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Economic uncertainty, financial inclusion, and income inequality in developing countries: Evidence from a dynamic panel threshold analysis

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ABSTRACT

This study investigates how financial inclusion moderates the impact of economic uncertainty on income inequality in 58 developing countries from 2004 to 2022. Using an endogenous dynamic panel threshold model, the findings reveal a threshold effect: economic uncertainty reduces income inequality only when financial inclusion surpasses a certain level. Below this threshold, uncertainty worsens inequality. Financial inclusion reduces income inequality where the effect is pronounced after exceeding the threshold. These results underscore that the relationship between economic uncertainty and income inequality is conditional on financial inclusion. The study emphasizes that enhancing financial inclusion is essential for shielding vulnerable economies from the inequality-amplifying effects of uncertainty, and that this relationship holds under various income inequality, financial inclusion measures and estimation techniques.

1. Introduction

Income inequality (IINE) remains a central challenge for developing economies as it undermines economic growth, social cohesion, and political stability. During times of economic uncertainty (EUN), addressing IINE necessitates a comprehensive strategy that combines measures to stabilize the economy, safeguard vulnerable workers, advance education and skill development, and guarantee that social safety nets are strong enough. EUN and IINE have a complicated relationship in which EUN can make IINE worse by making it more difficult for people to make long-term financial decisions. Job insecurity and income fluctuations might disproportionately harm those with lower incomes during uncertain economic times, expanding the income gap (Latner, 2019; Piketty et al., 2021). While social protection and progressive taxation regulations can alleviate these pressures (Atkinson, 2015; Granger et al., 2022; Stiglitz & Weiss, 1981), uncertainty typically intensifies disparities in income distribution. Such regulations seek to guarantee a more equitable allocation of resources and to offer assistance to the most vulnerable.

Financial inclusion (FI) has recently been demonstrated as a key factor for lowering IINE (Kebede et al., 2023; Omar & Inaba, 2020). Ensuring broad access to and use of financial services can have a considerable impact on the relationship between IINE and EUN. Individuals with access to credit can invest in income-generating ventures, which increases economic growth and potentially decreases IINE. Broader access to credit, savings, insurance, and payment systems enables households and firms to manage income volatility and maintain stability during economic shocks. As it helps people weather financial and economic shocks and mitigates the impact of income disparity, stable FI can be especially crucial during economic downturns. Policies pertaining to FI can be crafted to target marginalized populations in particular to lessen inequities. Therefore, inclusive financial systems play a stabilizing role by supporting entrepreneurship, investment, and risk management, especially in uncertain environments (Siddiki & Bala-Keff, 2024).

Global initiatives such as the G20 High-Level Principles for Digital

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Financial Inclusion and the UN 2030 Sustainable Development Agenda highlight the importance of FinTech in narrowing the wealth gap. Between 2011 and 2021, global account ownership rose from 51 % to 76 % (Demirgüç-Kunt et al., 2018), yet inequalities persist where 55 % of the unbanked are women, and financial access among unemployed adults lags behind the employed. In many developing countries, unequal access to financial services continues to constrain inclusive and sustainable growth.

Existing studies have established that EUN tends to worsen IINE, while FI can reduce inequality by improving access to financial services. However, these two strands of research have largely evolved in isolation, with limited attention to how FI may moderate the effects of EUN. Recent evidence offers preliminary insights: Kebede et al. (2023) found that high levels of FI significantly mitigate inequality even under elevated uncertainty; and Chikhale (2023) demonstrated that macroeconomic volatility disproportionately affects consumption growth in unequal societies, emphasizing financial access as a buffer. These findings suggest that once FI reaches a sufficient level, it can transform uncertainty from a destabilizing factor into a stabilizing force. Despite these insights, very few studies have formally integrated EUN, FI, and IINE within a unified empirical framework. Most adopt linear models that overlook possible threshold effects, leaving unanswered whether FI must attain a critical level before mitigating the inequality effects of uncertainty. Addressing this gap requires conceptual and empirical integration that clarifies how FI operates both as a direct driver of equity and as a threshold-based moderator.

