




“Causal and nonlinear effects of digital financial inclusion on bank stability: Evidence from emerging and advanced economies”

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CAUSAL AND NONLINEAR EFFECTS OF DIGITAL FINANCIAL INCLUSION ON BANK STABILITY: EVIDENCE FROM EMERGING AND ADVANCED ECONOMIES

Abstract

Digital financial inclusion (DFI) has become a critical driver of sustainable growth and financial resilience in the digital era, yet its implications for bank stability remain ambiguous, particularly across heterogeneous institutional contexts. This study examines whether and under what conditions DFI fosters bank stability, using data from 65 emerging and advanced economies during 2010–2022. Employing Double Machine Learning (DML) and Causal Forests to address endogeneity and treatment heterogeneity, together with Panel Threshold Regression (PTR) to capture nonlinear dynamics, the paper provides a causal and structural assessment of the DFI–stability nexus. Results reveal that, on average, DFI exerts no statistically significant impact on bank stability across the full sample. However, substantial heterogeneity emerges in financially developed and institutionally strong economies, DFI significantly enhances stability (CATE = +0.0165, $p < 0.001$), while in underdeveloped systems it weakens it (CATE = –0.0082, $p < 0.001$). The PTR model identifies a critical DFI threshold (–1.3611), below which DFI undermines stability and above which its effect becomes neutral, confirming nonlinear regime behavior. These findings highlight that DFI alone cannot guarantee stability; its benefits materialize only within robust institutional and financial ecosystems. Methodologically, the integration of causal machine learning and threshold modeling offers a novel framework for examining digital finance policies and contributes to a deeper understanding of conditional digital effectiveness in modern banking systems.

Keywords

digital financial inclusion, banking stability, causality, machine learning, threshold regression, institutional quality, financial development

JEL Classification

G21, O33, C55, E44

INTRODUCTION

The rapid digital transformation of the global financial system represents one of the most profound structural shifts in the modern economy. As digital technologies increasingly permeate financial intermediation, digital financial inclusion (DFI) has emerged as a cornerstone of contemporary economic development, expanding access to formal financial services and integrating previously excluded populations into the digital economy. The diffusion of digital banking, mobile payments, and fintech ecosystems has redefined how financial services are delivered, fostering new pathways toward inclusive growth and economic resilience across both advanced and emerging markets.

However, this unprecedented expansion of digital access also introduces a new spectrum of systemic challenges. Digitalization has made financial networks more interconnected, data-intensive, and technology-dependent, amplifying exposure to cyber threats, operational disruptions, and cross-platform contagion. In parallel, the competitive pressures and risk-shifting behaviors associated with fintech



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proliferation may undermine prudential safeguards, particularly in weakly regulated or institutionally fragile environments. The very mechanisms that democratize finance can, under certain conditions, generate instability, transforming inclusion from a stabilizing force into a potential source of systemic vulnerability.

This paradox gives rise to a core scientific problem at the intersection of digital transformation and financial stability: the ambiguous and context-dependent relationship between DFI and bank stability. Theoretically, DFI may strengthen resilience by diversifying funding sources, improving efficiency, and enhancing information transparency. Yet, the same dynamics can erode credit discipline and supervisory capacity when institutional quality and financial depth are insufficient to contain emerging risks. The complexity of this relationship suggests that the impact of DFI is not linear, universal, or automatic, but rather conditional upon the structural and institutional foundations of each economy.

Accordingly, the central question that motivates this study is: Under what institutional and financial conditions does digital financial inclusion enhance the stability of the banking system, and when might it instead intensify systemic risk? Answering this question is essential to understanding the evolving architecture of financial resilience in the digital era, where inclusion and stability may no longer move in tandem, but instead depend on the delicate balance between innovation, regulation, and institutional strength.

1. LITERATURE REVIEW

In the contemporary era of rapid digital transformation, the global financial landscape is being fundamentally reshaped by the forces of technology-driven inclusion. Digital financial inclusion (DFI) has evolved into a pivotal concept, not merely as an instrument for expanding access to financial services but as a cornerstone of inclusive and sustainable economic growth. While digital technologies offer unprecedented opportunities to enhance efficiency, transparency, and outreach, the implications of DFI for banking stability remain theoretically complex and empirically contested. The growing divergence in findings underscores the need for a comprehensive synthesis that integrates economic theory, institutional context, and methodological innovation.

The extant literature identifies two main transmission channels through which DFI influences banking stability: the risk-mitigating and risk-shifting mechanisms. The risk-mitigating perspective posits that digitalization enhances the efficiency of financial intermediation, improves credit risk assessment, reduces information asymmetry, and stabilizes funding bases, thereby strengthening systemic resilience (Ahamed & Mallick, 2019; Chen et al., 2022; Srivastava et al., 2025). This view aligns with empirical evidence

showing that fintech adoption promotes financial diversification, improves capital allocation, and enhances risk management capabilities (Banna, 2025; Du et al., 2023). Conversely, the risk-shifting mechanism warns that the unregulated expansion of digital finance can encourage over-borrowing, increase competitive pressures, and heighten risk-taking behavior, leading to credit deterioration and systemic vulnerabilities (Boyd & Nicoló, 2005; Chinoda & Kapingura, 2024; Fu et al., 2014; Nguyen et al., 2025). When digital innovation outpaces regulatory adaptation, fintech activities may introduce new forms of operational and cyber risk, threatening financial stability (Khan et al., 2024; Liang et al., 2023; Sun et al., 2024). Consequently, the dual nature of DFI highlights the necessity for robust governance and regulatory architectures that ensure innovation contributes to, rather than undermines, macro-financial stability.

Empirical findings increasingly emphasize that the DFI-stability nexus is highly conditional on structural and institutional contexts. Financial development (FD) provides the necessary infrastructure for effective digital intermediation, while institutional quality (WGI) ensures regulatory oversight, contractual enforcement, and market discipline (Čihák et al., 2021; Ha & Nguyen, 2023). In well-developed financial systems, DFI fosters efficiency and resilience, but in less developed or

weakly governed environments, it may amplify instability (Damane & Ho, 2024; Li et al., 2025). Cross-country analyses reveal that the stabilizing effect of DFI emerges only beyond certain thresholds of institutional quality and financial depth (Setianto et al., 2025). This threshold behavior suggests that digital inclusion cannot be treated as a universal remedy; rather, its impact depends critically on the maturity and integrity of the financial ecosystem (Arner et al., 2015; Kass-Hanna et al., 2022). However, much of the literature still treats DFI as an isolated construct, often neglecting its interaction with institutional governance and regulatory frameworks. This omission contributes to the incomplete understanding of why similar DFI policies produce divergent outcomes across countries (Oanh & Dinh, 2024; Vo, 2025).

