI on bank stability is attenuated when liquidity and capital adequacy buffers are high.

4. Data and Variables

This study uses an unbalanced panel of commercial banks in Indonesia, Malaysia, the Philippines, Thailand and Vietnam over 2010–2023, covering approximately 62 banks and up to 826 bank-year observations. The sample reflects both the systemic importance of ASEAN banking sectors and their exposure to global shocks. Data are drawn from Bankscope/Orbis, the World Bank (*World Development Indicators*), IMF and established uncertainty datasets (Ahir et al., 2018; Baker et al., 2016; Caldara & Iacoviello, 2022).

A composite macroeconomic uncertainty index (CMUI) is constructed using principal component analysis (PCA) to extract a common factor from EPU, WPUI, GPR and WSI, avoiding arbitrary weighting. These indicators are comparable across ASEAN, ensuring consistency, while robustness checks confirm that results are not sensitive to PCA-derived weights (Appendix A, B).

Bank stability is measured by ZSCORE, with return on assets (ROA) as a robustness proxy. Key explanatory variables include liquidity (LIQ) and equity-to-total assets (ETA), alongside bank-level controls (SIZE, leverage, asset growth and technology) and macroeconomic factors (GDP growth, inflation, COVID-19 dummy, and CMUI) to mitigate omitted variable bias (see Table 1).

5. Method

This study adopts a dual-method econometric strategy that integrates structural nonlinearity identification with modern causal machine learning. The approach is motivated by the financial fragility literature, which posits that the effects of bank-specific buffers on stability may be regime-dependent and heterogeneous across institutions. Accordingly, the empirical framework combines: (i) PTR to capture potential regime

Table 1. Variable definitions, measurement methods and data sources

Variable	Symbol	Definition / Calculation
Dependent variables		
Bank stability	ZSCORE	(ROA+(Equity/Assets))/σ(ROA) Higher values imply greater distance from insolvency.
Profitability (robustness)	ROA	Net income / Total assets
Key explanatory variables		
Liquidity	LIQ	(Cash + Liquid assets) / Total assets
Capital adequacy	ETA	Equity / Total assets
Bank-level controls		
Bank size	SIZE	Natural logarithm of total assets
Leverage	DAR	Total debt / Total assets
Asset growth	GTA	(Total assets_t − Total assets_{t-1}) / Total assets_{t-1}
Economic growth	GDP	Annual growth rate of real GDP (%)
Inflation	INF	Annual growth rate of CPI (%)
COVID-19 shock	COVID-19	Dummy = 1 for 2020–2021; 0 otherwise
Composite macroeconomic uncertainty	CMUI	PCA-based index constructed from EPU, WPUI, GPR and WSI. Details of the PCA procedure and component loadings are presented in Appendix A and B, respectively.
Technological innovation	TII	Country-level Technology Innovation Index

shifts and identify nonlinear threshold effects of capital and liquidity buffers, and (ii) causal forests within the DML framework to estimate heterogeneous treatment effects of CMUI on bank stability and to assess how liquidity and capital moderate this relationship. This integration allows the analysis to detect both structural thresholds and conditional heterogeneity, providing a comprehensive view of the mechanisms through which uncertainty transmits to financial stability.

To address potential non-stationarity due to the relatively long sample period and the inclusion of macro-financial variables, panel unit root tests and panel cointegration tests are conducted (Appendix E). The results confirm that the variables are either stationary in levels or exhibit stable long-run relationships.

5.1 Panel Threshold Regression

To examine the presence of threshold effects in the relationship between bank-specific variables and financial stability, the study employs the PTR framework proposed by Hansen (1999). This methodology allows for the endogenously determined estimation of structural breakpoints in panel data settings. Time fixed effects are included to control for unobserved common shocks across periods. Specifically, the model takes the following general form:

$$Z_{it} = \mu_i + \tau_t + \beta_1 X_{it} \bullet 1(q_{it} \leq \gamma) + \beta_2 X_{it} \bullet 1(q_{it} > \gamma) + \varepsilon_{it} \quad (1)$$

where Z_{it} denotes the ZSCORE, a proxy for bank stability; X_{it} is a vector of explanatory variables; $q_{it} \in$ {LIQ, ETA} is the threshold variable; γ is the threshold value, estimated via grid search; μ_i captures unobserved bank fixed effects; τ_t represents time fixed effects capturing common macroeconomic shocks affecting all banks.

To ensure the robustness of the estimated thresholds, this study conducts non-parametric bootstrap procedures with 1000 replications to test for the statistical significance of the threshold effects. This method allows to formally validate the existence of structural breaks in the relationship between bank liquidity/capital and financial stability, aligning with the post-crisis literature on regulatory thresholds.

