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Beyond the Threshold: Nonlinear Effects of Financial Development on Income Inequality in Emerging Economies

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Beyond the Threshold: Nonlinear Effects of Financial Development on Income Inequality in Emerging Economies

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Abstract
This study examines the dynamic relationship between financial development and income inequality, with particular emphasis on the threshold effects of financial development on income inequality and the direction of causality between the two variables. Using a balanced panel of 17 emerging economies over the period 1990 to 2020, the study applies the bias-corrected dynamic panel approach of Breitung et al. (2022), the dynamic panel threshold model of Seo and Shin (2016), and panel causality analysis. The findings reveal a significant long-run negative relationship between financial development and income inequality, supporting the inequality-narrowing hypothesis. The threshold analysis identifies a significant threshold of 30.284%, below which financial development increases income inequality and above which it significantly reduces inequality, confirming an inverted U-shaped relationship. The causality results further indicate a significant relationship between financial development and income inequality. These findings suggest that financial deepening alone may not ensure inclusive development. Emerging economies should strengthen financial inclusion, institutional quality, and equitable access to credit and financial services, particularly during the early stages of financial development. The study contributes to the finance and inequality literature by identifying a critical financial development threshold and demonstrating that the distributional effects of financial development vary according to its level.
Keywords: Financial development, income inequality, threshold effects, inverted U-shaped relationship, dynamic panel, emerging economies

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1. Introduction

Income inequality has become a major economic and social concern across countries. Persistent disparities in income and economic resources affect economic growth, equality of opportunity, social cohesion, political stability, and macroeconomic performance. High inequality can also increase unequal political influence and financial vulnerability (Akan et al., 2017; Chiu and Lee, 2019; Lee et al., 2022). These effects can constrain economic, social, and political development.

Income distribution is therefore an important policy concern, particularly in developing economies seeking sustained growth and convergence with advanced economies. Governments use fiscal policies, social protection, labour market measures, and reforms to improve access to economic opportunities (Destek et al., 2017). Financial development has received increasing attention within this policy agenda because well-functioning financial systems can mobilise savings, allocate capital, support investment, and broaden access to economic opportunities (Azam and Raza, 2018).

Income inequality reflects unequal access to resources, opportunities, and capabilities and remains central to development and social justice debates (Atkinson, 1973). Persistent inequality can restrict economic and social mobility, reinforce poverty and exclusion, and limit access to education, employment, healthcare, and productive opportunities (Jolly, 2006; Jaumotte et al., 2013; Dabla-Norris et al., 2015; Piketty, 2015). It has also been associated with weaker human capital development, lower economic mobility, reduced life expectancy, and greater social and political instability (Perotti, 1996; Stiglitz, 2012). Concentration of economic resources can further translate into concentrated political power (Akan et al., 2017; Lee et al., 2022; Öndes and Kızılgö, 2024).

These concerns are particularly relevant to emerging economies, where rapid economic transformation has often occurred alongside substantial disparities in income and access to opportunities. Although economic growth can raise average incomes, barriers involving education, employment, financial resources, and productive assets continue to constrain lower-income groups (Dabla-Norris et al., 2015). Understanding how economic institutions affect income distribution is therefore essential for achieving both economic growth and social inclusion.

Financial development is an important factor in this relationship. It encompasses improvements in the availability, accessibility, efficiency, and diversity of financial institutions and markets. Financial systems mobilise savings, allocate capital, facilitate investment, manage risk, and expand access to financial services. Greater access to credit and other financial instruments can enable households to invest in education, entrepreneurship, housing, and productive activities while reducing dependence on inherited wealth and informal finance (Demirgüç-Kunt et al., 2008).

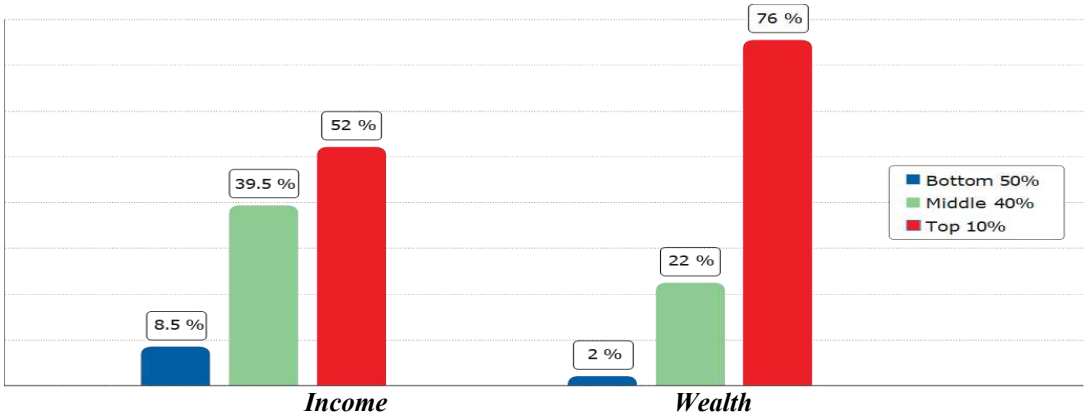
1.1 Global Trends in Income Inequality

Income inequality remains a major global development challenge across emerging and developing economies as well as advanced industrialised countries. Nearly two-thirds of advanced economies experienced increases in inequality over the past two decades (OECD, 2008, 2015). This trend highlights the importance of examining the economic and institutional factors that shape income distribution, particularly the interaction among financial development, economic growth, and inequality.

The scale of global inequality is evident from the World Inequality Report. In 2021, the global top 10 per cent received approximately 52 per cent of total income, while the bottom 50 per cent received only 8.5 per cent (Chancel et al., 2022). Wealth is even more concentrated among the global top 10 per cent. These disparities extend

beyond income and wealth to health, education, economic opportunities, and social mobility (Acemoglu and Robinson, 2001; Pickett and Wilkinson, 2015; Berg and Ostry, 2017). Income and wealth should therefore be treated as related but distinct dimensions of inequality, as high wealth does not necessarily imply high current income.