Methodologically, recent advancements in econometrics and data science have opened new avenues to reexamine the DFI-bank stability relationship. Traditional linear approaches, such as fixed effects and GMM estimations, are often inadequate in capturing complex, nonlinear, and heterogeneous effects across diverse financial systems. Causal Machine Learning (CML) techniques, including Double Machine Learning and Causal Forests, provide powerful tools for identifying causal relationships in high-dimensional settings while controlling for endogeneity (Athey & Imbens, 2019; Chernozhukov et al., 2018; Wager & Athey, 2018). Likewise, nonlinear econometric models such as Panel Threshold Regression (PTR) and Panel Smooth Transition Regression (PSTR) are particularly effective in capturing regime-dependent relationships and identifying structural breaks in DFI's effects (Becha et al., 2025; González et al., 2017; Hansen, 1999). Integrating these approaches enhances the capacity to detect conditional causal patterns, offering a more nuanced and empirically grounded understanding of how DFI interacts with institutional and financial environments (Ni et al., 2023; Tian et al., 2024).

The theoretical foundation of this study rests upon three complementary perspectives. The risk-shifting hypothesis (Boyd & Nicoló, 2005) suggests that intensified competition under weak regulation can lead to excessive risk-taking, a tendency that digitalization may exacerbate. The institutional asymmetry theory (North, 1990) posits that the

success and sustainability of financial innovations depend on institutional quality and governance capacity. In this context, weak institutional frameworks may amplify instability, while strong governance enhances digital resilience. Finally, the financial deepening–fragility paradox (Arcand et al., 2015; Kaminsky & Reinhart, 1999) warns that excessive or poorly supervised financial expansion can undermine stability, an effect that extends to the digital realm. Together, these theories underscore the conditionality of DFI's effects and justify the examination of threshold behavior within the DFI-stability nexus.

Synthesizing the literature reveals several critical research gaps. First, few studies provide an integrated analytical framework that jointly considers DFI, FD, and institutional quality, despite their evident interdependence (Čihák et al., 2021; Ozili, 2018). Second, the application of causal inference and nonlinear modeling remains limited, restricting the ability to establish robust and generalizable conclusions. Third, cross-country comparative analyses differentiating advanced from developing economies are scarce, leaving unexplained heterogeneity in DFI's effects (Kass-Hanna et al., 2022; Liang et al., 2023). Addressing these deficiencies requires methodological and theoretical innovation capable of capturing causal, nonlinear, and context-specific interactions.

Considering these insights, the objective of this study is to investigate whether and under what conditions DFI enhances banking stability across different institutional and financial settings. Specifically, it aims to assess the causal impact of DFI on bank stability, identify nonlinear threshold effects, and determine the moderating roles of financial development and institutional quality. By doing so, this study contributes to the growing body of research that seeks to reconcile inclusion with stability within the digital finance paradigm.

Based on the synthesis of theoretical and empirical evidence, the following hypotheses are proposed:

- H1: *Digital financial inclusion (DFI) has a significant causal effect on bank stability (ZSC).*
- H2: *The relationship between DFI and ZSC is nonlinear, exhibiting threshold effects that*

vary with institutional and financial development levels.

H3: The effect of DFI on ZSC is moderated by financial development (FD) and institutional quality (WGI).

H4: The relationship between DFI and ZSC differs significantly between advanced and developing economies.

2. METHODS

This study employs a balanced panel dataset encompassing 65 countries from 2010 to 2022. The dataset comprises two primary country groups: advanced economies and emerging and developing economies. Data are sourced from reputable international databases, including the Global Financial Development Database (GFDD), World Development Indicators (WDI), IMF Financial Access Survey (FAS), Worldwide Governance Indicators (WGI), and IMF International Financial Statistics (IFS). A detailed classification of all countries by income group and data source is presented in Appendix D.

The primary dependent variable is ZSC, measured by the Z-score, which integrates profitability, leverage, and return volatility to quantify the distance to default. A higher Z-score implies greater stability and lower default risk.

DFI is constructed using Principal Component Analysis (PCA) based on eight indicators reflecting access, usage, and digital penetration in financial services (e.g., mobile accounts per 1,000 adults, ATMs per 100,000 adults, digital transactions, and internet banking adoption). The Kaiser-Meyer-Olkin (KMO) statistic (0.7413) and Bartlett's Test of Sphericity ($p < 0.001$) confirmed data suitability for factor analysis. Five principal components were retained, explaining over 85% of the total variance, leading to a composite DFI index used in the empirical models (Appendix A, Table A1-A2).

To isolate the impact of DFI, several macroeconomic and financial controls are included: GDP (economic size, log-transformed), INF (inflation rate), UNE (unemployment rate), CCR (bank con-

centration ratio), FD (financial development index), and WGI (institutional quality index). The WGI is derived using PCA from six institutional indicators, confirming factor adequacy ($KMO = 0.6902$, Bartlett's $p < 0.001$). The first principal component explained 87.68% of the variance, resulting in a composite institutional quality measure standardized for inclusion in the model (Appendix A, Table A3).

Countries are categorized along three analytical dimensions: Income level (low/middle/high), based on the World Bank classification, Institutional quality, using WGI percentile rankings, and financial development level, determined by FD index quartiles. This classification allows the study to analyze heterogeneous effects of DFI across economic and institutional structures, providing insights into the differing dynamics between advanced and emerging economies.

To mitigate outlier influence and enhance parameter reliability, all continuous variables are winsorized at the 1st and 99th percentiles. Observations outside this range are replaced with boundary values, preserving data integrity while minimizing the impact of extreme values. This approach reduces distortion from measurement errors or abnormal economic shocks common in macro-financial datasets, ensuring stable statistical inference without excluding data points.

The resulting dataset forms a robust foundation for the subsequent causal and nonlinear analyses, enabling rigorous testing of the hypotheses within a consistent multi-country empirical framework.

The empirical analysis follows four main steps:

- *Step 1:* Data preprocessing, variables are winsorized to reduce the influence of outliers and standardized for cross-country comparability.
- *Step 2:* Estimation of causal effects using Causal Machine Learning (CML), including Double Machine Learning (DML) and Causal Forests, to assess both Average Treatment Effects (ATE) and Conditional Average Treatment Effects (CATEs) (Athey & Imbens, 2019; Chernozhukov et al., 2018; Wager & Athey, 2018).

- *Step 3:* Identification of nonlinear structures using Panel Threshold Regression (PTR) as developed by Hansen (1999), where the threshold variable represents either FD or WGI. This step detects statistically significant breakpoints beyond which DFI alters its effect on stability.
- *Step 4:* Robustness validation, performed through Panel Smooth Transition Regression (PSTR) (González et al., 2017) and cross-model comparison among OLS, PTR, PSTR, and DML results. These tests ensure the consistency and robustness of findings across linear, nonlinear, and causal frameworks. The analysis confirms that the DFI-ZSC relationship remains stable across specifications, with results converging on the conditional and nonlinear nature of DFI's impact on bank stability.

The first analytical stage employs DML to estimate the unbiased causal effect of DFI on ZSC while addressing high-dimensional confounders. DML combines traditional econometric identification with modern machine learning algorithms, mitigating endogeneity and overfitting. Subsequently, Causal Forests are implemented to uncover treatment effect heterogeneity across subgroups defined by institutional strength and financial development. These methods reveal how DFI's impact varies across different macro-financial environments, aligning with Hypotheses *H1-H4*.