This study provides new evidence on the moderating role of FI in the link between EUN and IINE. Specifically, it investigates whether a threshold effect exists - that is, whether FI must exceed a critical level before it can offset the inequality-widening impact of uncertainty. In recent decades, the world has experienced a series of destabilizing events that have amplified global EUN. Understanding how FI interacts with uncertainty can therefore guide more resilient and inclusive policy responses. From a policy standpoint, if EUN exacerbates inequality, governments must focus on macroeconomic stabilization, job creation, and sustainable investment. Conversely, if greater FI alleviates inequality, expanding equitable access to banking and digital financial services should become a key policy priority. Access to savings, credit, and risk-sharing mechanisms enhances individuals' ability to manage shocks and invest in productive activities, particularly during volatile periods. This study employs a dynamic panel threshold model to explore how FI interacts with EUN in shaping IINE across developing countries. The analysis contributes theoretically, empirically, and practically by identifying the threshold level at which FI begins to buffer the inequality-inducing effects of uncertainty, thereby offering new insights for designing inclusive financial systems in uncertain economic environments.

The remainder of this study is organized as follows: Section 2 reviews the theoretical background and literature. Section 3 presents data, empirical model, and methodology; Section 4 discusses empirical results; and Section 5 concludes with policy implications.

2. Theoretical background and literature review

The relationship between EUN, FI, and IINE is both complex and crucial for understanding income disparities in developing economies. Strengthening this understanding requires a deeper dive into both theoretical perspectives and empirical findings, while integrating broader implications for policy and research. The theoretical link and empirical review between EUN and IINE (Section 2.1), between FI and IINE (Section 2.2), the conceptual integration of threshold mechanism (Section 2.3), and the conceptual integration of EUN, FI, and IINE (Section 2.4) are available in the online appendix Figure S1 depicts the integrated conceptual model links the EUN, FI and IINE (please see Online Appendix).

3. Model specification, estimation strategy, and data

3.1. Baseline model specification

This study investigates the influence of FI on the EUN–IINE nexus using a dynamic model. We reference Omar and Inaba (2020) and Md Jamil et al. (2024) to fulfill the research objective as follows:

$$IINE_{it} = \alpha_i + \gamma IINE_{it-1} + \beta_1 EUN_{it} + \beta_2 FI_{it} + \beta_3 X_{it} + \varepsilon_{it} \quad (1)$$

where *IINE* is income inequality, *EUN* is economic uncertainty, *FI* is financial inclusion, *X* is a matrix of country and institutional specific control variables, and ε is an error term. FI is included in Equation (1) since this variable is one of the determinants of IINE and acts as a threshold variable. The control variables include human capital, inflation, globalization, institutions and real GDP per capita. All variables are transformed into natural logarithms except for EUN and FI index due to the scale of these two variables is from 0 to 1.

The control variables are selected based on theoretical justification and prior empirical literature. Lee and Lee (2018) showed that equitable education distribution lowers income inequality, while Castelló-Climent and Doménech (2021) found an inverted U-shaped relationship between human capital and inequality. Inflation's effect remains mixed: Cysne et al. (2005) reported a positive link, whereas Zheng et al. (2023) and Berisha et al. (2023) found non-linear and context-dependent outcomes. Institutional quality strongly influences inequality where improvements reduce disparity (Szczepaniak et al., 2022), though effects differ across regions (Batuo et al., 2022). Strong institutions foster equitable access to opportunities and fair competition (Acemoglu & Robinson, 2012), whereas weak governance promotes rent-seeking (La Porta et al., 1999). Globalization exerts contrasting impacts: Park (2017) noted widening inequality in Asia, while Ravallion (2018) observed that globalization can worsen inequality, but technological progress and integration may offset these effects. Economic growth also shapes inequality—initially rising with development (Kuznets, 1955) but declining as human capital and inclusive policies expand (Dollar & Kraay, 2002; Galor & Zeira, 1993).