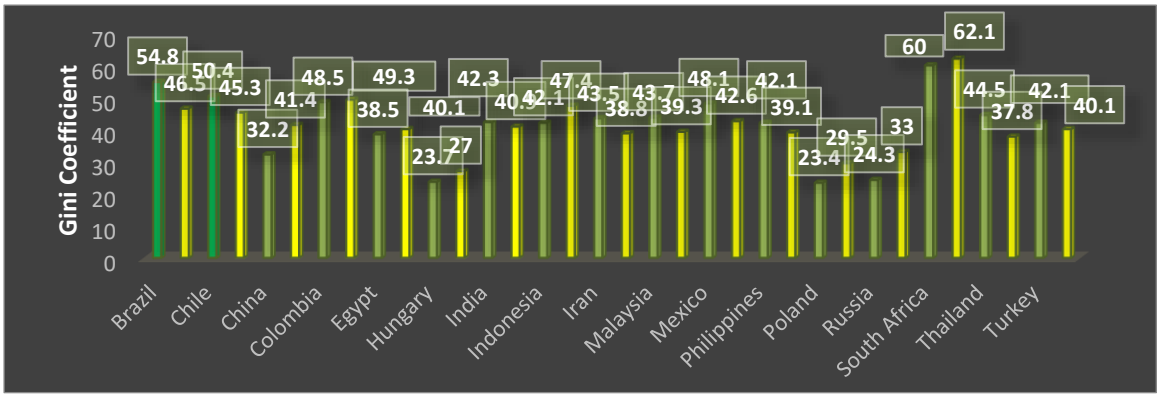
Figure 1: Global Income and Wealth Inequality



Source: (*Chancel et al., 2022 World Inequality Report)*

Emerging economies have recorded substantial increases in real income per capita over the past three decades. Nevertheless, higher average incomes have not necessarily resulted in more equitable distribution. In many emerging economies, Gini coefficients remain relatively high, indicating persistent income disparities (Solt, 2023)

Figure 2: Trends in Income Inequality in Emerging Economies Over Time



Source: Standardised World Income Inequality Database (SWIID), (Solt, 2023).

The relationship between financial development and income inequality warrants closer examination because its distributional effects may depend on the level and inclusiveness of financial development. Financial development can reduce inequality by expanding access to financial services, education, investment, and entrepreneurial opportunities. However, when financial systems remain inaccessible to disadvantaged groups, financial deepening may initially benefit higher income households, established firms, and politically connected groups. Its effect on inequality may therefore change as financial systems mature and access becomes more inclusive.

This possibility motivates the present study, which examines whether the distributional effects of financial development change beyond a critical threshold rather than following a uniform linear relationship with income inequality. Focusing on emerging economies, the study investigates whether financial development initially increases inequality but subsequently reduces it once financial systems reach a sufficient level of development. Identifying this potential nonlinearity contributes to the literature on inclusive growth and sustainable development by clarifying the level and nature of financial development required for broader distributional benefits.

1. Financial Development and Income Inequality: Three Competing Perspectives

The literature presents three main perspectives on the finance inequality relationship. The inequality narrowing hypothesis, the inequality widening hypothesis and the inverted U shape hypothesis.

2.1. Income Inequality Narrowing Hypothesis

The inequality narrowing hypothesis holds that financial development improves income distribution by easing credit constraints and expanding access to productive opportunities. Galor and Zeira (1993) show that borrowing constraints limit human

capital investment among poorer households, while Banerjee and Newman (1993) demonstrate that credit market imperfections restrict occupational mobility and entrepreneurship among individuals with limited wealth. Financial access can therefore enable lower income groups to invest in education and productive activities.

Empirical evidence generally supports this view. Li et al. (1998) identify financial development as an important determinant of income inequality across 40 developed and developing countries. Clarke et al. (2006), using 83 countries, find that greater financial development is associated with lower inequality. Ang (2009) finds that financial development reduces inequality in India, while Gimet and Lagoarde Segot (2011) report a significant causal effect across 49 countries. Kapingura (2017) finds that inclusive financial development reduces inequality in South Africa in both the short and long run. Bolarinwa et al. (2021) similarly find that broader financial development reduces inequality in high and middle low-income African countries, although the effect is insignificant in low-income countries.

2.2. Inequality Widening Hypothesis

The inequality widening hypothesis argues that financial development can increase inequality when access to financial resources remains concentrated among wealthier households, established firms, and politically connected groups. Wealthier agents often have greater collateral, financial information, and access to formal credit, allowing them to capture a larger share of the benefits from financial deepening (Rajan and Zingales, 2003; Claessens and Perotti, 2007). Weak institutions, political capture, market concentration, and rent seeking can further reinforce these effects (Jauch and Watzka, 2016).

Empirical evidence supports this perspective across several economies. Jalil and Feridun (2011) find that financial development increased long run inequality in China,

partly because financial resources were concentrated in urban and coastal regions. Wahid et al. (2012) report similar evidence for Bangladesh, while Sehrawat and Giri (2014) find that financial development increased inequality in India in both the short and long run. Mehta and Bhattacharya (2020) show that financial development channels affect population groups unevenly and generally increase inequality across Indian states. Shi et al. (2022) also identify a positive long run relationship between financial development and inequality in Australia. De Haan and Sturm (2017), using data for 121 countries, find that financial development, liberalisation, and banking crises can increase inequality, with effects conditioned by financial sector development and political institutions.

2.3. Inverted U Shape Hypothesis

The inverted U shape hypothesis provides a possible explanation for the contrasting evidence. Greenwood and Jovanovic (1990) propose that financial development initially increases inequality because formal financial services are concentrated among higher income groups. As financial institutions mature and access expands, financial benefits become more widely distributed, causing inequality to decline.

Several studies support this nonlinear relationship. Kim and Lin (2011), using an instrumental variable threshold approach, find that financial development increases inequality below a critical threshold but improves income distribution after that threshold is exceeded. Evidence from China also supports this pattern. Zhang and Chen (2015) find that inequality rises during the early stages of financial development but declines as the financial system matures. Rehman et al. (2019) identify an inverted U shaped relationship across Chinese provinces, with effects varying across income groups. Chakroun (2020) finds a hump shaped relationship between banking development and inequality across 60 developed and developing economies, although

evidence for stock market development is weaker and varies with economic development. Öndes and Kızılgöl (2024) similarly find that financial development and GDP initially increase inequality, while their squared terms reduce it, supporting the financial Kuznets curve.

Taken together, the three perspectives indicate that the finance inequality relationship cannot be adequately captured by a simple linear specification. Differences across studies may reflect variations in countries, periods, financial development measures, institutional quality, financial inclusion, and economic development. More importantly, the evidence suggests that the distributional effects of financial development may change as financial systems mature.

This issue is particularly relevant to emerging economies, which differ substantially in financial depth, access, institutional quality, and economic structure. Financial development may therefore widen inequality at lower levels but reduce it once financial systems become sufficiently developed and inclusive.