5.2 Causal Forests with Double Machine Learning

This study implements causal forests (Athey & Imbens, 2019) within the DML framework (Chernozhukov et al., 2018), enabling reliable identification of heterogeneous treatment effects (HTE). This approach is well suited to examine the moderating roles of ETA and LIQ in the relationship between CMUI and ZSCORE.

The framework is defined as follows: (i) ZSCORE as the outcome variable; (ii) CMUI as the treatment; (iii) ETA and LIQ as moderators; and (iv) control variables including SIZE, DAR, GTA, GDP, INF, COVID-19 and TII. Detailed parameter settings for DML and causal forest estimations are provided in Appendix D to ensure transparency and reproducibility.

A key advantage of causal forests is their ability to capture nonlinear heterogeneity in the impact of uncertainty, providing detailed estimates of how capital and liquidity attenuate or amplify the effects of CMUI. The DML procedure, through orthogonalisation and cross-fitting, mitigates endogeneity arising from the joint determination of bank stability, capital and liquidity under macroeconomic conditions, thereby improving inference reliability (Bach et al., 2024). However, it may not fully eliminate bias from unobserved factors or measurement errors, so results are interpreted as robust associations with strong causal indications.

To ensure robustness, several sensitivity analyses are conducted. First, models are re-estimated using ROA to confirm results are not driven by the stability proxy. Second, the sample is split into pre- and post-COVID periods to assess temporal stability and potential structural shifts in macro-financial transmission. The findings remain consistent across specifications and periods, supporting result robustness.

6. Results

6.1 Descriptive Statistics and Correlations

Table 2 presents descriptive statistics for the main variables employed in the analysis. The results presented in Table 2 and Figure 1 reveal considerable dispersion in banking stability (ZSCORE), reflecting structural heterogeneity across ASEAN countries. Average LIQ and ETA are approximately 74% and 13.6%, respectively, yet the high standard deviations suggest that the protective role of these buffers may only become effective once optimal thresholds are surpassed, consistent with Hypotheses H1 and H2.

Figure 1 illustrates substantial cross-country differences in banking stability among the ASEAN-5 during 2010–2023. The regional average remained relatively stable prior to 2020 but declined markedly following the COVID-19 shock, confirming the hypothesis

Table 2. Descriptive statistics

	Count	Mean	Standard deviation	Minimum	Median	Maximum
ZSCORE	826	8.115	5.031	-4.201	7.060	51.950
LIQ	826	0.741	1.047	0.044	0.609	2.6038
SIZE	826	8.495	1.835	2.688	8.818	11.982
ETA	826	0.136	0.094	0.000	0.117	1.000
GTA	826	0.152	0.591	-0.999	0.091	10.770
DAR	826	0.882	0.423	0.117	0.883	9.280
GDP	826	0.049	0.026	-0.095	0.052	0.087
INF	826	0.047	0.060	-0.019	0.038	0.423
TII	826	0.715	0.085	0.497	0.726	0.895
CMUI	826	0.000	0.879	-1.364	-0.195	3.536

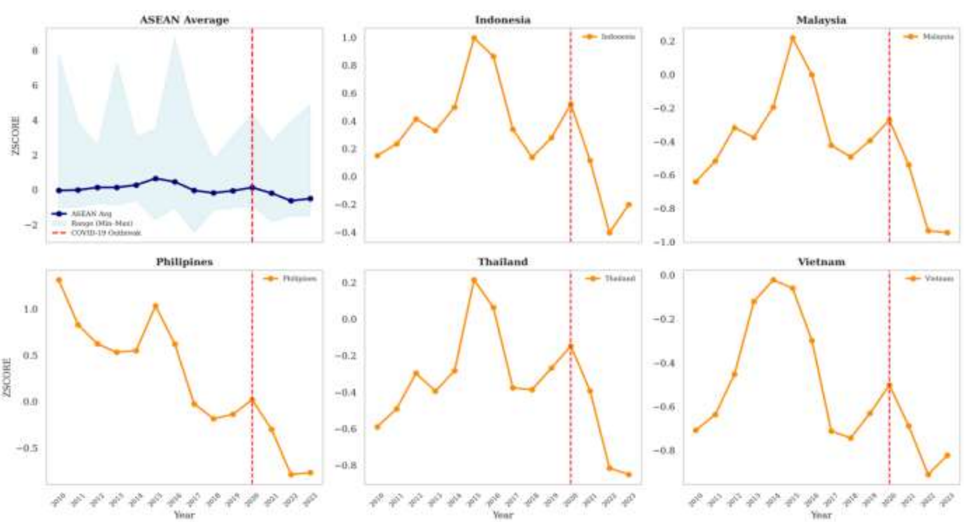

Figure 1. Average ZSCORE trend by country

that macroeconomic uncertainty reduces banking stability (H3). At the country level, Indonesia and the Philippines exhibited higher ZSCORE values, though these declined after 2015; by contrast, Malaysia, Thailand, and Vietnam maintained lower and more volatile levels, reflecting the vulnerability of emerging markets. This pattern is consistent with the “buffer hypothesis” and prior studies, while also suggesting that the protective roles of capital and liquidity (H1–H2) may differ across contexts (H4).