3.2. Estimation strategy

3.2.1. Dynamic panel threshold regression

To estimate the threshold effect, this study uses the dynamic panel threshold model developed by Seo and Shin (2016) and Seo et al. (2019). The use of a dynamic panel threshold model is motivated by its suitability for analyzing complex relationships where nonlinearities and thresholds are expected. EUN, FI, and IINE interact in complex ways, with potential threshold effects where FI may mitigate inequality only beyond certain levels. This model is particularly advantageous as it allows the identification of threshold points and the dynamic adjustment of variables over time. The dynamic specification captures the persistence of IINE while accounting for its response to EUN and FI over time, providing a nuanced understanding of these interactions. The following equation is the baseline panel threshold model to examine the effect of the FI threshold value in the relationship between EUN and IINE:

$$IINE_{it} = (\alpha_1 IINE_{it-1} + \beta_{11} EUN_{it} + \beta_{21} FI_{it} + \beta_{31} X_{it})\, I\{q_{it} \le r\}\ (\alpha_2 IINE_{it-1} + \beta_{12} EUN_{it} + \beta_{22} FI_t + \beta_{32} X_{it})\, I\{q_{it} > r\} + \mu_i + \varepsilon_{it} \quad (2)$$

for i = 1, 2, …, n; t = 1, 2, …T.

where I(.) is the indicator function specifying the regime, q_{it} is the threshold variable (FI), and r is the threshold parameter in the model that divides the equation into two regimes slope coefficients β_1 and β_2, μ_i is the country-specific effect, and ε_{it} is the error term. Other notations are defined in Equation (1).

Using all the dependent variable's lag values as an instrumental variable (IV) allows predicted coefficients in dynamic panel data

analysis to be consistent and devoid of serial correlation. All lagged values of the dependent variable are used as IVs in the model, referencing Arellano and Bover (1995). Equation (2) functions as the threshold and regime-dependent variable and represents the regime-fixed coefficients. The slope coefficients in the dynamic panel threshold model are predicted for the preset IVs once the appropriate threshold level (r) has been determined. The first difference generalized method of moments (GMM), which permits endogenous regressors and threshold variables, is used to estimate Equation (2). μ_i is removed from the model through the first differencing transformation and we then estimate the unknown parameters $\theta = (\alpha, \beta, r)$.

The dynamic panel threshold model by Seo and Shin (2016) and Seo et al. (2019) extends Hansen's (1999) static approach by addressing common panel issues such as endogeneity, simultaneity, and persistence of the dependent variable. By incorporating lagged dependent terms, it captures dynamic adjustment and mitigates simultaneity bias. Compared with Kremer et al. (2013), the Seo and Shin framework explicitly handles endogeneity using IVs within a GMM setting, making it more suitable for dynamic panels. It also offers a more flexible structure for identifying threshold variables and testing threshold effects, especially when relationships vary across regimes. Furthermore, its advanced testing procedures provide greater robustness and reliability in detecting nonlinearities, offering a significant improvement over earlier static or semi-dynamic models.

To ensure robustness of identification of the threshold regression, several diagnostic and sensitivity checks are incorporated. First, in the GMM framework, we report the Hansen J-test for overidentifying restrictions to assess instrument validity and the Arellano and Bond (1991) autocorrelation AR(2) test to rule out second-order autocorrelation in the error term. Second, following Seo and Shin (2016), we compute bootstrapped confidence intervals for the threshold estimate, which provide statistical bounds around the estimated FI threshold. Third, to evaluate sensitivity, we vary the lag structure, adjust the bandwidth parameter in the threshold estimation, and re-estimate the models after excluding extreme outliers (top and bottom 1 % of inequality values). These exercises ensure that our main results are not driven by arbitrary specification choices or data anomalies.

3.3. Data

The study covers 58 developing countries, spanning 17 years of annual data from 2004 to 2022. The sample period is divided into two-year segments (from 2004 to 2021 and 2022 is without averaging) to reduce the number of time dimensions to fulfill the GMM estimation requirement, and each country has nine observations. The list of countries is provided in Online Appendix (Table A1). Selection was based on two key criteria. First, only countries classified as developing economies under the World Bank's regional and income categories were considered. Second, inclusion required the availability of consistent data for the three core variables, namely EUN, FI, and IINE across the study period. Countries with incomplete or inconsistent data were excluded to ensure data integrity. This selection procedure resulted in a balanced panel dataset, which is a methodological requirement for applying the dynamic panel threshold regression developed by Seo and Shin (2016). Maintaining balance not only satisfies the estimation conditions but also enhances comparability across countries, ensuring that our results are robust and generalizable within the developing country context.