This gap motivates the present study. Rather than examining only whether financial development increases or reduces inequality, the study investigates whether its distributional effect changes beyond a critical level of financial development. Focusing on emerging economies, it seeks to identify the threshold at which financial development shifts from an inequality widening to an inequality narrowing force. This threshold perspective provides the central theoretical and empirical foundation of the study.

3. The Data and Variables

The study examines the dynamic relationship among financial development, income inequality, and economic growth, with particular attention to the nonlinear threshold effects of financial development on inequality. It uses a balanced panel of 17

emerging economies covering 1990 to 2020. Data are obtained from the Standardised World Income Inequality Database (SWIID), World Development Indicators (WDI), and the International Monetary Fund (IMF). The sample follows the IMF classification of emerging economies includes Brazil, Chile, China, Colombia, Egypt, Hungary, India, Indonesia, Iran, Malaysia, Mexico, Philippines, Poland, Russia, South Africa, Thailand, and Turkey.

Table 1: Description of variables

Variable	Notation	Definition	Source
Gini coefficient	GINI	Measures income inequality. A value of 0 indicates perfect equality, while values approaching 100 indicate extreme inequality.	SWIID, Version 9.5 (Solt, 2023)
Financial Development Index	FD	Measures financial development across financial institutions and markets using three dimensions: access, efficiency, and depth.	IMF (2023)
General government final consumption expenditure (% of GDP)	GSIZE	Measures government current expenditure on goods and services, including employee compensation, as a percentage of GDP.	WDI (2024)
GDP per capita growth (annual %)	PGR	Measures the annual percentage growth in GDP per capita based on constant local currency.	WDI (2024)
Inflation, CPI (annual %)	INF	Measures the annual percentage change in the cost of a basket of goods and services based on the consumer price index.	WDI (2024)

Gini Coefficient

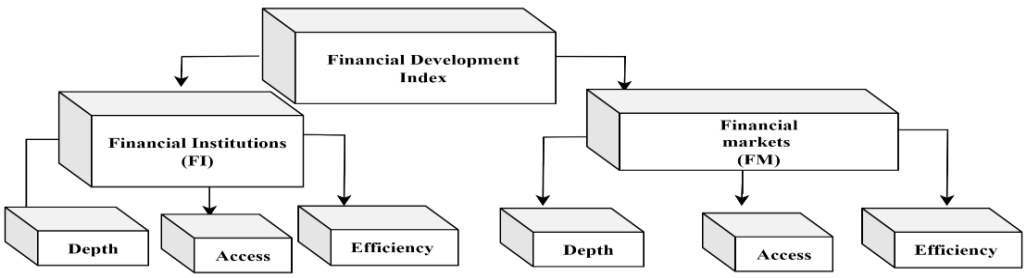
The Gini coefficient measures income inequality across the population and ranges from 0 to 100. A value of 0 represents perfect equality, while 100 represents perfect inequality. Its broad availability and cross-country comparability make it suitable for panel analysis. Following Law et al. (2014) and Vo et al. (2023), this study used the Gini coefficient as the measure of income inequality.

2. Financial Development Index

Financial development encompasses the depth, access, and efficiency of financial institutions and markets. Conventional measures such as M2 to GDP, private sector credit to GDP, or stock market capitalisation capture only specific dimensions of financial development and may provide an incomplete measure (Seven and Coskun, 2016).

This study therefore employed the Financial Development Index, developed from the work of Čihák et al. (2012), Sahay et al. (2015), and Svirydzenka (2016). The index captures financial institutions and markets across three dimensions: depth, which reflects the size and liquidity of the financial system; access, which measures the availability and use of financial services; and efficiency, which captures the effectiveness of financial service provision. Following Mbona (2022) and Sikhawal (2023), the index serves as the primary measure of financial development.

Figure 3: Financial Development Index Pyramid



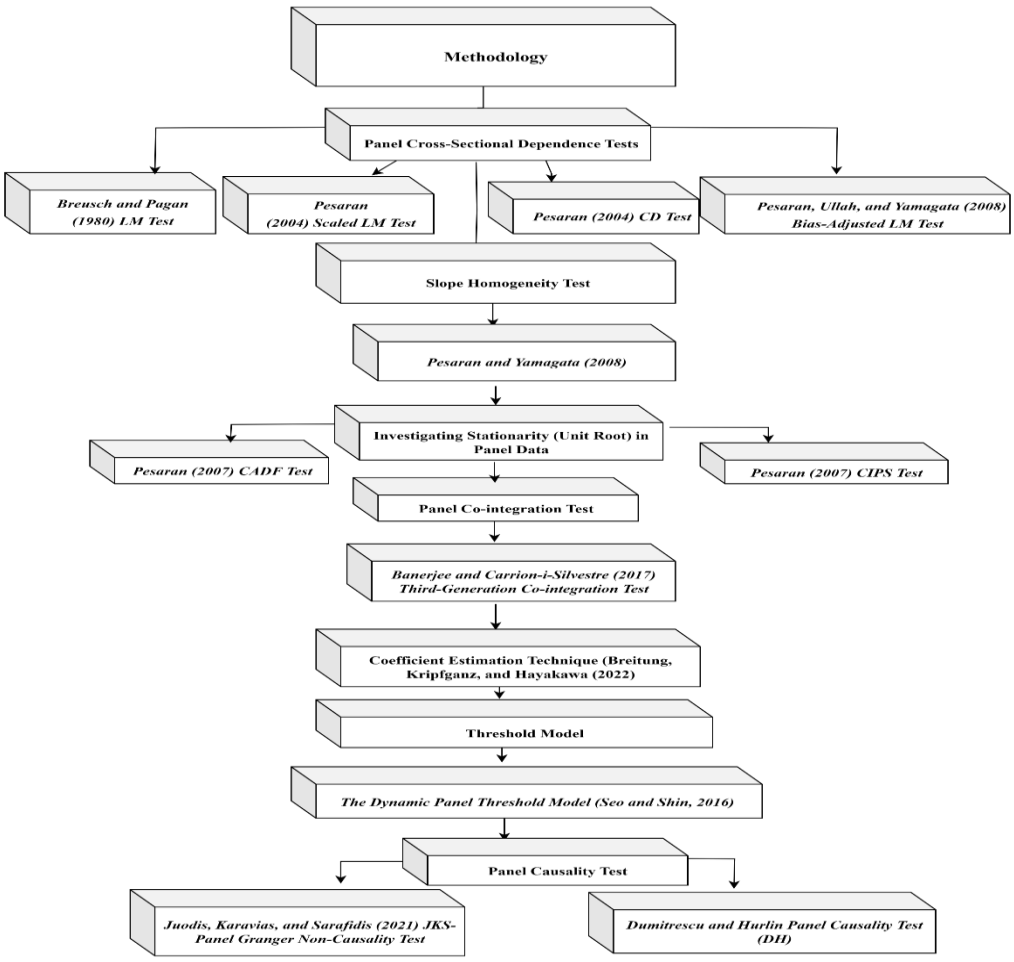
Source: IMF staff, based on Čihák et al. (2012)

3.1. Control Variables and Model Specification

The models include additional control variables to reduce omitted variable bias and potential misspecification. These variables account for other factors that may influence the relationship between financial development and income inequality. Their inclusion is supported by theoretical considerations and previous empirical research.