In the second stage, the PTR model tests for nonlinear threshold effects in the DFI-ZSC relationship. The model differentiates between low- and high-regime states of FD and WGI, quantifying shifts in the DFI impact once critical institutional or financial thresholds are surpassed. This regime-switching framework provides empirical evidence for Hypothesis *H2* and validates the existence of structural asymmetries within digital financial systems.

Additional robustness checks include:

- PSTR estimation to test for smooth, gradual transitions in the DFI-ZSC nexus.
- Cross-model triangulation comparing DML, Causal Forests, and PTR results for consistency.

This integrated empirical design enhances methodological rigor by bridging causal inference and nonlinear econometrics, providing a comprehensive understanding of how DFI contributes to or threatens banking stability under varying institutional and financial conditions.

3. EMPIRICAL RESULTS

To test Hypothesis *H1*, this study begins with an Exploratory Data Analysis (EDA) to identify key patterns, correlations, and distributional characteristics of the dataset comprising 65 countries (2010–2022).

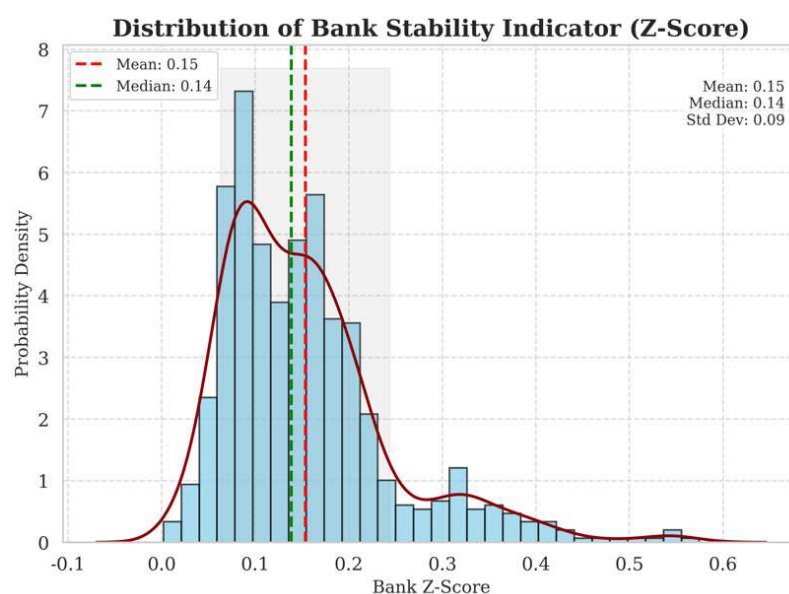
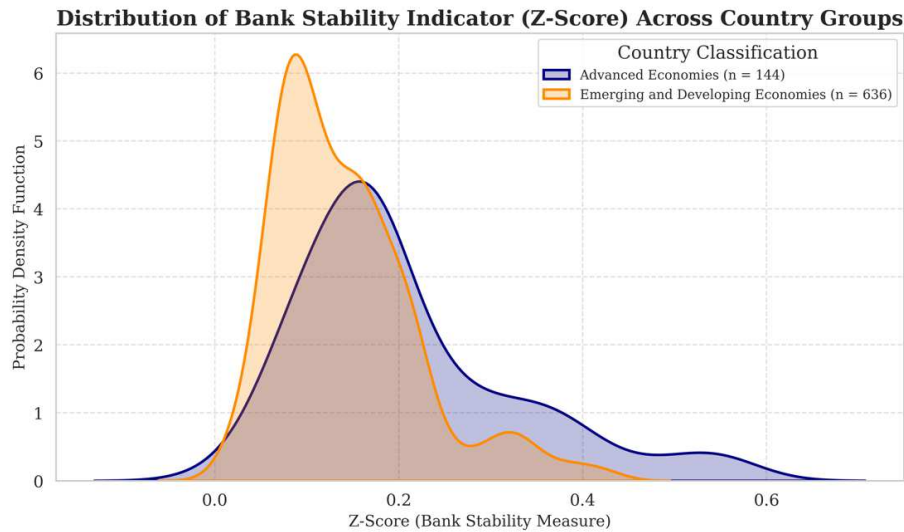


Figure 1. Distribution of the bank stability indicator (ZSC)



Note: Advanced Economies (n = 144) ra Emerging and Developing Economies (n = 636).

Figure 2. Distribution of the bank stability indicator (ZSC) across country groups

Figure 1 illustrates that the distribution of the ZSC index is positively skewed, indicating that a small number of countries, such as Switzerland and Singapore, exhibit exceptionally high levels of bank stability, while the majority of countries are clustered around the median. This skewness suggests that traditional linear regression models may be inappropriate and instead supports the application of nonlinear modeling techniques to better capture the asymmetric distribution of bank stability, consistent with the insights of Setianto et al. (2025).

Figure 2 presents the probability density distribution of the ZSC index across two country groups: developed and developing economies. The distribution for developed countries is right-skewed, with a higher average ZSC value, indicating greater bank stability. In contrast, developing countries exhibit a tighter concentration around lower ZSC values, reflecting higher financial risk and weaker resilience. The pronounced divergence between the two density curves suggests the presence of heterogeneous effects in the relationship between DFI and ZSC, a hypothesis that will be examined in greater depth in subsequent sections.

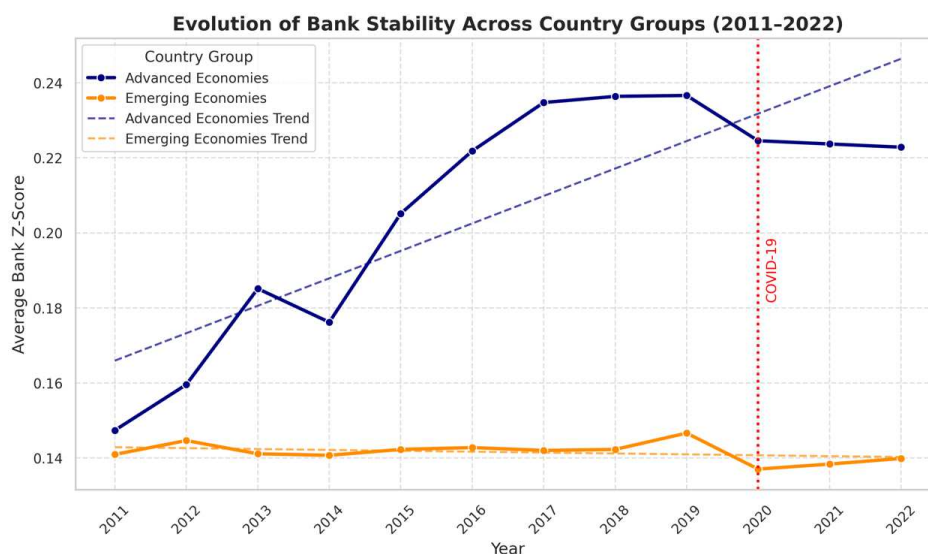


Figure 3. Evolution of bank stability across country groups (2011–2022)