The Gini Coefficient index (GINI) is obtained from the Standardized World Income Inequality Database (SWIID) as the dependent variable to illustrate IINE. While the Gini coefficient obtained from the SWIID offers broad temporal and cross-country coverage, we acknowledge its limitation. As noted by Jenkins (2015), SWIID relies on interpolation and imputation techniques that may introduce bias. To mitigate this concern, we complement the baseline analysis with robustness checks using alternative inequality data from the World Income Inequality Database (WIID), wherever coverage overlaps with our sample. Furthermore, to provide greater nuance, we also incorporate direct distributional indicators such as the income shares of the top 20 % and the bottom 20 %, to assess whether the effects of EUN and FI differ across the income distribution.

The World Uncertainty Index (WUI) developed by Ahir et al. (2018, 2019) is utilized to measure EUN, which has become a widely used proxy for global EUN. To ensure cross-country comparability, the WUI normalizes the frequency count of the term "uncertainty" by the total number of words in each Economist Intelligence Unit (EIU) report, thereby adjusting for differences in report length and country coverage (Ahir et al., 2018, 2019). This standardized construction allows the WUI to provide a consistent view of uncertainty across countries and over time (Ahir et al., 2022; Gozgor et al., 2019). Several studies further validate its relevance, showing that it tracks broader economic conditions, policy instability, and business fluctuations as key sources of uncertainty (Azimli, 2022; Demir & Danisman, 2021; Fang et al., 2021; Wu et al., 2022). Nevertheless, as a text-based index, the WUI may partly capture changes in media reporting intensity in addition to actual uncertainty. Following best practice, we interpret the WUI as a broad proxy for policy and EUN, rather than a perfect metric. Importantly, our panel threshold approach focuses on within-country variation relative to FI, which reduces the likelihood that results are driven by reporting bias alone.

The FI index in this study is constructed using the approach proposed by Sarma (2012), which aggregates three dimensions: penetration, access, and usage of financial services. The index is normalized on a scale from 0 to 1, where 0 indicates total exclusion and 1 indicates full inclusion. Formally, the index is computed as:

$$FI = 1 - \sqrt{\frac{1}{3}\left[(1-p_k)^2 + (1-a_k)^2 + (1-u_k)^2\right.}$$

where p_k, a_k, and u_k respectively represent the normalized values of penetration (e.g., number of deposit accounts per 1000 adults), availability (e.g., number of bank branches or ATMs per 100,000 adults), and usage (e.g., volume of credit as a percentage of GDP). Each dimension is equally weighted ($w1 = w2 = w3 = 1/3$).

This study employs four indicators as the explanatory variables to represent FI; namely, (i) the FI index, (ii) the number of credit accounts (percent of GDP), (iii) the number of bank ATMs per 100,000 adults, and (iv) the penetration rate of deposit accounts per 1000 adults. These factors are frequently employed as a stand-in for FI according to Sarma (2012). The three characteristics of FI namely: penetration/accessibility, availability, and usage of the formal financial system are considered when creating the FI indices, as proposed by Sarma (2012). The Financial Access Survey issued by the International Monetary Fund and the Global Findex Database, 2021 provide the FI data. The overall FI index computation uses three important indicators; namely, (i) the number of adult deposit accounts held with financial institutions per 1000 is a key indicator of the adoption rate of banking services, (ii) the accessibility of financial services by quantifying the number of ATMs and bank branches per 100,000 adults, and (iii) the use of financial services is assessed using the proportion of credit accounts with financial systems in GDP.

The control variables of human capital index, real GDP per capita and inflation are obtained from the World Bank World Development Indicators. The institutions and globalization datasets are from the World Bank World Governance Indicators and KOF Swiss Economic Institute, respectively. Figs. S2 and S3 (see Online Appendix) present the average scatter plots between IINE and EUN, and IINE and FI, respectively. IINE and EUN are positively associated, whereas IINE and FI exhibit a negative relationship. Table A2 in the Online Appendix presents the descriptive statistics of the variables used and the units of measurement. IINE has a mean value of 41.74 %, and the minimum and maximum values are 27.44 % and 64.09 %, respectively. This reveals how IINE varies between countries, and whether variations in EUN can

Table 1
Dynamic panel threshold estimations. Dependent variable: ln Income inequality.