Meanwhile, CMUI, the composite measure of macroeconomic uncertainty, illustrated in Figure 2, has an average value close to zero but exhibits wide dispersion, capturing periods of systemic stress, particularly during crises. This finding provides further support for H3, namely that uncertainty erodes banking stability.

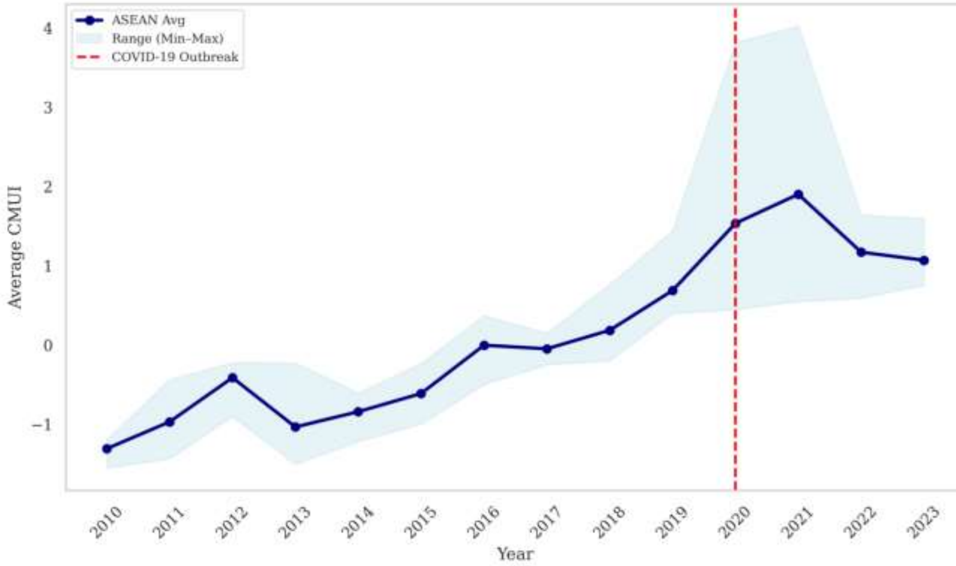

Figure 2. Macroeconomic Uncertainty (CMUI) trends across ASEAN countries

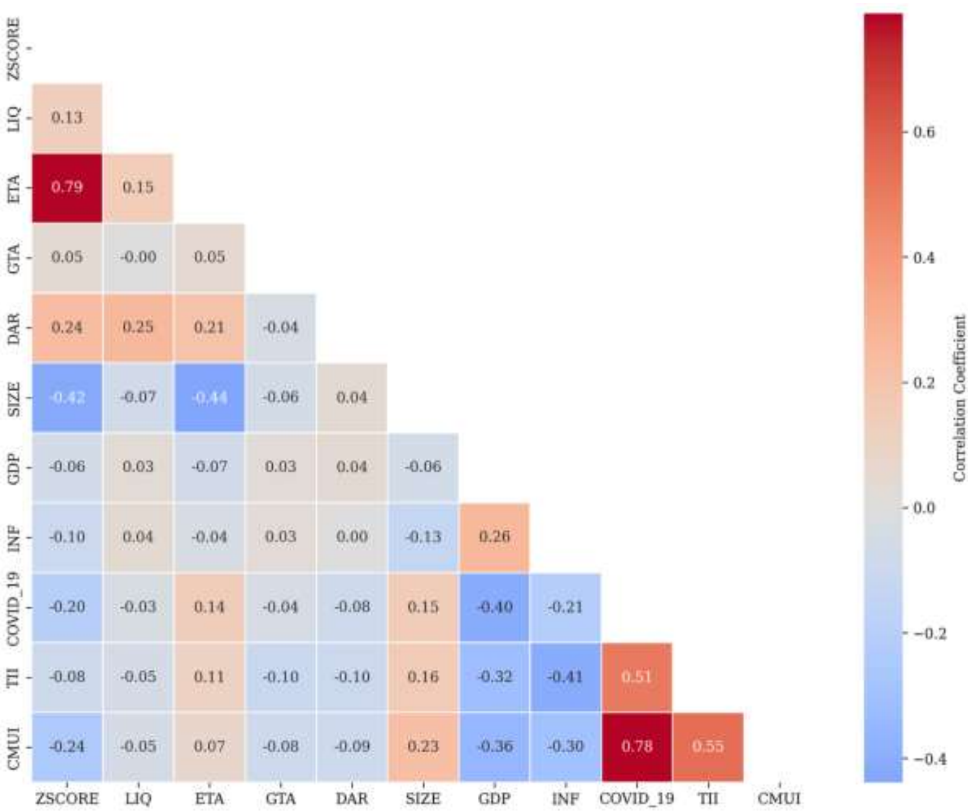

Figure 3. Correlation matrix

Figure 3 presents the correlation matrix of the key variables in the model. The results show that ETA and LIQ are positively correlated with ZSCORE, underscoring the importance of capital and liquidity in strengthening banking stability, consistent with Hypotheses H1–H2 and the Basel III framework. In contrast, CMUI and COVID-19 are negatively correlated with ZSCORE, reflecting the adverse effects of macroeconomic uncertainty and the pandemic shock, in line with Hypothesis H3 and the findings of Bloom (2014), and Danisman and Tarazi (2024).

The correlation matrix results indicate that CMUI, INF, GDP, COVID-19 and TII are all negatively correlated with ZSCORE, suggesting that macroeconomic uncertainty, pandemic shocks, as well as institutional and technological factors may undermine banking stability. These negative associations imply a complex interaction structure between uncertainty, institutions and technological innovation that goes beyond static analysis, thereby providing the foundation for nonlinear testing through PTR and causal forests with DML.

6.2 Panel Threshold Regression Results

To test the hypothesis of nonlinearity in the impact of macroeconomic uncertainty on banking stability, particularly the moderating role of financial buffers (capital and liquidity), this study applies the PTR model proposed by Hansen (1999). This model allows for the identification of whether the effect of uncertainty changes at specific thresholds of moderating variables such as ETA or LIQ, thereby clarifying the regime-dependent nature of the relationship under investigation. The detailed PTR results are reported in Table 3.