1. GDP per capita growth rate
2. Government general final consumption expenditure as a percentage of GDP
3. Inflation, consumer prices, annual percentage

Figure 4: Flowchart Illustrating the Methodology



Source: Author's own creation

3.2. The Econometric Model

Econometric models are widely used to examine relationships among economic and social variables. Traditional linear models assume that the effect of an explanatory variable remains constant across observations. This assumption may be restrictive when relationships change across conditions or development levels. Nonlinear models address this limitation by allowing threshold effects and regime changes.

Hansen (1999) introduced a static panel threshold model in which coefficients vary according to a threshold variable. Gonzalez et al. (2005) extended this approach through the Panel Smooth Transition Regression model, which allows coefficients to change gradually across regimes. Fouquau et al. (2008) further extended the framework to capture variation across countries and over time. However, these approaches generally assume exogenous regressors or threshold variables, limiting their applicability to dynamic panels with endogenous variables (Seo & Shin, 2016).

Kremer et al. (2013) addressed endogeneity by extending Hansen's (1999) framework using GMM-type estimators based on the cross-sectional threshold model of Caner and Hansen (2004). However, their approach does not fully account for heterogeneity across time, regions, and countries (Oloaye et al., 2021).

Seo and Shin (2016) developed a dynamic panel threshold model that accommodates lagged dependent variables and endogenous covariates. The model uses first-differenced GMM estimators and provides inference without requiring prior assumptions about the continuity of the regression function. It also avoids potential sample selection bias associated with arbitrary sample splitting and dummy variable approaches.

Given these advantages, this study employs the Seo and Shin (2016) dynamic panel threshold framework to examine whether the effect of financial development on income inequality changes beyond a critical threshold.

3.2.1. The Dynamic Panel Threshold Model (Seo and Shin, 2016)

To evaluate the intricate nonlinearities and threshold impacts of financial development on income inequality, on income in emerging nations, we employed the "dynamic panel threshold regression" model developed by Seo and Shin (2016). Consistent with the methodology outlined by Seo and Shin (2016), we adopted the general specification of the dynamic panel threshold regression model in the ensuing analysis.

$$y_{it} = (1, x_{it}')\, \varphi_1\, 1\{q_{it} \le \gamma\} + (1, x_{it}')\varphi_2 1\{q_{it} > \gamma\} + \mu_{it} \quad (1)$$

where *i*=1,…..*n; t*=1,…..,*T,* y_{it} is the scalar stochastic variable of interest, x_{it} is the $k_1 \times 1$ vector of regressors that vary over time and may also include the past values of the outcome variables themselves, *1{.}* is an indicator function, and q_{it} is the threshold or transition variable. φ_1 and φ_2 are the slope coefficients associated with different regimes, and γ is the hypothetical threshold parameter. The error of the threshold regression model is a composite error term which is comprises two error components:

$$\mu_{it} = \alpha_i + \varepsilon_{it}, \quad (2)$$

where α_i is the fixed unobserved individual panel-specific effect and ε_{it} is the usual zero-mean idiosyncratic random error term. ε_{it} is specifically assumed to be a martingale difference sequence,

$$E(\varepsilon_{it}|F_{t-1}) = 0 \quad (3)$$

In the above Equation (3, F_t is a natural filtration at time *t*. In addition, it is assumed that x_{it} and q_{it} are not measurable, concerning F_{t-1}, say for example $E\ (\varepsilon_{it}x_{it}) \neq 0$ or $E\ (\varepsilon_{it}q_{it}) \neq 0$. This way, we would be allowing endogeneity in both the regressors x_{it} as well as in the transition or threshold variable q_{it}.

In addition, the dynamic panel data threshold regression model of Seo and Shin (2016) allows for both "fixed threshold effect" and "diminishing or small threshold effect" for the statistical appraisal for γ, which is the transition or threshold parameter by defining (e.g. Hansen, 2000):

$$\delta = \delta_n = \delta_0 n^{-\alpha} \text{ for } 0 \leq \alpha < 1/2. \quad (4)$$

Across the literature on linear dynamic panel data models, it is a known fact that the "fixed effect estimator" of the autoregressive coefficients has a downward bias (e.g. Nickel, 1981). To cope with the correlation of variables with individual effects in Equation (1) and Equation (2), we take into account the first-difference transformation of Equation (1) by following Arellano and Bond (1991), Seo and Shin (2016), and Seo et al. (2019) as follows:

$$\Delta y_{it} = \beta' \Delta x_{it} + \delta' X'_{it} 1_{it}(\gamma) + \Delta \mu_{it}, \quad (5)$$

the transition or threshold variable. Given the considerations mentioned earlier, this study employs the "dynamic panel threshold" regression model proposed by Seo and Shin (2016) for its analytical framework.

As previously mentioned, the model by Seo and Shin (2016) utilises a "First Difference Generalised Method of Moments (FD-GMM)" transformation to estimate coefficients. By treating the regressors and the transition variable as potentially endogenous, this transformation ensures that the estimators asymptotically conform to a normal distribution. Consequently, the application of the Wald test is justified for standard statistical inference for the threshold and other parameters

Where Δ is the difference operator, $\underset{k_1\times 1}{\beta} = (\phi_{12}, \dots, \phi_{1,k_{1+1}})'$, $\underset{k_1\times 1}{\delta} = \phi_2 - \phi_1$, and

$\underset{2x(1+k_1)}{X_{it}} = \begin{pmatrix} (1, x'_{it}) \\ (1, x'_{i,t-1}) \end{pmatrix}$ and $= 1_{it}(\gamma) \underset{2\times 1\times 1}{\begin{pmatrix} \mathbf{1}(q_{it} > \gamma) \end{pmatrix}}$.