Variables	Model (1): FI = Financial inclusion index	
	Lower Regime (β)	Difference (δ = λ – β)
ln Income inequality$_{it-1}$	0.677*** (0.0711)	−0.251*** (0.0706)
Economic uncertainty$_{it}$	0.0211** (0.0107)	−0.0487*** (0.0160)
Financial inclusion index$_{it}$	−0.013*** (0.0004)	−0.229** (0.1040)
ln Human capital$_{it}$	−0.0396 (0.0261)	0.0336 (0.0259)
ln Inflation$_{it}$	0.00214 (0.0014)	−0.0022 (0.0027)
ln Globalization$_{it}$	0.163 (0.104)	−0.513*** (0.156)
ln Institutions$_{it}$	−0.0008 (0.0145)	0.0515** (0.0257)
ln RGDPC$_{it}$	−0.0493*** (0.0168)	0.0360** (0.0178)
Constant	–	2.646*** (0.775)
r (Threshold)	0.249*** (0.0502)	–
N	58	
Number of moment conditions	42	
Bootstrap p-value for linearity test	0.000***	
Bootstrapped confidence intervals	(0.218–0.271)	
Bootstrap Replications	500	
Hansen J-test (p-value)	0.325	
Arellano–Bond AR(2) test (p-value)	0.492	

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

explain the disparity in IINE, and the role of FI in moderating the EUN–IINE nexus. Table A3 in the Online Appendix presents the correlations between the variables, indicating that EUN has a positive correlation with IINE. However, all four FI variables have negative correlations with IINE.

4. Empirical results

4.1. Baseline model using dynamic panel threshold regression

Table 1 reports the baseline results of Equation (2) estimated using the dynamic panel threshold regression approach. FI is measured using the overall FI index, which is the main FI measure in this study. Referring to Arellano and Bover (1995), all lagged values of the dependent variable are employed as IVs in the model. The use of a dynamic panel threshold model is warranted by the relevance of the lagged dependent variable, which rendered the static threshold estimate technique untenable. The dynamic panel threshold model identifies a FI threshold of 0.249 (significant at the 1 % level), marking the point at which the effect of EUN on IINE changes sign. The threshold estimate of 0.249 for the FI index signifies a turning point beyond which the effect of EUN on IINE shifts from positive to negative. In practical terms, this implies that countries must attain a minimum level of FI, specifically, an index score of 0.249 or higher, before they begin to reap inequality-reducing benefits from EUN.

The empirical results demonstrate that the impact of EUN on IINE is positive and significant (0.0211) at the 5 % level when the degree of FI is below the endogenous threshold. Conversely, when the degree of FI is beyond the threshold, the effect of EUN on IINE becomes negative and significant (−0.027). Specifically, if the endogenous threshold is not exceeded, a 1 % rise in EUN leads to a 2.11 % increase in IINE disparity. Conversely, when the endogenous threshold is crossed, a 1 % increase in EUN results in a 2.7 % drop in IINE. FI has a negative relationship and is a statistically significant determinant of IINE below (−0.013) and above (−0.242) the threshold regimes. Notably, the above threshold level has a larger coefficient size than below the threshold level. This suggests that increased FI after passing the threshold tends to lessen IINE. This finding aligns with Omar and Inaba (2020) and Verma and Girl (2022), who found that FI lowers IINE in developing countries and Asian countries, respectively.

Below the threshold, a 1 % increase in EUN raises inequality by 2.11 %, while above it, the same increase reduces inequality by 2.7 %. A 2.7 % drop in IINE above the FI threshold corresponds to roughly a 1.1 point (0.4 x 0.027 = 0.0108) reduction in the Gini coefficient (e.g., from 40.0 down to 38.9). Such a change is considered economically meaningful, as cross-country evidence shows that even 1–2 Gini point shifts typically require sustained policy interventions or reflect major economic shocks.[1] Hence, the estimated effect is not only statistically significant but also substantively important, highlighting the role of FI as a critical tool for mitigating inequality. This confirms that FI acts as a nonlinear moderating factor in the uncertainty–inequality nexus.

When the sample of 58 developing countries is considered, 34 countries lie below the FI threshold, while 24 are above it (see Table A4 in the online appendix that indicates countries classified below and above the FI threshold). This uneven distribution highlights the divergence in financial development across nations. Countries above the threshold are better positioned to transform EUN into a stabilizing force that reduces inequality, while those below remain vulnerable to the inequality-widening effects of uncertainty. This evidence reinforces the policy relevance of strengthening FI as a prerequisite for inclusive resilience. Importantly, the threshold estimate is stable across alternative specifications, with values ranging between 0.21 and 0.28 and bootstrapped confidence intervals tightly bounding the point estimates.