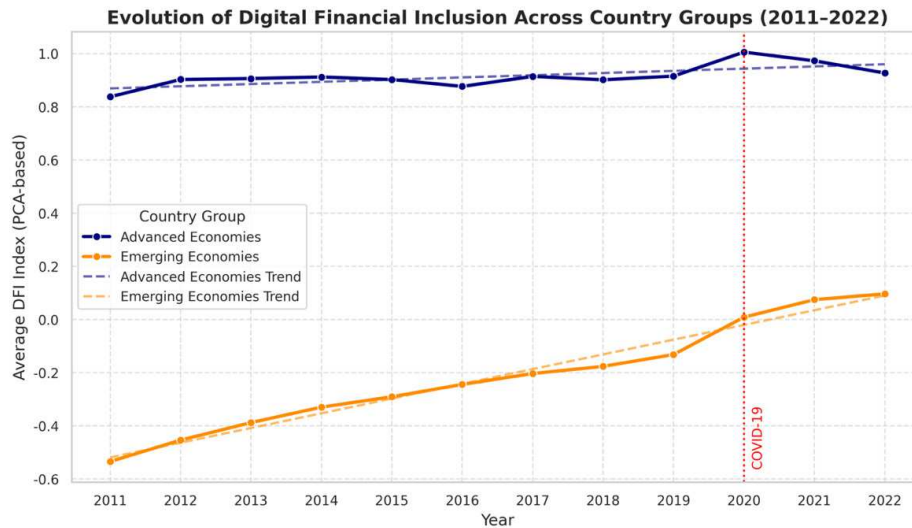


Figure 4. Evolution of digital financial inclusion across country groups (2011–2022)

Figures 3 and 4 illustrate the trends of ZSC and DFI across developed and developing countries. In the aftermath of the global financial crisis and particularly following the COVID-19 pandemic, developing economies have experienced a rapid surge in DFI, driven primarily by the expansion of FinTech innovations and mobile payment platforms. However, the improvement in ZSC within this group has remained modest and unstable, suggesting that the relationship between DFI and bank stability may exhibit lagged effects or that underlying conditions remain insufficient to activate the positive impact (Ha et al., 2025). In contrast, developed countries have shown a parallel

upward trend in both DFI and ZSC, implying that a positive effect of DFI on financial stability may be more likely to materialize under strong institutional quality and advanced financial development (Chen & Shen, 2024).

Figure 5 presents the correlation matrix of key financial variables. Notably, there is a positive correlation between DFI and ZSC, suggesting a preliminary indication of a favorable relationship. However, linear correlations alone do not fully capture the nonlinear and heterogeneous nature of this relationship, particularly in the context of digital financial inclusion (Becha et al., 2025). In



Figure 5. Correlation matrix of key financial indicators

addition, DFI exhibits strong positive correlations with macro-financial variables such as institutional quality (WGI) and financial development (FD), providing a basis for investigating their moderating roles in later sections.

To formally evaluate *H1* and *H3*, the study employs a Causal Machine Learning (CML) framework integrating Double Machine Learning (DML) and Causal Forests. These methods effectively address omitted variable bias, capture non-linear and heterogeneous treatment effects, and leverage the strengths of modern machine learning algorithms in high-dimensional data settings (Athey & Imbens, 2019; Chernozhukov et al., 2018; Wager & Athey, 2018).

Specifically, the DML estimation is implemented using the `econml` library, with Random Forest Regressors (100 trees, `max_depth = 5`) employed for the nuisance functions (`model_y`, `model_t`). All continuous variables are standardized using `StandardScaler`, and the input includes macro-financial covariates (*X*) and structural background conditions (*W*: financial development, institutional quality, country type). Categorical variables are numerically encoded and normalized prior to modeling.

To estimate Conditional Average Treatment Effects (CATE), the study employs Causal Forests,

also from `econml`, with 1,000 trees, `min_samples_leaf = 10`, `max_depth = 10`, and `random_state = 42`. The model is trained on an expanded feature set combining *X* and *W*, ensuring the ability to detect contextual heterogeneity in the DFI-ZSC relationship.

The Average Treatment Effect (ATE) of DFI on ZSC is estimated at 0.0027, but the 95% confidence interval ranges from -0.0102 to 0.0156. This indicates no statistically significant average causal effect across the full sample. This result aligns with real-world observations where many developing countries have expanded DFI rapidly but failed to improve financial stability, likely due to institutional weaknesses, limited regulatory capacity, or inadequate digital infrastructure.

Figure 6 shows the distribution of CATE, revealing substantial heterogeneity in the causal impact of DFI on ZSC across countries and observations. The distribution is centered near zero but slightly left-skewed, with a mean CATE of -0.0037, suggesting that, on average, the conditional effect is mildly negative for certain subgroups. This finding supports the earlier ATE results, highlighting that while the average impact may be slightly positive, DFI may reduce bank stability in specific contexts. These patterns reinforce the importance of enabling conditions, such as institutional quality (WGI), financial system maturity (FD), and coun-

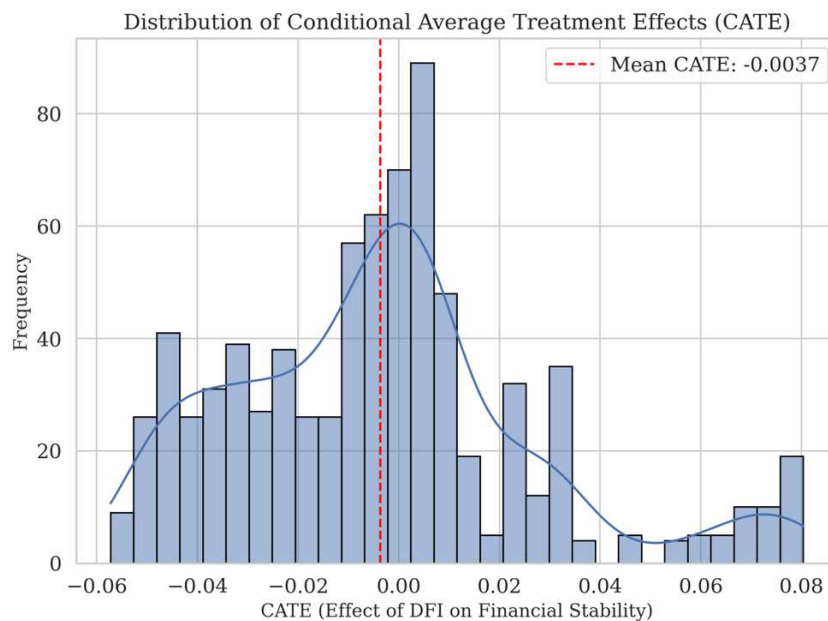


Figure 6. Distribution of conditional average treatment effects (CATE)

Table 1. Heterogeneous conditional average treatment effects (CATE) by country characteristics

Subgroup	Mean CATE	95% CI	Std. Error	t-stat	p-value	Significance	N (Obs.)
Low WGI (WGI < Median)	-0.0032	[-0.0060, -0.0004]	0.0014	-2.2526	0.0248	**	390
High WGI (WGI ≥ Median)	-0.0041	[-0.0073, -0.0009]	0.0016	-2.5340	0.0117	**	390
Low FD (FD < Median)	-0.0129	[-0.0158, -0.0100]	0.0015	-8.6549	0.0000	***	390
High FD (FD ≥ Median)	0.0056	[0.0028, 0.0084]	0.0014	3.9135	0.0001	***	390
Developing Countries (Type = 0)	-0.0082	[-0.0105, -0.0060]	0.0011	-7.1693	0.0000	***	636
Developed Countries (Type = 1)	0.0165	[0.0119, 0.0210]	0.0023	7.1902	0.0000	***	144

try type, in shaping the effectiveness of digital financial inclusion initiatives.