Now, if we let $\theta = (\beta', \delta', \gamma)'$ and we assume that θ belongs to a compact set $\Theta = \Phi\, x\, \Gamma \subset \mathbb{R}^k$, with $k = 2k_1 + 2$. The first-difference transformed model, as given by equation (5), consists of four different regimes, which are produced by the two threshold variables q_{it} and q_{it-1} (Seo and Shin, 2016). Moreover, the OLS estimators secured from Equation (5) are not unbiased because the transformed estimators are still correlated with $\Delta\mu_{it}$. As suggested by Seo and Shin (2016), to rectify this issue of collinearity, an $l \times 1$ vector of instrument variables is required, $\left(z'_{it_0}, \dots\dots, z'_{iT}\right)'$ for $2 < t_o \leq T$ with $l > k$ such that either

$$E\left(z'_{it_0}\Delta\mu_{it_0}, \dots, z'_{iT}\Delta\mu_{iT}\right)' = 0, \tag{6}$$

or for each $t = t_0, \dots\dots, T$,

$$E(\Delta\mu_{it}/z_{it}) = 0 \tag{7}$$

In this context, it is important to highlight that z_{it} may encompass past values of x_{it} and q_{it}, as well as lagged values of dependent variables, particularly if they are not part of x_{it} and q_{it}. Additionally, the count of instruments may vary at each time t. Thus, the dynamic panel data model originated by Seo and Shin (2016), which incorporates threshold effects and endogeneity, satisfies the conditions specified in Equation (6) and Equation (7). This model effectively addresses both cross-sectional heterogeneity and nonlinear asymmetric dynamics within a dynamic threshold panel data framework, allowing for the endogeneity of both regressors and

3.3. Coefficient Estimation Technique (Breitung, Kripfganz, and Hayakawa, 2022)

Dynamic panel models are widely used to account for persistence in dependent variables and unobserved individual effects. Early approaches relied on instrumental variable and GMM estimators, including those developed by Anderson and Hsiao (1982), Holtz-Eakin et al. (1988), and Arellano and Bond (1991). However, these estimators can suffer from weak instruments when the dependent variable is highly persistent (Blundell and Bond, 1998). System GMM can reduce this problem by combining level and first-difference moment conditions, although weak instruments may remain when individual-specific effects are large relative to idiosyncratic errors (Bun and Windmeijer, 2010).

These limitations led to the development of maximum likelihood and bias-corrected within-groups estimators. Hsiao et al. (2002) introduced a transformed maximum likelihood estimator, which Hayakawa and Pesaran (2015) extended to accommodate cross-sectional heteroskedasticity and robust standard errors. Kiviet (1995) and Judson and Owen (1999) developed bias-corrected within-groups estimators, while subsequent contributions by Bun and Carree (2005), Dhaene and Jochmans (2016), and Kruiniger (2018) further refined bias correction through iterative, profile likelihood, and modified maximum likelihood procedures.

Breitung, Kripfganz, and Hayakawa (2022) extend this framework by deriving bias-corrected estimators from an adjusted profile score. Their approach encompasses the estimators of Bun and Carree (2005), Dhaene and Jochmans (2016), and Kruiniger (2018) as special cases. It also provides a flexible framework for dynamic fixed-effects, random-effects, and hybrid correlated random-effects models.

The approach offers several advantages for dynamic panel estimation. It can distinguish between covariates related and unrelated to unit-specific effects, accommodate time-invariant regressors under appropriate orthogonality conditions,

and account for individual-specific and time-series heteroskedasticity. Cluster-robust and panel-corrected standard errors can address cross-sectional dependence.

Given these advantages, this study adopts the bias-corrected dynamic panel approach proposed by Breitung, Kripfganz, and Hayakawa (2022). The higher-order dynamic specification is expressed as follows:

$$y_{it} = \sum_{j=1}^{p} \gamma_i \, y_{i,t-j} + \beta x_{it} + \alpha_i + \varepsilon_{it} \qquad (8)$$

Where, i, = 1,2,3, . . . , N, t = 1, 2, 3, ...,T and ε_{it} is specified as normally distributed, having zero mean and homoscedastic variance, γ_i and vector β denotes the true values of the parameters of interest, and αi denotes the individual-specific effects or unobserved heterogeneity.

3.4. Juodis, Karavias, and Sarafidis (2021) JKS- Panel Granger Non-Causality Test.

Juodis, Karavias, and Sarafidis (2021) recently advanced an innovative method to test for the null of no Granger causality. The procedure leverages the half-panel jackknife (HPJ) to improve finite-sample properties of the estimators and evaluates restrictions using a Wald statistic. Under the SPJ (split-panel jackknife) setup, which presumes stationarity of the series, the HPJ adjustment effectively attenuates higher-order bias. The approach explicitly accounts for cross-sectional correlation and heterogeneous unit-specific effects, making it suitable for both balanced and unbalanced panels. A central innovation of their method hinges on the null hypothesis that the Granger-causality parameters vanish for all units, implying parameter homogeneity. This assumption facilitates pooling across units and applying a fixed-effects estimator to those parameters, delivering an NT rate of convergence (with *N* denoting the cross sections).

The method developed by Juodis et al. (2021) presents several advantages compared to existing approaches. Specifically, the "GMM" approach by Holtz-Eakin et al. (1988) becomes less appealing as the number of observations, T, increases. This is because using too many instruments can result in inaccuracies in the inference obtained through GMM-based methods, as has been demonstrated by Bun and Sarafidis (2015) and Juodis et al. (2021).

In our study, a bias-corrected Granger non-causality test is employed using a linear dynamic panel model. The model is specified as follows.

In our study, a bias-corrected Granger non-causality test is employed using a linear dynamic panel model. The model is specified as follows.

$$y_{i,t} = \varphi_{0,i} + \sum_{p=1}^{P} \varphi_{p,i} y_{i,t-p} + \sum_{p=1}^{P} \alpha_{p,i} x_{i,t-p} + \mu_{i,t} \quad (9)$$

where the subscripts *i = 1,2,3,....N* denote the individual countries in the panel and *t = 1,2,3,...T* represents the time dimension of the panel.

To facilitate clarity in exposition while maintaining generalisation, it is postulated that $x_{i,t}$ is a scalar. The parameters $\varphi_{0,i}$ captures the unit-specific effect, $\mu_{i,t}$ is the random disturbance term, $\varphi_{p,i}$ are unit-specific AR coefficients; *p=1,2,....,P* and $\alpha_{p,i}$ are the coefficients governing Granger causality, alternatively described as heterogeneous feedback coefficients. In this approach, the limitation of equating the number of lags between $y_{i,t}$ and $x_{i,t}$ offers the advantage of incurring minimal computational costs when selecting the appropriate lag length.