The PTR results reveal distinct dynamics between liquidity and capital buffers. The estimated LIQ threshold is 97.6% with a positive coefficient (0.089), but the bootstrap p-value (0.460) indicates weak statistical support, suggesting that regime differentiation based on liquidity should be interpreted with caution.

By contrast, the ETA threshold is identified at 8%, with a strong and highly significant coefficient (8.174), and the bootstrap test ($p = 0.000$) confirms its robustness. Economically, this threshold separates a low-capital (vulnerable) regime, where banks lack sufficient loss-absorbing capacity and are more exposed to uncertainty, from a high-capital (resilient) regime, where buffers effectively enhance stability. This finding aligns with the Basel II–III minimum capital requirement (8%) and provides strong evidence that capital buffers mitigate financial fragility under macroeconomic uncertainty. While liquidity does not exhibit a statistically significant threshold in the PTR framework, this does not imply that it is economically irrelevant. Rather, it suggests that liquidity may not operate through a discrete regime-switching mechanism but instead exerts a more gradual and continuous stabilising effect.

These results are consistent with the buffer hypothesis (Diamond & Dybvig, 1983) and prior studies (Altunbas et al., 2017; Danisman & Tarazi, 2024), which identify capital adequacy as central to banking stability. In contrast, the weaker role of liquidity supports mixed evidence in Berger and Bouwman (2009), suggesting that liquidity effects are more context-dependent. Overall, the findings strongly support H2, partially support H1, and provide indirect support for H4, as capital above the threshold enhances resilience to macroeconomic uncertainty.

Table 3. Panel threshold regression results

Threshold variable	Best threshold	RSS	R^2 Adj.	R^2	p-value (Bootstrap)	Const.	Regime	Coefficient
LIQ	0.9763	806.01	0.024	0.022	0.460	-0.105	0.274	0.089 (LIQ)
ETA	0.0795	308.84	0.626	0.625	0.000	-1.276	0.188	8.174 (ETA)

Note: This table reports the estimated thresholds for LIQ and ETA using PTR. Bootstrap p-values are based on 1000 replications.