The results, presented in Table 1 and visualized in Figure 7, demonstrate that the causal impact of DFI on ZSC is heterogeneous, contingent upon underlying structural conditions. FD emerges as a significant moderator: in countries with high FD, DFI strengthens financial stability (CATE = +0.0056, $p < 0.001$); conversely, in low-FD economies, DFI has a significantly negative effect on ZSC (CATE = -0.0129, $p < 0.001$).

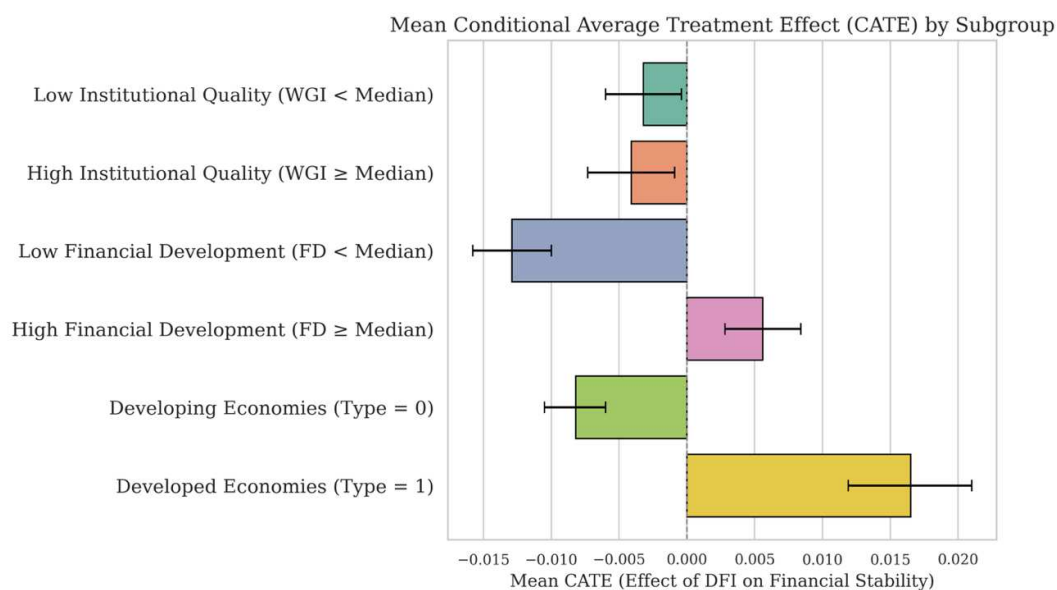
In contrast, both high and low WGI groups exhibit statistically significant negative effects of DFI on ZSC (CATE = -0.0032 and -0.0041, respectively). This suggests that institutional quality alone is insufficient to convert DFI into a stabilizing force in the absence of well-developed financial systems.

These findings support the hypothesis of contextual conditionality in digital financial development, wherein the same policy intervention (i.e.,

DFI expansion) may yield opposite effects depending on the financial-institutional context of each country (Kass-Hanna et al., 2022; Vo, 2025). Such asymmetry underscores the need for coordinated development of institutional and financial infrastructure to unlock the stabilizing potential of DFI.

As illustrated in Figure 8, FD and WGI emerge as the two most influential factors contributing to the model's prediction error, significantly outweighing DFI.

This finding implies that while DFI holds potential as a policy instrument for promoting financial stability, it cannot function effectively as a standalone measure. Rather, it must be embedded within a robust institutional framework and well-developed financial infrastructure. This reinforces the earlier proposition that the effectiveness of digital financial innovation is conditional upon a supportive institutional environment, strong governance capacity, and sufficient financial depth.

**Figure 7.** Mean conditional average treatment effect (CATE) by subgroup

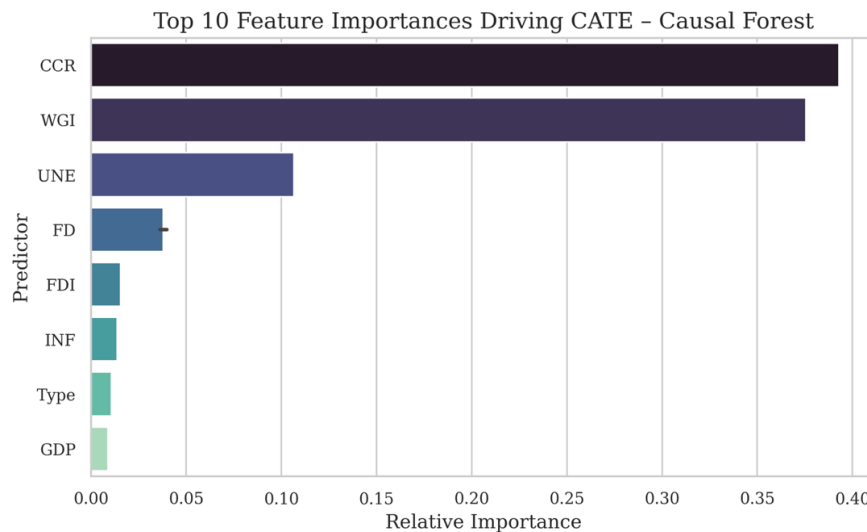


Figure 8. Feature importances driving CATE – Causal Forest

For developing countries, characterized by limited digital infrastructure, weak institutional capacity, and underdeveloped financial markets, DFI not only fails to significantly enhance systemic stability but may also exacerbate systemic risks, unless accompanied by appropriate regulatory safeguards. This result aligns with the Causal Forest analysis (Table 1), which demonstrated that DFI yields positive and statistically significant effects only in countries with high FD or developed economies.

The causal analysis confirms *H1*, indicating that DFI has a measurable but context-dependent causal impact on bank stability. The ATE is statistically insignificant across the full sample, but the CATE shows strong heterogeneity across financial and institutional contexts. Specifically, the positive and significant CATE in high-FD countries ($p < 0.001$) supports the moderating role of financial development, thereby validating *H3*. In contrast, the negative effects in low-FD or weakly governed economies further reinforce that DFI's effectiveness is conditional upon enabling structural factors.

To test *H2*, the study applies the Panel Threshold Regression (PTR) model by Hansen (1999). The estimation results, presented in Table 2, reveal the existence of a statistically significant threshold at $DFI = -1.3611^*$. This threshold was identified through 300 bootstrap replications, with the LR statistic reaching $F = 21.63$ ($p < 0.01$), confirm-

ing the presence of a regime-switching structure within the data.

Specifically, in the low-DFI regime ($DFI \leq -1.3611$), the effect of DFI on ZSC is negative and statistically significant, with a coefficient of -0.0145 , standard error of 0.0062 , and p -value of 0.0195 . This indicates that in countries with low levels of digitalization, expanding DFI may increase financial risk or, at the very least, fail to enhance bank stability due to weak institutional frameworks, limited regulatory capacity, or underdeveloped financial infrastructures (Hoque et al., 2024).