Testing the H_0 that does not "Granger-cause" involves framing it as a series of linear restrictions on the parameter in Equation (9);

= 0, for all i and p.

0, for some i and p

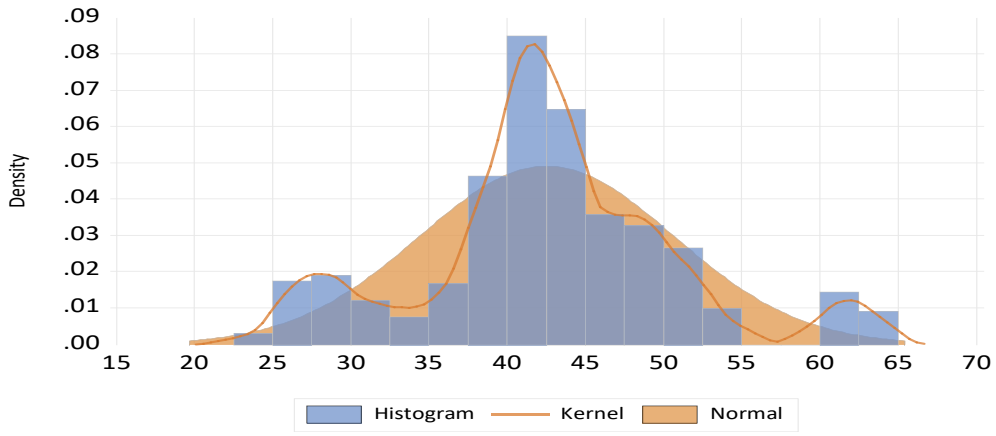
4. Empirical results

Table 2 reports the descriptive statistics for the key variables over the study period. The Gini coefficient has a mean of 42.531, ranging from 23.4 to 63.4, with a standard deviation of 8.128. The financial development (FD) index has a mean of 40.893 and ranges from 11.438 to 73.720, with a standard deviation of 12.271. GDP per capita growth averages 2.537 and varies substantially from −16.890 to 13.635. Government size and inflation have mean values of 14.182 and 40.961, respectively.

Table 2: Summary Statistics of Variables

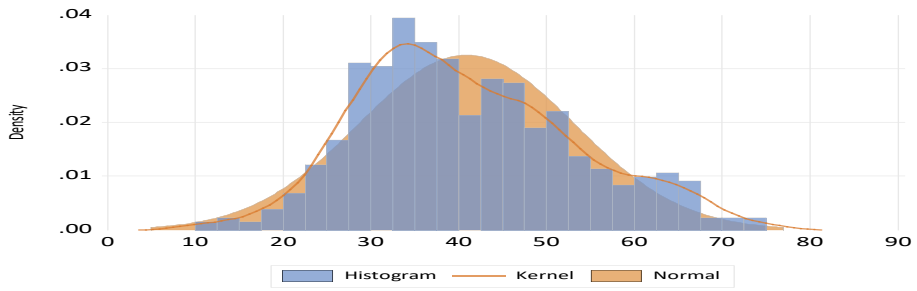
Variable	Obs	Mean	Std. Dev.	Min	Max
$GINI_{it}$	527	42.531	8.128	23.4	63.4
FD_{it}	527	40.893	12.271	11.438	73.72
PGR_{it}	527	2.537	4.041	-16.890	13.635
$GSIZE_{it}$	527	14.182	3.952	5.693	27.727
INF_{it}	527	40.961	242.872	-1.401	2947.733

Figure 5: Distribution of Income Inequality



Source: Author's own creation

Figure 6: Distribution of Financial Development



Source: Author's own creation

4.1. Cross-sectional dependence tests

Table 3 reports the results of the cross-sectional dependence tests. The results show statistically significant p-values at the 1% level, leading to rejection of the null hypothesis of no cross-sectional dependence. This indicates that the variables exhibit significant interdependence across countries, which should be considered in the subsequent panel analysis

Table 3: Results of Cross-Sectional Dependence Tests

Test	Statistic	p-value
Breusch-Pagan LM	1198.734***	0.0000
Pesaran scaled LM	63.40693***	0.0000
Pesaran CD LM	11.56549***	0.0000
Pesaran, Ullah and Yamagata LM adj*	56.76 ***	0.0000

*Note: *** $p<0.01$*

4.2. Slope homogeneity Test

Following the confirmation of cross-sectional dependence, the study tests slope homogeneity using the methodology of Pesaran and Yamagata (2008). The results in Table 4 provide strong evidence against slope homogeneity at the 1% significance level, indicating that the relationships among the variables differ significantly across

countries. This finding supports the use of estimation techniques that account for cross-country parameter heterogeneity to obtain robust and reliable results.

Table 4: Results of Slope Homogeneity Test

Statistics	**Test value**	**(P-Value)**
Delta tilde	21.628***	(0.000)
Delta tilde Adjusted	24.084***	(0.000)

*Note: *** p<0.01*

4.3 Panel Heterogeneous Unit Root Tests (Second-Generation Tests)

Table 6 reports the unit root results. Income inequality (GINIit) is non-stationary at level but becomes stationary after first differencing. In contrast, financial development (FD_{it}), GDP per capita growth (PGR_{it} it), government size ($GSIZE_{it}$ it), and inflation (INF_{it}) are stationary at levels across all tests.

Table 5: Results of Heterogeneous (Second-Generation) Panel Unit Root Tests

Variables	**CIPS**		**CADF**		**Order of integration**
$GINI_{it}$	-1.152	-2.694***	-1.223	-2.296***	*I(1)*
	(-2.25)	(-2.32)	(0.992)	(0.010)	
FD_{it}	-2.369***	-5.611***	-2.210**	-4.007***	*I(0)*
	(-2.25)	(-2.32)	(0.027)	(0.000)	
PGR_{it}	-3.604***	-5.835***	-2.730 ***	-4.363***	*I(0)*
	(-2.25)	(-2.32)	(0.000)	(0.00)	
$GSIZE_{it}$	-2.191**	-4.377***	-2.283***	-3.299***	*I(0)*
	(-2.11)	(-2.32)	(0.012)	(0.000)	
INF_{it}	-3.730***	-5.182***	-2.881***	-4.099***	*I(0)*
	(-2.25)	(-2.32)	(0.000)	(0.000)	

*Note: *** p<0.01, **p<0.05,*

4.4 Panel Cointegration Test

The results of cointegration test are reported in Table 6. As shown in Table 6, the null hypothesis is consistently rejected under all deterministic specifications, including none, constant, and constant with trend, confirming a stable long-run relationship among the variables.