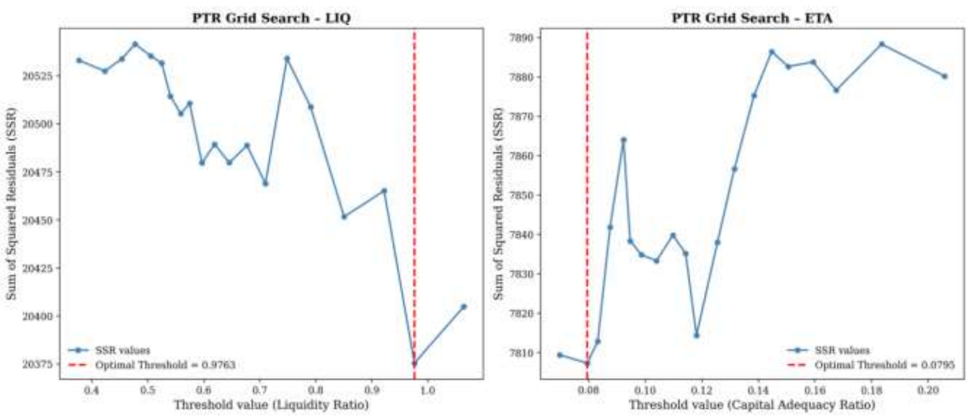

Figure 4. Grid search results for threshold estimation in the PTR

Note: Figure 4 plots the sum of squared residuals (SSR) across candidate thresholds for liquidity (LIQ, left) and capital (ETA, right). Vertical dashed lines indicate the optimal thresholds following Hansen (1999).

Table 4. Moderating role of LIQ and ETA in the effect of CMUI on ZSCORE

Variables (regimes)	Coefficient	Std. error	t-statistic	p-value
CMUI when LIQ ≤ 0.9763 and ETA ≤ 0.0795	-0.0357	0.491	-0.073	0.942
CMUI when LIQ > 0.9763 and ETA ≤ 0.0795	1.2929	1.657	0.780	0.435
CMUI when LIQ ≤ 0.9763 and ETA > 0.0795	-0.9596***	0.269	-3.564	0.000
CMUI when LIQ > 0.9763 and ETA > 0.0795	-0.9407**	0.380	-2.477	0.013

The panel threshold regression results in Table 4 provide direct evidence for Hypothesis H4. The moderating role of LIQ is weak, as the estimated threshold (0.9763) does not significantly alter the CMUI-ZSCORE relationship, suggesting that liquidity alone does not systematically mitigate the destabilising effects of macroeconomic uncertainty in ASEAN banks.

In contrast, ETA emerges as a robust moderator. The identified threshold (0.0795) is highly significant (bootstrap p-value = 0.000), with a clear nonlinear pattern. Below the threshold, macroeconomic uncertainty strongly reduces bank stability (CMUI = -0.9596,

$p < 0.01$), while above it, the negative effect persists but is less pronounced (CMUI = -0.9407, $p < 0.05$). This supports H4 and highlights the critical role of capital buffers in absorbing shocks.

Overall, PTR results indicate that ETA is decisive for stability, whereas LIQ plays a supplementary role. However, PTR captures only static nonlinear relationships. To further examine dynamic and heterogeneous effects, the study applies causal forests within the DML framework.

6.3 Causal Forests with DML Results

To test Hypothesis H4, this study applies double machine learning (DML) combined with causal forests to estimate both average and heterogeneous effects of macroeconomic uncertainty (CMUI) on bank stability. While DML provides reliable average treatment effects, causal forests uncover heterogeneity across liquidity (LIQ) and capital (ETA) levels. Table 5 reports results for the full sample and key subsamples (pre/post-COVID-19, bank size and uncertainty regimes). This distinction is important for reconciling the PTR findings. While PTR captures global threshold effects, causal forests identify local heterogeneous effects across banks. As a result, liquidity may appear insignificant in a threshold framework but still play a meaningful moderating role in specific contexts.

The results show that CMUI is consistently associated with a decline in ZSCORE, confirming the destabilising effect of macroeconomic uncertainty (Acharya & Steffen, 2020; Bloom, 2014). The magnitude is economically meaningful: for the full sample, a one-unit increase in CMUI reduces bank stability by approximately 1.2–1.7 units, indicating a substantial deterioration rather than a purely statistical effect.

This impact is heterogeneous across time and bank characteristics. It is stronger in the pre-COVID period and weakens post-COVID, likely reflecting policy support and improved risk management. Smaller banks experience larger adverse effects than larger ones, consistent with lower resilience during shocks (Berger & Bouwman, 2013). Under high uncertainty, the negative effect intensifies, while it becomes insignificant under low uncertainty, confirming state-dependent transmission.

The causal forest results further clarify the moderating roles of liquidity and capital, consistent with but extending PTR findings. Higher liquidity is associated with smaller declines in stability, confirming its buffering role, particularly for vulnerable banks (Tran, T.N.T. et al., 2025). This complements the PTR results, suggesting that liquidity operates as a continuous stabiliser rather than a threshold-dependent factor. In contrast, capital exhibits a more complex effect. While PTR identifies a threshold beyond which capital enhances stability, causal forest estimates show that higher ETA does not uniformly reduce risk and may amplify adverse effects in some contexts. This indicates that capital effectiveness is conditional on institutional and market conditions (Haq et al., 2025), but still reflects threshold-dependent behaviour consistent with PTR.