Conversely, in the high-DFI regime ($DFI > -1.3611$), the coefficient is -0.0062 but statistically insignificant ($p = 0.3211$), suggesting that once a critical threshold of digital financial inclusion has been surpassed, the effect of DFI on ZSC becomes statistically indistinct. While the coefficient remains negative, the magnitude of the effect diminishes, implying that economies with high levels of digitalization may have reached a policy saturation point, where the marginal benefit of further DFI becomes negligible.

The PTR findings confirm the nonlinear structure predicted by *H2* and complement CML results by emphasizing conditionality in the DFI-ZSC nexus. From a policy standpoint, uniform DFI promotion is ineffective. Economies with low DFI should pair expansion with institutional reforms and regulatory strengthening. High-DFI economies should

Table 2. Estimated effects of DFI below and above the threshold

Threshold Regime	Coefficient	Std. Error	p-value	95% CI	Significance
DFI \leq -1.3611 (Low DFI)	-0.0145	0.0062	0.0195	[-0.0266, -0.0023]	Yes (significant)
DFI $>$ -1.3611 (High DFI)	-0.0062	0.0063	0.3211	[-0.0185, 0.0061]	No (not significant)

Table 3. Robustness check – summary of regression results

Model	DFI Coefficient	DFI \times FD Coefficient	Remarks
Baseline OLS (Full sample)	-0.0139**	0.0185***	Full sample OLS regression
OLS with Interaction (DFI \times FD)	-	0.0185***	Test for the interaction effect
PSTR with Soft Threshold	-0.0453***	-	Logistic transition (nonlinear)
Bootstrap Threshold: Low DFI	-0.0435	-	Below threshold DFI \leq -1.3611
Bootstrap Threshold: High DFI	0.0126*	-	Above threshold DFI $>$ -1.3611
OLS – Developing Countries	0.0052	0.0081**	Emerging economies only
OLS – Developed Countries	0.1461***	-0.0817***	Advanced economies only

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

focus on optimizing marginal efficiency and managing emerging fintech risks (Ni et al., 2023; Sun et al., 2024).

To ensure the reliability and generalizability of the empirical findings, the study implements a series of robustness checks, combining traditional and modern econometric techniques, both linear and nonlinear, as well as causal inference models. These checks assess the stability of the DFI-ZSC relationship across developed and developing country groups. A summary is provided in Table 3.

1. Interaction effects: DFI \times FD

First, the study replaces DFI with the interaction term DFI \times FD to test the moderating role of financial development in the DFI-ZSC relationship. Results indicate a positive and significant coefficient for developing countries (coef = 0.0081, $p = 0.048$), while for developed countries, the coefficient is negative and significant (coef = -0.0817, $p = 0.004$). These findings reinforce the hypothesis of structural heterogeneity by development level.

2. PSTR and bootstrap threshold

To test nonlinearity, the Panel Smooth Transition Regression (PSTR) is implemented using a logistic transition function. At low DFI levels, the impact on ZSC is negative (coef = -0.0453, $p < 0.001$), reflecting heightened risk in the absence of supportive institutions. However, beyond a soft threshold, the effect turns positive (coef = +0.0635, $p < 0.001$), confirming the existence of a smooth nonlinear regime.

Additionally, Hansen's bootstrap threshold regression confirms a significant threshold at DFI = -1.3611 ($p < 0.05$). When split:

- Low DFI Group: Effect is statistically insignificant.
- High DFI Group: DFI has a positive and significant impact (coef = +0.0126, $p = 0.035$), confirming a discrete regime shift.

These findings align with recent literature (e.g., ...), which indicates that DFI yields positive outcomes only beyond a minimum development threshold.

3. Country group heterogeneity (PTR & DML)

Separate regressions by country group reveal significant disparities:

- In developing countries, DFI shows no statistically significant effect, while DFI \times FD is weakly positive. Institutional quality (WGI) exerts a negative impact, indicating potential governance limitations in managing digitalization risks.
- In developed countries, DFI shows a strong positive effect (coef = +0.1461, $p = 0.003$), whereas DFI \times FD is negative (coef = -0.0817), suggesting a diminishing return effect in more mature environments.

The DML estimations reaffirm a significant and positive causal impact of DFI on bank stabili-

ty in developed economies, consistent with the outcomes of recent causal machine learning research. Complementary cross-country regressions and subgroup analyses reveal substantial heterogeneity across development levels: in advanced financial systems, DFI exerts a robust stabilizing effect (coef = +0.1461, $p = 0.003$), whereas in developing economies, its influence is weaker or negative, thereby confirming *H4*.

Integrating results across all models, the empirical evidence collectively supports *H1-H4*. Specifically, the CML analysis confirms DFI's causal and context-dependent effect (*H1, H3*), the PTR validates its nonlinear nature (*H2*), and the subgroup analysis establishes cross-country heterogeneity (*H4*). Robustness tests, including PSTR and cross-model comparisons, further reinforce these findings. Overall, the results demonstrate that the stabilizing benefits of digital financial inclusion are conditional: they emerge only where digital transformation aligns with adequate financial development and institutional capacity, affirming the notion of conditional effectiveness in the digital finance–stability nexus.

4. DISCUSSION

The empirical findings demonstrate that DF exerts a causal but context-dependent influence on ZSC. While the overall average effect (ATE), estimated through DML, is positive but statistically insignificant, the CATE reveals substantial heterogeneity. Specifically, DFI enhances stability in financially developed and institutionally strong economies but weakens it in less developed or poorly governed ones. This asymmetric pattern supports the conditional effectiveness hypothesis, indicating that DFI contributes to stability only when underpinned by sound financial systems and effective governance structures.

These findings provide empirical confirmation of the theoretical arguments proposed by Boyd and Nicoló (2005) and North (1990), which emphasize that institutional and structural conditions critically determine financial outcomes. The results are consistent with Ahamed

and Mallick (2019), Feghali et al. (2021), and Setianto et al. (2025), who find that financial inclusion supports stability primarily in mature financial systems. Conversely, the negative or insignificant effects observed in emerging markets align with the cautionary conclusions of Fu et al. (2014), Ozili (2018), and Sun et al. (2024), who warn that unchecked digital expansion can exacerbate systemic vulnerabilities.

The PTR results complement the CML analysis by revealing a statistically significant nonlinear threshold (DFI = -1.3611) that delineates destabilizing and neutral regimes. Below this threshold, DFI expansion increases financial fragility ($\beta = -0.0145$, $p < 0.05$), supporting the findings of Ni et al. (2023) and Chen and Shen (2024), who document inverted-U or threshold effects between fintech activity and bank stability. Above the threshold, the marginal gains of further digitalization become statistically insignificant, suggesting diminishing returns once the financial system reaches a certain level of digital maturity. This aligns with the “digital saturation” hypothesis highlighted by Li et al. (2025) and Tian et al. (2024).