Table 6: Results of Panel Cointegration Test

Specification	**Test Statistic**
No deterministic component	-3.648**
Constant	-3.664**
Constant and trend	-3.621**

*Note: Critical Value (CV) at ** p<0.05, * p<0.10% with a constant is - 2.32, -2.18 and with the trend is -2.92 and - 2.82.*

4.5 Hausman Test for Model Selection

As previously mentioned, the Hausman test is typically used to select between the dynamic fixed effects model and the dynamic random effects model. Based on the Hausman test statistic, which is statistically significant at a 1% significance level, the dynamic fixed effects model is preferred to the dynamic random effects model (Table 7).

Table 7: Results of Hausman Specification Test

Generalized Hausman test	chi2(4)	33.9973***
H_0: coefficients do not systematically differ	Prob > chi2 =	0.0000

*Note: *** p<0.01*

Table 8: Bias-Corrected Fixed Effects Model Results: Financial Development and Income Inequality

Variables	Coefficient	std.err.	Z	P>|z|
$GINI_{it}$				
L1	0.9481074 ***	0.0183629	51.63	0.000
FD_{it}	-0.0174295 ***	0.0027907	-6.25	0.000
PGR_{it}	-.0121852	0.0101975	-1.19	0.232
$GSIZE_{it}$	0.0337518*	0.0199071	1.70	0.090
INF_{it}	0.0006329	0.0003958	1.60	0.110
Cons	2.454979	0.4877	2.72	0.007

*Note: *** p<0.01, * p<0.10*

Table 8 presents the results from the linear dynamic model. The empirical findings indicate that financial development has a statistically significant effect in reducing income inequality, thereby lending credence to the inequality-narrowing hypothesis. In alignment with the extensive existing literature, the model corroborates the overall narrowing impact of FD on income inequality. These findings resonate with the conclusions drawn by Cong Nguyen et al. (2019), as well as those of Galor and Zeira (1993) and Banerjee and Newman (1993). Notably, Galor and Zeira (1993) and Banerjee and Newman (1993) underscore the pivotal role of financial development in mitigating income inequality by addressing imperfections in credit markets and alleviating financial constraints, which are particularly onerous for low-income individuals and small enterprises lacking collateral, credit histories, and robust networks. The coefficient representing economic growth is found to be positive but lacks statistical significance concerning income inequality. In contrast, the coefficient

for government size is positive and exhibits a statistically significant association with inequality.

Our analysis suggests that an increase in government size leads to an increase in income inequality. These findings are consistent with the results presented by Shabaz and Islam (2011) and Jauch and Watzka (2016). Jauch and Watzka (2016) argue that a substantial proportion of government expenditure, when disproportionately managed by elite groups through rent-seeking activities, can exacerbate inequality. Moreover, the coefficient for inflation is also positive and is statistically insignificant.

Table 9: Results of Arellano-Bond Test for Autocorrelation

H_0: no autocorrelation of order 1:	z = -2.6235	Prob > |z| =	0.0087
H_0: no autocorrelation of order 2:	z = -1.4400	Prob > |z| =	0.1499
H_0: no autocorrelation of order 3:	z = -0.5166	Prob > |z| =	0.6054

Table 10: Results of the Hansen Test

Hansen test of the overidentifying restrictions	chi2(4) =	5.3625
H_0: overidentifying restrictions are valid	Prob > chi2 =	0.2521

The results of the autocorrelation test and the Hansen over-identification test are reported in Table 9 and Table 10. Both confirm the suitability of the chosen instruments. The Hansen J-test supports their exogeneity and validity. The Arellano-Bond tests show no evidence of higher-order autocorrelation at (AR_2) and (AR_3)

4.6 Threshold Effects of Financial Development on Income Inequality

The findings, given in Table 13, indicate that the value of the threshold parameter *(γ)* is 30.284 with a p-value of 0.000, indicating statistical significance at a 1% level where financial development serves as the transition (threshold) variable. The estimated value of the threshold parameter for financial development falls within the

confidence interval of [12.175, 48.393] for emerging countries. Below this threshold, the financial development index has a positive and statistically significant coefficient of 0.341 at the 1% level. Above the threshold, the coefficient becomes negative, at −0.368, and remains significant at the 1% level. These results provide strong evidence of a nonlinear relationship between financial development and income inequality in emerging economies. Financial development initially increases inequality but reduces it after reaching the critical threshold, supporting the inverted U-shaped hypothesis.

The findings are consistent with Greenwood and Jovanovich (1990) and with empirical evidence reported by Azam and Raza (2018), Rehman et al. (2019), Destek et al. (2020), and Amin et al. (2023). The initial increase in inequality can be explained by the high costs and access barriers associated with less developed financial systems. Screening costs, risk-pooling requirements, limited financial information, inadequate intermediary support, high transaction costs, lack of collateral and credit histories, and weak social or political connections can restrict credit access for low-income households and less-connected entrepreneurs (Dollar and Kraay, 2002; Behrman et al., 2007; Beck et al., 2007).

As financial systems mature, these constraints gradually decline and access to financial services broadens. Greater financial inclusion allows poorer households and less-connected entrepreneurs to obtain external finance, invest in productive activities, and improve their economic opportunities. This improves capital allocation and can reduce income inequality (Greenwood & Jovanovic, 1990; Kim & Lin, 2011). Thus, the findings suggest that financial development becomes inequality-reducing only after reaching a critical level of development.

The control variables also show regime-dependent effects. The lagged Gini coefficient is positive and statistically significant in the lower financial development

regime, indicating persistence in income inequality. It remains positive but insignificant in the higher financial development regime. Economic growth is negative in the higher regime but statistically insignificant.

Government size is positive but insignificant in the lower financial development regime. In the higher regime, its coefficient becomes negative and significant at the 5% level, suggesting that government spending has greater redistributive effects when financial systems are more developed. In less developed systems, institutional inefficiencies and resource misallocation may limit the effectiveness of public spending in reducing inequality.

Inflation also has contrasting regime-dependent effects. In the lower financial development regime, its coefficient is negative and significant at the 5% level, consistent with Sikhawal (2023). This may reflect the lower exposure of low-income households to inflation-induced asset losses and the potential reduction in their real debt burden. In the higher financial development regime, inflation has a positive and significant effect, also consistent with Sikhawal (2023). Wealthier households in financially developed systems may better protect their assets through diversified investments and financial instruments, while low-income households have fewer options to offset rising prices. Inflation may therefore widen inequality at higher levels of financial development.