Liquidity acts as a continuous buffer, whereas capital exhibits threshold-dependent and context-specific effects. These approaches are therefore complementary rather than contradictory, jointly explaining how buffers operate under macroeconomic uncertainty and providing stronger support for H4. From a policy perspective, both buffers

Table 5. Moderating effects of LIQ and ETA on the CMUI-ZSCORE relationship

Sample	DoubleML coef	Std. err	p-value	Causal forest ATE	95% CI (Low–High)	CATE (LIQ low)	CATE (LIQ high)	CATE (ETA low)	CATE (ETA high)
Full sample	-1.242	0.197	0.000	-1.737	[-6.178, -0.283]	-1.703	-1.771	-0.926	-2.548
Pre-Covid	-2.588	0.696	0.000	-1.345	[-4.800, 0.609]	-1.491	-1.198	-0.658	-2.034
Post-Covid	-0.743	0.132	0.000	-0.927	[-5.930, 0.608]	-0.842	-1.012	0.065	-1.926
Small banks	-2.897	1.544	0.061	-2.061	[-6.777, -0.170]	-1.999	-2.124	-0.870	-3.258
Large banks	-0.828	0.164	0.000	-1.183	[-2.040, -0.739]	-1.235	-1.130	-0.981	-1.386
Low uncertainty	3.437	1.781	0.054	0.045	[-4.521, 3.286]	-0.166	0.257	0.726	-0.636
High uncertainty	-0.564	0.118	0.000	-1.102	[-4.494, -0.082]	-1.040	-1.164	-0.441	-1.763

Notes: Groups are classified into three dimensions: (i) Pre- and Post-Covid-19, based on the dummy variable COVID_19 (0 = before 2020, 1 = from 2020 onward); (ii) Small vs. Large banks, determined by the median of SIZE; and (iii) Low vs. High uncertainty, determined by the median of CMUI. Estimates from DoubleML report the average treatment effect (ATE), while causal forests provide heterogeneous effects conditional on capital (ETA) and liquidity (LIQ) buffers.

are important, but their effectiveness depends on appropriate levels and economic conditions, highlighting the need for flexible, context-specific macroprudential policies in ASEAN.

6.4 Robustness Checks

To ensure the reliability of the findings, the study conducts a series of robustness checks by: (i) replacing the dependent variable with alternative measures of banking stability (ROA), (ii) performing subgroup analyses (pre- and post-COVID-19, small versus large banks, high- versus low-uncertainty regimes), and (iii) employing alternative model specifications. Table 6 below summarises the main results.

The robustness checks confirm the stability and reliability of the main findings. Specifically, CMUI consistently exhibits a negative effect on banking stability, even when the dependent variable is replaced with an alternative measure (ROA). This reinforces the theoretical foundation of the systemic risk transmission channel, whereby uncertainty shocks weaken banks' resilience (Acharya & Steffen, 2020; Bloom, 2014).

In addition, subgroup analyses reveal marked heterogeneity: prior to COVID-19, the negative coefficient of CMUI is stronger, whereas in the post-COVID-19 period the effect is weaker, reflecting the mitigating role of policy support packages and improvements in risk management (Appendix C). Smaller banks are also more vulnerable than larger ones, consistent with the argument of "size-dependent buffers" in Berger and Bouwman (2013). Finally, results across uncertainty regimes indicate a nonlinear relationship: the negative impact becomes significant only under high-uncertainty conditions.

Table 6. Robustness checks of the CMUI-bank stability nexus

Sample / Dependent variable	Variable	Coef.	Std. err.	p-value
Dependent variable = ZSCORE				
Full sample	CMUI	-1.006	0.125	0.000***
	LIQ	-0.053	0.065	0.418
	ETA	43.545	3.891	0.000***
	SIZE	-0.037	0.090	0.686
	DAR	0.527	0.587	0.369
	GTA	-0.120	0.175	0.493
	GDP	-27.941	2.812	0.000***
	INF	-13.518	1.457	0.000***
	COVID	-2.470	0.255	0.000***
	TII	-3.641	1.198	0.002***
Dependent variable = ROA				
Full sample	CMUI	-0.0014	0.0012	0.037**
	LIQ	0.0003	0.0006	0.644
	ETA	0.0081	0.0108	0.043**
	SIZE	0.0036	0.0005	0.000***
	DAR	-0.0004	0.0061	0.946

Notes: Standard errors are robust. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Overall, the robustness checks not only reinforce Hypothesis H4 regarding the conditional role of capital and liquidity buffers but also extend empirical evidence showing that the transmission mechanism of uncertainty is heterogeneous and state-dependent – an aspect that traditional linear models fail to capture.