The robustness checks, including PSTR and cross-model validation, further confirm that DFI's effect on stability is nonlinear and conditional. FD and WGI emerge as stronger determinants of banking stability than DFI itself. This reinforces the findings of Ha and Nguyen (2023) and Nguyen et al. (2025), emphasizing that institutional capacity magnifies the positive potential of digital financial expansion. Consequently, DFI should be treated not as a substitute for institutional and financial development but as a complementary mechanism that requires coordinated policy design, prudent supervision, and adaptive regulation.

From a methodological perspective, this study advances the literature by integrating causal machine learning and nonlinear econometric modeling within a multi-country framework. The combination of DML and PTR enables simultaneous identification of causal directionality and threshold effects, addressing key limitations in earlier linear studies. This integrated approach strengthens the empirical foundations of

digital finance research and showcases the potential of advanced econometric and AI-driven tools in macro-financial analysis.

In conclusion, the findings confirm that digital financial inclusion is a double-edged policy instrument. While it can enhance efficiency, accessibility, and inclusion, it may also amplify systemic vulnerabilities when implemented without adequate institutional and regulatory safeguards. By empirically demonstrating the conditional and nonlinear nature of DFI's influence, this study contributes to the theoretical understanding of digital financial resilience and offers actionable policy insights for balancing innovation with financial stability.

CONCLUSION AND POLICY IMPLICATIONS

This study investigated whether and under what conditions digital financial inclusion (DFI) contributes to banking stability across 65 countries using Causal Machine Learning and Panel Threshold Regression. The analysis revealed that DFI's impact is conditional and nonlinear. It enhances stability only in economies with strong institutional quality and developed financial systems, while in weaker environments, its effect is insignificant or even destabilizing. A significant threshold (DFI = -1.3611) was identified, confirming that the stabilizing role of DFI emerges only beyond a minimum level of institutional and financial development.

The novelty of this study lies in integrating causal inference and nonlinear modeling to uncover the contextual dynamics of DFI effectiveness. By demonstrating the coexistence of stabilizing and destabilizing regimes, the research advances the concept of conditional digital finance effectiveness, offering a new empirical framework for analyzing digital transformation in the banking sector. In practical terms, the findings suggest that policymakers in low- and middle-income countries should first strengthen institutional capacity, financial depth, and regulatory governance before scaling up digital finance initiatives. In advanced economies, emphasis should shift from access expansion to risk management and resilience-building within digital financial ecosystems.

Future research should extend this work using micro-level data from banks and fintech firms to explore how digital inclusion affects risk-taking and profitability at the institutional level. Incorporating measures of digital literacy, service quality, and infrastructure efficiency would further refine understanding of DFI's real-world implications.

AUTHOR CONTRIBUTIONS

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APPENDIX A. Principal component analysis results

Table A1. Principal component analysis results (DFI)

Component	Eigenvalue	Explained Variance Ratio	Cumulative Variance Ratio
PC1	3.5557	0.4439	0.4439
PC2	1.4385	0.1796	0.6235
PC3	0.8601	0.1074	0.7308
PC4	0.6957	0.0869	0.8177
PC5	0.5606	0.0700	0.8877
PC6	0.5072	0.0633	0.9510
PC7	0.2749	0.0343	0.9853
PC8	0.1175	0.0147	1.0000

Note: Five components (PC1 to PC5) were retained to explain $\geq 85\%$ of the total variance.

Table A2. Normalized weights for constructing the composite index (DFI)

Principal Component	Explained Variance Ratio	Normalized Weight
PC1	0.4439	0.5001
PC2	0.1796	0.2023
PC3	0.1074	0.1210
PC4	0.0869	0.0978
PC5	0.0700	0.0788

Note: $DFI = 0.5001 \cdot PC1 + 0.2023 \cdot PC2 + 0.1210 \cdot PC3 + 0.0978 \cdot PC4 + 0.0788 \cdot PC5$; the composite index (DFI) has been added to the dataset as a new variable; all variables used in the PCA were standardized before estimation.

Table A3. Principal component analysis results (WGI)

Principal Component	Eigenvalue	Explained Variance Ratio	Cumulative Variance Ratio
PC1	5.2677	0.8768	0.8768
PC2	0.3744	0.0623	0.9391
PC3	0.2532	0.0421	0.9813
PC4	0.1125	0.0187	1.0000
PC5	~0	~0	1.0000
PC6	~0	~0	1.0000

Note: The first component (PC1) alone explains more than 87% of the total variance, indicating strong dimensionality reduction and high internal consistency among governance indicators.

APPENDIX B

Table B1. Variable description, measurement, and data sources

Variable	Description	Measurement / Construction	Source
ZSC	Bank stability	$ZSC = (ROA + Capital/Assets) / \sigma(ROA)$	GFDD (WB)
DFI	Digital financial inclusion index	Constructed via PCA from 8 digital access and usage indicators: Mobile money accounts per 1,000 adults; ATMs per 100,000 adults; Commercial bank branches per 100,000 adults; Internet banking usage (% of population); Mobile banking usage (% of population); Digital payments (% of adults making or receiving digital payments); Debit card ownership (% of adults); Digital savings (% of adults saving using digital platforms)	FAS (IMF), WDI (WB)
GDP	Economic development	Natural logarithm of GDP per capita	WDI (WB)
INF	Inflation rate	Annual % change in CPI	WDI (WB)
UNE	Unemployment rate	% of total labor force unemployed	WDI (WB)
FD	Financial development index	Composite index: depth, access, and efficiency of financial institutions and markets	GFDD (IMF)
CCR	Bank market concentration	Share of assets held by the 3 largest banks (%)	GFDD (WB)

Table B1 (cont.). Variable description, measurement, and data sources

Variable	Description	Measurement / Construction	Source
WGI	Overall institutional quality	Composite index: Voice and Accountability; Political Stability and Absence of Violence/Terrorism; Government Effectiveness; Regulatory Quality; Rule of Law; Control of Corruption	WGI (WB)
Income Group	Country income classification	Low / Middle / High income (World Bank Atlas Method)	WB classification
Type	Country development classification	Takes the value of 1 if the country is classified as developed, and 0 if classified as developing or an emerging economy	WB classification