The dynamic panel threshold model also addresses endogeneity by incorporating the lagged dependent variable. Following Seo and Shin (2016), a bootstrap procedure tests the threshold specification against the linear alternative. The null hypothesis assumes that a single-regime linear model is sufficient.

Table 11 presents the bootstrap linearity test. The bootstrap p-value is 0.00, leading to rejection of the null hypothesis of linearity at the 1% significance level. The results

therefore provide strong evidence of a nonlinear relationship and confirm the presence of a statistically significant threshold effect in the model.

Table 11: Threshold Model Results: Financial Development and Income Inequality

Variables	**Coefficient**	**Std.err**	**z**	**P>z**
Threshold *()*	30.284***	9.239	3.28	0.001
95% confidence interval	[12.175	48.393]		
Financial development				
	0.341**	0.149	2.29	0.022
	-0.368**	0.164	-2.24	0.025
Impact of Control Variables in Lower Regime				
$GINI_{it-1}$	0.830*	0.446	1.86	0.063
PGR_{it}	0006	0.179	0.00	0.997
$GSIZE_{it}$	0.587	0.620	0.95	0.344
INF_{it}	-0.006*	0.034	-1.83	0.067
Impact of Control Variables in Upper Regime				
$GINI_{it-1}$	0.135	0.228	0.06	0.953
PGR_{it}	-0.023	0.183	-0.013	0.899
$GSIZE_{it}$	-0.692*	0.394	-1.75	0.079
INF_{it}	0.006**	0.003	2.05	0.041
Constant	16.658	12.740	1.31	0.191
Bootstrap test p-value for	0.000			

linearity	
Linearity test (p-value)	0.066
Countries	17
Time	31
Total Obs.	986

*Note: The bootstrap algorithm to test for the presence of the threshold effect is set under the null hypothesis ; *** p<0.01, **p<0.05, and * p<0.10*

4.7 Results of Juodis, Karavias and Sarafidis (2021) Granger non-causality Test

Table 12 displays the outcomes derived from the JKS Granger non-causality test. The null hypothesis under the panel framework asserts that financial development *()* does not Granger-cause income inequality *()*. The results, however, reject this hypothesis at the 1% level of significance. With an HPJ Wald statistic of 44.1899 and a p-value of 0.000, the results provide compelling evidence of a causal effect of financial development (FD) on income inequality. These outcomes corroborate the findings of Younsi et al. (2022), who also observed a unidirectional effect from financial development to income inequality.

Table 12: Results of Panel Causality Test (JKS-2021)

H_0: Financial development does not Granger-cause Income Inequality						
H_1: H_0 is violated.						
HPJ Wald test: 44.1899***						
p-value: 0.0000						
	Coefficient	Std.err	Z	p>|z|	[95% conf. interval]	
FD_{it}						
L1.	-0.2758***	0.0041	-6.5	0.000	-0.0357	-0.019

*Note: BIC selection: lag= 1, BIC = -849.2556: *** p<0.01*

4.8 Results of Dumitrescu–Hurlin Panel Causality Test

To strengthen the robustness of the findings, the Dumitrescu-Hurlin panel causality test was employed to examine the causal relationship between financial development and income inequality. Table A1 reports the results and shows evidence of causality from financial development to income inequality. The null hypothesis of no Granger causality is rejected at the 1% significance level. These findings are consistent with the results in Table 12, supporting the robustness of the estimated relationship across alternative estimation approaches and reinforcing the reliability of the study's conclusions

Table A1: Results of Dumitrescu–Hurlin Panel Causality Test

H_0: Financial development does not Granger-cause Income Inequality		
H_1: H_0 is violated		
Lag order: 1		p-value
W-bar =	5.9720	
Z-bar =	14.4958 ***	0.000
Z-bar tilde =	12.4208***	0.000

*Note: *** p<0.01*

5. Summary of the Study

This study examines the dynamic relationship and threshold effects between financial development and income inequality in 17 emerging economies over 1990 to 2020. Given the mixed findings in the existing literature, the study investigates whether the effect of financial development on inequality changes across different levels of financial development. The analysis employs the bias-corrected estimator of Breitung et al. (2022) to examine dynamic relationships, the dynamic panel threshold model of

Seo and Shin (2016) to identify nonlinear effects, and the JKS-2021 panel causality test to establish causal relationships.

5.1. Summary of Main Findings and Policy Suggestions

The results show a significant long-run negative relationship between financial development and income inequality, supporting the inequality-narrowing hypothesis. This suggests that expanding access to banking, credit, and digital financial services, alongside financial literacy, stronger institutions, greater transparency, and effective regulation, can promote more equitable income distribution.

The threshold analysis identifies a statistically significant financial development threshold of 30.28%. Below this level, financial development increases income inequality, whereas above it, financial development reduces inequality, confirming an inverted U-shaped relationship. The bootstrap linearity test further supports the presence of a threshold effect. These findings suggest that financial development initially benefits higher-income groups, but its distributional effects become more inclusive once financial development exceeds a critical level. Policymakers should therefore focus on expanding access, depth, and efficiency while recognising country-specific financial structures. Economies below the threshold may require targeted financial inclusion policies, whereas those above it should ensure that further financial deepening remains equitable.

The causality results also confirm a significant relationship between financial development and income inequality. Policy should therefore promote inclusive access to credit and capital for underserved groups, including SMEs, informal workers, and marginalised regions, through targeted microfinance, differentiated interest rates, and incentives for inclusive banking.

5.2. Limitations and Future Research

The study is limited to 17 emerging economies and the 1990 to 2020 period due to data availability. It therefore does not capture post-2020 developments, including the COVID-19 pandemic and subsequent global financial changes, or explicitly account for major financial crises. Although the models include key macroeconomic controls, omitted variables may still affect the estimated relationships.

Future research should incorporate additional determinants of the finance inequality and examine the mechanisms through which financial development affect inequality. Longitudinal and cross-country analyses could provide further insight into how these relationships vary across time and institutional contexts. Future studies could also examine other dimensions of inequality beyond income inequality to provide a broader assessment of economic and social disparities**.**

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Aadil Amin: Conceptualization, Methodology, Formal Analysis and Writing original Draft. Writing, Editing, Data curation and Software 2. Dr. Masroor Ahmad: Supervision and Visualization, Review and Editing.

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Availability of data and materials

The data used in this paper is extracted from the World Development Indicators (WDI) database of the World Bank Standardised World Income Inequality Database (SWIID), and the International Monetary Fund (IMFS

Declarations

Ethics approval and consent to participate

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Competing interests

The authors declare that they have no competing interests