7. Discussion

The findings demonstrate that macroeconomic uncertainty (CMUI) significantly weakens banking stability in ASEAN, consistent with theoretical models of uncertainty-driven financial fragility (Acharya & Steffen, 2020; Bloom, 2014). This adverse effect aligns with evidence from other emerging economies (Mdandalaza & Jeke, 2025) but varies over time and across banks. It was stronger before COVID-19 and moderated afterward, reflecting the impact of policy interventions and enhanced risk management. The differential responses between small and large banks confirm the "size-dependent resilience" effect proposed by Berger and Bouwman (2013).

Results from the PTR highlight the nonlinear nature of financial buffers. Capital adequacy (ETA) enhances stability only beyond a specific threshold, around 8%, consistent with the buffer capital theory (Diamond & Rajan, 2000). Liquidity (LIQ) shows a weaker and less consistent threshold effect, suggesting that its stabilising power depends on market and institutional conditions. These results validate Hypotheses H1–H3 and provide new empirical evidence of nonlinear dynamics often missed in linear models (Vuong et al., 2024; Wahyudi et al., 2024).

The causal forest analysis within the DML framework further reveals conditional heterogeneity in the moderating roles of capital and liquidity. Banks with higher liquidity exhibit greater resilience to uncertainty shocks (Tran, D.V. et al., 2025), while capital remains the more robust buffer once thresholds are surpassed. However, in weak institutional environments, excessive capitalisation may amplify risk-taking or regulatory costs, reducing its protective value.

Taken together, these findings indicate that macroeconomic uncertainty is a systemic and heterogeneous source of risk. Capital buffers provide stability only beyond effective thresholds and under strong institutional conditions, while liquidity offers a flexible yet fragile safeguard. For ASEAN regulators, the results underscore the need to strengthen liquidity standards, enhance institutional quality and design adaptive macro-prudential frameworks that complement Basel III requirements to sustain financial stability amid persistent global uncertainty.

8. Conclusion and Policy Implications

This study provides robust empirical evidence that macroeconomic uncertainty, as captured by the composite macroeconomic uncertainty index (CMUI), exerts a significant and persistent adverse impact on banking stability in ASEAN emerging markets, while also revealing the nonlinear and heterogeneous nature of this relationship. The findings yield three core insights. First, financial buffers, capital adequacy (ETA) and liquidity (LIQ), enhance resilience only after surpassing specific thresholds. A capital adequacy ratio of approximately 8% is identified as a statistically validated benchmark mitigating the destabilising effects of uncertainty, whereas liquidity demonstrates a positive but less consistent threshold effect, reflecting its context-dependent nature. Second, CMUI emerges as the most potent and enduring source of instability, exerting stronger and longer-lasting effects on bank stability than conventional macroeconomic variables such as GDP growth or inflation, underscoring the structural and systemic dimension of uncertainty shocks. Third, the magnitude of the destabilising impact varies over time and across bank characteristics, being more pronounced before the COVID-19 pandemic and among smaller banks, while post-pandemic policy interventions and larger balance sheets have enhanced resilience. These results confirm the conditional role of financial buffers and reinforce the moderating effect hypothesised in H4, namely that capital and liquidity interact with uncertainty in shaping stability outcomes.

The empirical findings have several important policy implications. At the institutional level, maintaining capital and liquidity buffers above Basel III minimums should be regarded not merely as regulatory compliance but as a strategic mechanism to mitigate uncertainty-driven risks. Liquidity functions as an immediate stabilising buffer, whereas capital adequacy requires adaptive management aligned with institutional quality and macroeconomic conditions. At the national level, reducing macroeconomic uncertainty must become a central policy objective through greater fiscal and monetary transparency, improved communication and enhanced inter-agency coordination, recognising that the effectiveness of financial buffers ultimately depends on the broader institutional and governance environment. At the regional level, institutional asymmetries among ASEAN economies produce uneven resilience, calling for stronger policy coordination through regional early warning systems, harmonisation of prudential standards, and more comprehensive data-sharing frameworks to assist countries with weaker institutional capacity.

Despite its contributions, the study has certain limitations that provide opportunities for future research. It does not explicitly incorporate emerging determinants of financial stability such as environmental, social and governance (ESG) factors, fintech innovation, or digital banking, which are increasingly shaping risk dynamics. Moreover, extending the analysis to other regional blocs, such as BRICS or MENA, would enrich comparative insights and enhance the generalisability of the findings. Future studies integrating these dimensions could further refine the understanding of capital-liquidity interactions and contribute to more adaptive macroprudential policy design in an era of persistent global uncertainty.