APPENDIX C. Visualizing heterogeneous treatment effects of DFI on bank stability

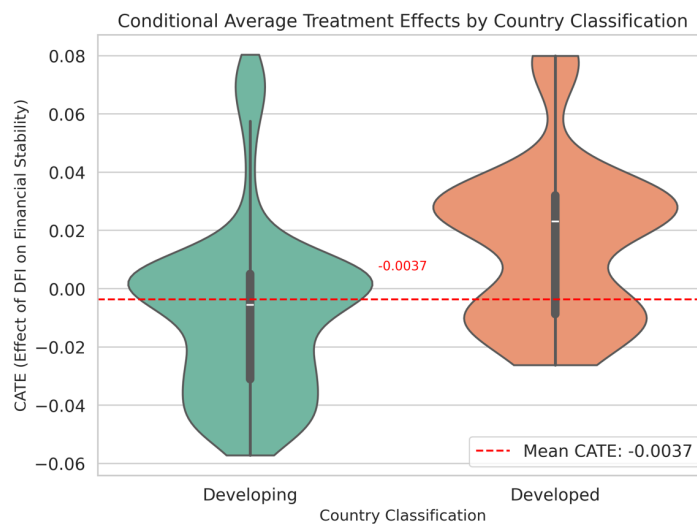


Figure C1. CATE distribution by country type: developed vs. developing economies

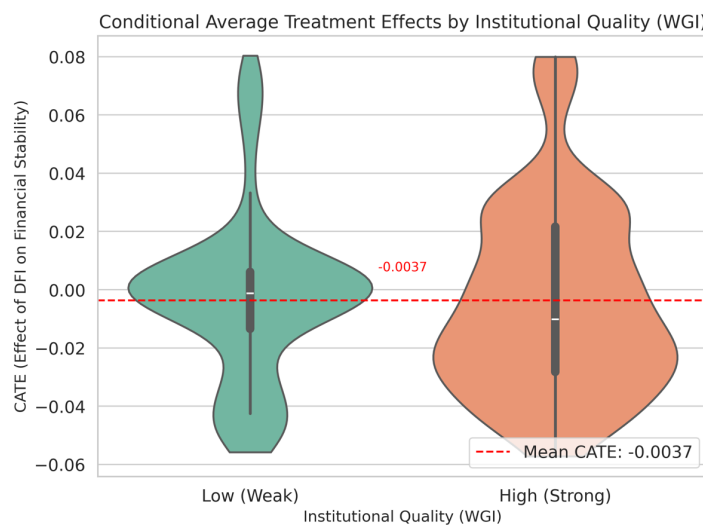


Figure C2. CATE distribution by institutional quality (WGI) **Figure C3.** CATE distribution by financial development (FD)

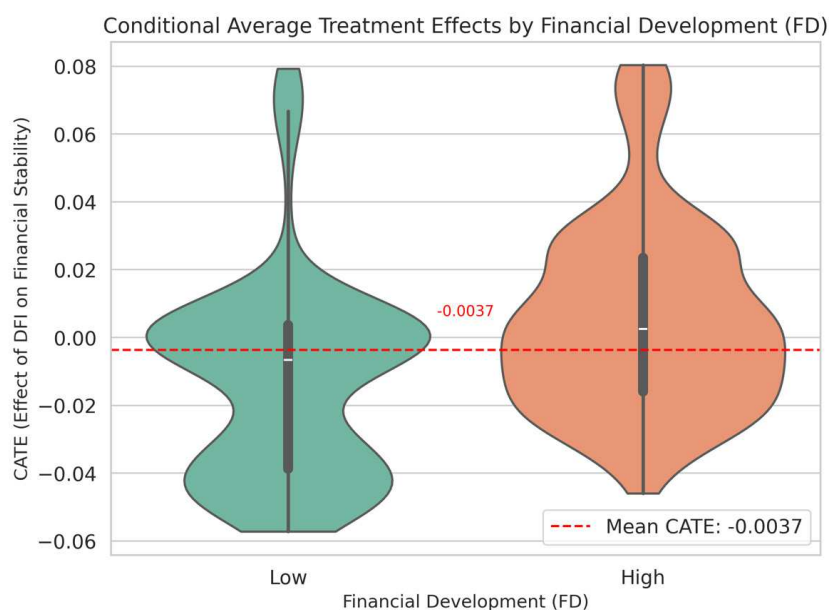


Figure C3. CATE distribution by institutional quality (WGI)

APPENDIX D

Table D1. Country classification

No.	Country	World Bank Income/Development Group	Data Source
Advanced Economies			
1	Austria	High-income / Advanced economy	World Bank (WDI), IMF (IFS), GFDD
2	Belgium	High-income / Advanced economy	
3	Denmark	High-income / Advanced economy	
4	Finland	High-income / Advanced economy	
5	France	High-income / Advanced economy	
6	Greece	High-income / Advanced economy	
7	Luxembourg	High-income / Advanced economy	
8	Norway	High-income / Advanced economy	
9	Portugal	High-income / Advanced economy	
10	Spain	High-income / Advanced economy	
11	Sweden	High-income / Advanced economy	
12	Switzerland	High-income / Advanced economy	
Emerging and Developing Economies			
13	Albania	Upper-middle-income / Emerging	WDI, GFDD, FAS, WGI
14	Argentina	Upper-middle-income / Emerging	
15	Armenia (Republic of)	Lower-middle-income / Emerging	
16	Bangladesh	Lower-middle-income / Developing	
17	Belarus (Republic of)	Upper-middle-income / Emerging	
18	Benin	Low-income / Developing	
19	Bolivia (Plurinational State of)	Lower-middle-income / Developing	
20	Brazil	Upper-middle-income / Emerging	
21	Bulgaria	Upper-middle-income / Emerging	
22	Burkina Faso	Low-income / Developing	
23	Chile	High-income / Emerging	
24	Colombia	Upper-middle-income / Emerging	
25	Costa Rica	Upper-middle-income / Emerging	
26	Croatia (Republic of)	High-income / Emerging	
27	Cyprus	High-income / Emerging	

Table D1 (cont.). Country classification

No.	Country	World Bank Income/Development Group	Data Source
Emerging and Developing Economies			
28	Czechia	High-income / Emerging	WDI, GFDD, FAS, WGI
29	Dominican Republic	Upper-middle-income / Developing	
30	Ecuador	Upper-middle-income / Developing	
31	Egypt (Arab Republic of)	Lower-middle-income / Developing	
32	Estonia (Republic of)	High-income / Emerging	
33	Georgia	Upper-middle-income / Emerging	
34	Honduras	Lower-middle-income / Developing	
35	Hungary	High-income / Emerging	
36	India	Lower-middle-income / Developing	
37	Indonesia	Upper-middle-income / Emerging	
38	Jamaica	Upper-middle-income / Developing	
39	Kazakhstan (Republic of)	Upper-middle-income / Emerging	
40	Kenya	Lower-middle-income / Developing	
41	Korea (Republic of)	High-income / Advanced	
42	Latvia	High-income / Emerging	
43	Lithuania	High-income / Emerging	
44	Malawi	Low-income / Developing	
45	Malaysia	Upper-middle-income / Emerging	
46	Mali	Low-income / Developing	
47	Mexico	Upper-middle-income / Emerging	
48	Niger	Low-income / Developing	
49	Nigeria	Lower-middle-income / Developing	
50	Pakistan	Lower-middle-income / Developing	
51	Panama	High-income / Emerging	
52	Paraguay	Upper-middle-income / Developing	
53	Philippines	Lower-middle-income / Developing	
54	Russian Federation	Upper-middle-income / Emerging	
55	Rwanda	Low-income / Developing	
56	Senegal	Lower-middle-income / Developing	
57	Serbia (Republic of)	Upper-middle-income / Emerging	
58	Slovenia	High-income / Emerging	
59	Thailand	Upper-middle-income / Emerging	
60	Togo	Low-income / Developing	
61	Tunisia	Lower-middle-income / Developing	
62	Türkiye (Republic of)	Upper-middle-income / Emerging	
63	Uganda	Low-income / Developing	
64	Uruguay	High-income / Emerging	
65	Vietnam	Lower-middle-income / Developing	