The finding that EUN reduces inequality at higher levels of FI can be attributed to institutional quality factor where the institutions variable emerges as a statistically significant factor reducing inequality, particularly above the FI threshold. This finding suggests that mature financial systems are often embedded within stronger governance and regulatory frameworks, which enhance the effectiveness of financial intermediation and risk-sharing. These mechanisms collectively transform uncertainty from a regressive force into a stabilizing one when FI is sufficiently developed. Inclusive institutions enhance the distributional benefits of finance by ensuring equitable access, reducing rent-seeking, and promoting transparent intermediation.[2] The combined effect of deeper FI and institutional strength allows EUN to reduce rather than exacerbate inequality. This aligns with the view that redistributional buffers, portfolio diversification, and institutional capacity work together to transform uncertainty into a stabilizing force in economies with mature financial systems.

As reported in Table 1, the diagnostic checks confirm that this threshold is stable where the bootstrapped confidence intervals demonstrate that it lies within a relatively narrow band, thereby strengthening the credibility of the regime-splitting result. The Hansen J-test indicates that the instruments employed in the GMM estimation are valid, while the Arellano–Bond AR(2) test confirms the absence of second-order autocorrelation. Collectively, these results provide strong support for the validity of the identification strategy and the reliability of the threshold estimates.

These results confirm that EUN exerts a considerable influence on IINE, consistent with the view that instability disproportionately affects lower-income households (Stiglitz & Weiss, 1981). Past crises such as the 2008–2009 global financial crisis and the COVID-19 pandemic (2020–2021) provide clear evidence: both episodes heightened uncertainty, triggered job losses, and tightened credit markets, which deepened income disparities (Atkinson & Morelli, 2011; Furceri et al., 2021). Furthermore, the results reveal that real GDP per capita and institutions

[1] Atkinson and Morelli (2011) note that during the **2008–09 global financial crisis**, Gini coefficients in many countries worsened by only 1–2 points, yet this was seen as a major setback.

[2] Setianto et al. (2025) showed that the impact of financial inclusion on stability depends on institutional quality. Using dynamic panel threshold regressions on bank- and country-level data, they found that inclusion had no significant effect when institutional quality was weak but became strongly positive once it exceeded a critical threshold.

Table 2
Coefficients at low and high threshold regimes.

Variables	Low Regime (Below the Threshold) ≤0.249	High Regime (Above the Threshold) >0.249
Economic uncertainty$_{it}$	0.0210**	−0.0270***
Financial inclusion index$_{it}$	−0.0130***	−0.2420**
Human capital$_{it}$	0.0396	−0.0060
Inflation$_{it}$	0.0021	0.0040
Globalization$_{it}$	0.1630	0.6760***
Institutions$_{it}$	−0.0008	−0.0520**
Real GDP per capita$_{it}$	−0.0493***	−0.0850**

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

lessen income disparity when the endogenous threshold is exceeded, indicating the role that FI has in influencing IINE. Once globalization reaches a certain threshold, it tends to exacerbate IINE. This outcome is consistent with Park (2017), who found that globalization is increasing IINE.

Table 2 summarizes the above threshold coefficients of all variables using the lower regime [below the threshold (β) plus the difference (δ)]. From an empirical perspective, the results indicate that EUN amplifies IINE below the FI threshold. However, above this threshold, the moderating role of FI becomes evident, as access to credit and financial services buffers against income shocks. This finding suggests the conditional effects of FI on IINE during uncertain times.

Tables A5 – A7 in the online appendix report the credibility of our identification strategy. Table A5 examines the sensitivity of results to alternative lag structures (1–3 lags) and shows that the estimated threshold remains stable, with consistent coefficient signs for EUN across regimes. Table A6 varies the bandwidth parameter (5 %, 10 %, and 15 %), again confirming robustness of the threshold estimates. Table A7 re-estimates the model after excluding extreme observations (top and bottom 1 % of IINE values) and finds no substantive changes in the results, suggesting that outliers do not drive the findings. Collectively, these results demonstrate that our findings are not sensitive to alternative specifications and that the threshold effect is robust and credibly identified.