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Appendix

***Appendix A**. Principal component analysis (PCA) for CMUI index*

Test	Statistic
KMO Overall	0.6177
Bartlett's Test of Sphericity	χ^2 = 1070.14, p = 0.0000

***Appendix B**. Eigenvalues and explained variance of principal components for CMUI index*

Principal component	Eigenvalue	Explained variance ratio	Cumulative variance ratio
PC1	2.155637	0.538257	0.538257
PC2	0.967521	0.241587	0.779844
PC3	0.692064	0.172806	0.952651
PC4	0.189627	0.047349	1.000000

Notes: The KMO value of 0.6177 indicates moderate sampling adequacy. Bartlett's Test of Sphericity was significant (χ^2 = 1070.14, $p < 0.001$), supporting the use of PCA. Three components with eigenvalues greater than 0.6 were retained to explain a cumulative variance of 95.27%, with the first three components accounting for over 85% of the total variance. A composite PCA index was computed and stored in the column 'CMUI'.

***Appendix C**. Robustness by Subsamples*

Sample	Variable	Coef.	Std. err.	p-value
Pre-Covid (≤2019)	CMUI	-2.588	0.696	0.000***
	LIQ	-0.091	0.072	0.205
	ETA	41.562	5.281	0.000***
Post-Covid (≥2020)	CMUI	-0.743	0.132	0.000***
	LIQ	-0.037	0.069	0.590
	ETA	44.213	4.118	0.000***
Small banks	CMUI	-2.897	1.544	0.061*
	LIQ	-0.085	0.089	0.335
	ETA	38.772	7.144	0.000***
Large banks	CMUI	-0.828	0.164	0.000***
	LIQ	-0.047	0.066	0.474
	ETA	45.125	3.992	0.000***
Low uncertainty	CMUI	3.437	1.781	0.054*
	LIQ	-0.123	0.081	0.132
	ETA	39.551	5.012	0.000***
High uncertainty	CMUI	-0.564	0.118	0.000***
	LIQ	-0.062	0.071	0.389
	ETA	46.328	4.321	0.000***

Notes: Robustness checks across sub-periods, bank size, and uncertainty levels. Robust standard errors are reported. ***, **, * denote significance at 1%, 5% and 10% levels, respectively.

***Appendix D**. Implementation details of double machine learning and causal forests*

To estimate heterogeneous effects of macroeconomic uncertainty (CMUI) on bank stability, the study employed double machine learning (DML) and causal forests (CF) with the following settings:

Method	Component/Parameter	Specification
Double machine learning (DML)	*Outcome variable*	*ZSCORE (bank stability)*
	Treatment variable	CMUI (composite macroeconomic uncertainty index)
	Controls	SIZE, DAR, GTA, GDP, INF, COVID-19, TII
	Moderators	LIQ (liquidity ratio), ETA (equity-to-assets ratio)
	Nuisance model for treatment (ml_m)	Random Forest, n_estimators = 500, max_depth = 5, random_state = 42
	Nuisance model for outcome (ml_g, ml_l)	LassoCV, 5-fold cross-validation
	Cross-fitting	5 folds
	Output	ATE (average treatment effect), robust SEs, p-values
Causal forests (CF)	*Number of trees*	*2000*
	Maximum depth	10
	Minimum samples per leaf	5
	Random state	42
	Splitting	Honest splitting (separate samples for tree construction and estimation)
	Outputs	ATE with 95% CI (bootstrap percentile); CATE by LIQ (High/Low), ETA (High/Low), and joint regimes (LIQ × ETA)
Subsample Analysis	Groups	Full sample; Pre-COVID vs. Post-COVID; Small vs. Large banks; Low vs. High uncertainty (median split)

***Appendix E**. Stationarity and cointegration tests*

Table E1. Panel unit root test results (IPS–ADF based)

Variable	Avg. ADF p-value	Stationarity	Conclusion
ZSCORE	0.0495	Yes	Stationary
CMUI	0.0000	Yes	Stationary
LIQ	0.0116	Yes	Stationary
ETA	0.0206	Yes	Stationary
SIZE	0.066	Yes	Stationary
DAR	0.0206	Yes	Stationary
GTA	0.0000	Yes	Stationary
GDP	0.0000	Yes	Stationary
INF	0.0000	Yes	Stationary

Notes: The table reports average p-values from individual augmented Dickey–Fuller (ADF) tests across panel units (IPS-style approach). Variables with p-values below 0.05 are considered stationary.

Table E2. Residual-based cointegration test

Test	Statistic	p-value	Conclusion
ADF (Residuals)	-7.9550	0.0000	Cointegration exists