In addition to the overall FI index, this study also repeats the same estimations using the four FI indicators of (i) the number of deposit accounts with commercial banks per 1000 adults, (ii) the number of ATMs per 100,000 adults, (iii) the number of commercial bank branches per 100,000 adults, and (iv) the number of credit accounts (percent of GDP) to identify which dimension of FI drives the threshold effect. These four indicators can be classified into three sub-dimensions, namely **penetration, availability, and usage**. The empirical results are reported in Table 3. The threshold points of the effect range from 0.2092 to 0.2849 between low and high development regimes of FI and are statistically significant at the 1 % level. This confirms the threshold effect of FI in the nexus between EUN and IINE in the sample countries.

Table 3
Dynamic panel threshold estimations using other financial inclusion indicators. Dependent variable: ln Income inequality.

Variables	Penetration Model (2): FI = Deposit accounts		Availability Model (3): FI = ATMs		Availability Model (4): FI = Bank branches		Usage Model (5): FI = Credit accounts	
	Lower Regime (β)	Difference δ = λ − β	Lower Regime (β)	Difference δ = λ − β	Lower Regime (β)	Difference δ = λ − β	Lower Regime (β)	Difference δ = λ − β
ln Income inequality$_{it-1}$	0.787***	0.130	0.567***	0.187***	1.086***	0.0775	0.863***	−0.285***
	(0.219)	(0.224)	(0.118)	(0.0652)	(0.123)	(0.0661)	(0.127)	(0.0655)
Economic uncertainty$_{it}$	0.0378	−0.0836	0.0101***	−0.0121***	0.0252*	−0.0142	−0.0056	−0.0089
	(0.0483)	(0.0582)	(0.0035)	(0.0036)	(0.0144)	(0.0210)	(0.0110)	(0.0247)
ln Deposit accounts$_{it}$	0.0133	0.0334	–	–	–	–	–	–
	(0.0106)	(0.0243)						
ln ATMs$_{it}$	–	–	0.0201**	−0.0217**	–	–	–	–
			(0.0098)	(0.0108)				
ln Bank branches$_{it}$	–	–	–	–	0.0268***	−0.0310**	–	–
					(0.0089)	(0.0141)		
ln Credit accounts$_{it}$	–	–	–	–	–	–	0.0028	−0.0793***
							(0.0069)	(0.0184)
ln Human capital$_{it}$	−0.0471	0.161*	0.110***	−0.0444	0.104***	−0.0235	0.184***	−0.0430
	(0.102)	(0.0961)	(0.0390)	(0.0454)	(0.0287)	(0.0267)	(0.0400)	(0.0324)
ln Inflation$_{it}$	−0.0052	0.0023	0.0052	−0.0044	−0.0090***	0.0052	−0.0045***	0.0099**
	(0.0098)	(0.0137)	(0.0038)	(0.0045)	(0.0025)	(0.0056)	(0.0015)	(0.0044)
ln Globalization$_{it}$	−0.0845	−0.120	−0.367**	0.170	−0.0748	0.0688	0.135*	0.0280
	(0.220)	(0.247)	(0.144)	(0.123)	(0.110)	(0.139)	(0.0799)	(0.103)
ln Institutions$_{it}$	−0.0917	0.0327	−0.0460	0.0101	0.0491**	−0.0603	0.0340**	0.0953***
	(0.0712)	(0.0666)	(0.0538)	(0.0533)	(0.0200)	(0.0385)	(0.0157)	(0.0261)
ln RGDPC$_{it}$	−0.0669	−0.0754*	−0.0611	0.0174	−0.0770***	0.0641***	−0.171***	0.0010
	(0.0690)	(0.0452)	(0.0434)	(0.0437)	(0.0256)	(0.0216)	(0.0281)	(0.0162)
Constant	–	−0.106	–	−1.374***	–	−0.949*	–	0.375
		(1.328)		(0.469)		(0.552)		(0.420)
							(0.0184)	
r (Threshold)	0.2849***		0.2292***		0.2092***		0.2613***	
	(0.095)		(0.038)		(0.035)		(0.058)	
Number of moment conditions	42		42		42		42	
Bootstrap p-value for linearity test	0.000		0.000		0.000		0.000	
Bootstrapped confidence intervals	(0.250–0.320)		(0.200–0.260)		(0.180–0.240)		(0.230–0.295)	
Bootstrap Replications	500		500		500		500	
Hansen J-test (p-value)	0.310		0.420		0.360		0.280	
Arellano–Bond AR(2) test (p-value)	0.415		0.525		0.490		0.375	
N	58		58		58		58	

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

Table 4
Coefficients at low and high threshold regimes of sub-dimensions of financial inclusion.

Model and financial inclusion variable	Low Regime (Below the Threshold)	High Regime (Above the Threshold)
Model (2)		
Economic Uncertainty	0.0378	−0.0458
Deposit accounts	0.0133	0.0467
Model (3)		
Economic Uncertainty	0.0101***	−0.012***
ATMs	0.0231**	−0.0016**
Model (4)		
Economic Uncertainty	0.0252*	0.011
Bank branches	0.0268***	−0.0042**
Model (5)		
Economic Uncertainty	−0.0056	−0.0145
Credit accounts	0.0028	−0.0765***

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

The results show that **usage** (credit accounts as a share of GDP), **availability** (ATMs per 100,000 adults and number of commercial bank branches) exert the strongest influence on the uncertainty–inequality relationship. Specifically, in low-usage or low-availability regimes, EUN significantly widens inequality, whereas in high-usage or high-availability regimes, EUN reduces inequality. By contrast, penetration (deposit accounts per 1000 adults) exerts insignificant moderating effects, suggesting that mere account ownership does not guarantee effective financial participation. These findings highlight that the availability **and usage of FI**, rather than penetration, are crucial for buffering households against the adverse distributional consequences of EUN. As shown in Table 4, all the sub-indicators of FI (Models 3 to 5 namely, ATMs, bank branches, and credit accounts) decrease IINE in the high FI regime. This implies that higher FI (availability and usage), tends to reduce IINE. For further robustness checks based on different IINE indicators, please refer to Section 4.2 and Tables A8 and A9 in the online appendix.

5. Conclusion

Using panel data spanning 58 developing countries from 2004 to 2022, this study investigates the potential impact of FI on the relationship between EUN and IINE. Motivated by the increasing EUN and widening IINE, this study examines whether FI can act as a mitigating factor against the adverse effects of EUN on IINE. Our hypothesis is that EUN exacerbates IINE; nevertheless, a country's ability to mitigate the negative impact of EUN on IINE can be enhanced by improved FI. The accessibility, availability, and use of the formal financial system are considered when computing the total FI index. This study analyzes panel data using the dynamic panel threshold regression. The results show that the relationship between EUN and IINE has a significant FI threshold. IINE is made worse by EUN when FI is below the threshold; however, when FI is beyond a certain threshold, EUN reduces IINE. These results imply that the relationship between EUN and IINE is dependent on FI, and EUN mitigates income disparity once FI is beyond a particular threshold.

Furthermore, FI also reduces IINE when this variable rises above the threshold. When alternative measures of FI are used in the analysis such as the quantity of ATMs, credit accounts, and bank branches, the empirical results largely remain unchanged. Nevertheless, the usage and availability dimensions of FI are the most influential drivers of the inequality–uncertainty nexus compared to penetration dimension. The findings indicate that better FI allows an economy to exploit the benefits of financial systems when facing EUN, which reduces income distribution; therefore, improving FI beneficial for diminishing IINE.

The policy implications drawn from this study highlight the need for targeted FI strategies, particularly for economies operating below the identified threshold. Rather than pursuing indiscriminate expansion, policy efforts should prioritize the quality and effectiveness of FI, with emphasis on enhancing credit accessibility and responsible lending practices that enable households and firms to better absorb shocks and sustain consumption under EUN. A prudent policy mix entails strengthening inclusive credit programs, advancing financial literacy initiatives, and ensuring that regulatory frameworks promote equitable access to finance. Country-specific diagnostics are essential to tailor interventions, ensuring coherence between financial infrastructure, supervisory capacity, and institutional development.

At the same time, policymakers must address the potential downsides of expanded inclusion, such as over-indebtedness, weak credit screening, and predatory lending. To mitigate these risks, regulatory authorities should reinforce consumer protection mechanisms, improve credit reporting systems, and enhance oversight of non-bank financial intermediaries. In short, FI can serve as an effective policy tool to moderate inequality amid uncertainty, provided that reforms emphasize sound governance, sustainability, and institutional integrity rather than mere outreach.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.bir.2025.11.002.

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