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The Effect of Globalization on Income Inequality in Developing Countries: A Bayesian Approach

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Abstract

The rapid advancement of economic globalization over the last several decades has sparked fierce disagreements about its impact on income inequality on a global and domestic scale. Whether globalization improves (neoclassical theory) or worsens (dependence theory) income inequality is a matter of debate at the theoretical level. The results of empirical studies have been contradictory as well. This study examines the effects of three lenses of globalization (financial openness, trade openness, and social globalization) on income inequality in developing countries. Using Bayesian estimation with Markov Chain Monte Carlo, we analyze a balanced panel of 36 developing countries from 2010 to 2022. The Bayesian method is particularly well-suited for social science research because of its capacity to effectively manage complex relationships and integrate prior information, resulting in more contextually relevant and robust results. The findings reveal significant nonlinear relationships between different dimensions of globalization and income inequality. Specifically, the impact of trade openness on income inequality is U-shaped, with a threshold of 83.35% of GDP, whereas the impact of direct foreign investment and migration is in an inverted-U shape, with respective thresholds of 13.4% of GDP and 1.276% of the total population. Importantly, all sampled countries remain below the identified thresholds for direct foreign investment and migration, indicating that these channels currently exacerbate inequality. Consequently, policy measures designed for "post-threshold" conditions should be viewed as forward-looking. This study contributes by clarifying how globalization can alternately worsen or reduce inequality depending on a country's stage of integration. From a policy perspective, developing countries should strengthen absorptive capacity and institutional readiness so that higher direct foreign investment inflows and migration eventually yield more equitable outcomes once thresholds are surpassed. Meanwhile, countries already beyond the trade openness threshold should proceed cautiously, prioritizing export diversification, vocational training, and inclusive trade policies to mitigate inequality risks.

Keywords: Bayesian Approach, Developing Countries, Globalization, Income Inequality, Markov Chain Monte Carlo

1. Introduction

Income inequality has long been recognized as an underlying factor contributing to social instability and a constraint on sustainable economic growth. Empirical studies suggest that widening income disparities are particularly damaging in countries with weak financial systems or high poverty rates, where inequality tends to persist across generations [1]. Beyond short-term distributional concerns, income inequality often reflects a deeper structural mechanism known as the Matthew effect: a cumulative process in which the already advantaged continue to gain more, while the disadvantaged fall further behind [2]. In this sense, inequality is not only a consequence but also a reinforcing cause of long-term income stratification. Globalization adds a complex layer to this dynamic.

While it holds the promise of economic expansion and integration, globalization can also magnify existing disparities by concentrating its benefits among individuals, regions, or sectors already well-positioned to compete globally. Understanding how globalization contributes to the persistence and widening of income inequality is therefore essential, particularly in contexts where economic advantages and disadvantages tend to accumulate over time. Ferocious disputes have broken out about the effects of economic globalization on income inequality, both domestically

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and internationally, as a result of its rapid progress over the last several decades. At the theoretical level, no consensus has been reached regarding the effect of globalization on improving (neoclassical theory) or exacerbating income inequality (dependency theory). Empirical research has produced conflicting findings, including i) globalization does not affect income inequality [3], ii) globalization increases income inequality [4], and iii) globalization decreases income inequality [5]. These diverse results are attributable to differing measures of globalization used, the sample countries examined, and the estimation methods employed.

Regarding measures of globalization, previous studies have employed both disaggregated and composite approaches. Some have relied on individual indicators such as Foreign Direct Investment (FDI) [3], FDI and trade openness [6], FDI, trade openness, and technology [5], FDI, trade openness, and democracy [7] Others have opted for composite indices such as the Kearney index [8] or the KOF index [4], [9]. While composite indices offer a comprehensive view of globalization, they differ in methodological design. The Kearney index, developed by A.T. Kearney and Foreign Policy magazine, is largely qualitative and perception-based, relying on a limited set of four broad dimensions, including economic integration, personal contact, technological connectivity, and political engagement, measured using relatively subjective and media-centric indicators. In contrast, the KOF index, developed by the Swiss Economic Institute, adopts a more comprehensive and systematic approach, offering three pillars (economic, social, and political globalization), each with several subcomponents. These methodological differences can lead to varying empirical interpretations and affect the ability to isolate the effects of specific globalization channels. The advantage of composite indices lies in their capacity to capture globalization in its totality. However, this strength also constitutes a limitation: such indices primarily reflect the overall effect of globalization, making it difficult to generate tailored policy implications for each dimension. Consequently, many studies have turned to disaggregated measures in order to better assess the individual impacts of different globalization channels. Nevertheless, these studies have emphasized trade and financial integration as the main proxies for globalization, while other dimensions have received less attention. Migration, by shaping labor supply and demand, plays a crucial role in income distribution but is frequently relegated to a control variable [10]. To capture the multidimensional nature of globalization, this study focuses on three distinct but complementary channels: financial openness (net FDI to GDP), trade openness (exports plus imports to GDP), and social globalization (net migration relative to population). This design facilitates the identification of nonlinear and threshold effects for each channel. Although this choice reduces comparability with composite-based studies, disaggregated measures are methodologically more appropriate for detecting turning points in specific globalization dimensions.

Concerning the sample of countries surveyed, it would be unsatisfactory to consider all countries as homogeneous; thus, previous research has classified samples for heterogeneous analysis, dividing them into groups of developing countries and developed countries [3], short-term and long-term effects [11], concentrating on a group of countries [12] and conducting research on a specific country [7]. Consequently, conclusions on globalization's impact vary depending on the sample examined. Developing countries, in particular, offer a compelling context for investigation. These nations have actively engaged in globalization through capital inflows, trade expansion, and labor migration, often realizing benefits in growth, technology, education, and healthcare. However, they also face structural challenges such as rising inequality, environmental degradation, and weakened cultural identity. Additionally, compared to developed economies, developing ones often have weaker institutional capacity and less effective policy tools to respond to the redistributive impacts of globalization. As a result, they are more vulnerable to rising income inequality triggered by trade, investment, and migration flows. Studying this group thus yields practical and policy-relevant insights. Moreover, existing empirical literature increasingly suggests that the effects of globalization on income inequality are nonlinear, meaning the marginal impact varies depending on a country's stage of integration into the global economy [5]. For developing countries, this nonlinearity implies that early-stage exposure to globalization may have different consequences compared to higher levels of openness. Therefore, identifying and quantifying these threshold effects is crucial for informing more adaptive and targeted policy responses. Focusing on developing countries allows this study to contribute meaningful insights into how globalization can be harnessed to reduce inequality, rather than exacerbate it, in contexts that are most vulnerable yet full of potential.

Finally, regarding research methods, most previous studies have employed the frequentist approach, which is based on the assumption that the observed sample is the result of a random process and that the model parameter is a fixed but unknown value. While this approach is often more suitable for the natural sciences, where phenomena are regular and reproducible, it is less effective for the social sciences, where data are complex, variable, and context-dependent [13]. Such contradictions in empirical evidence may also reflect the methodological constraints of frequentist estimators, which rely heavily on large-sample asymptotic and often provide limited guidance under nonlinear or threshold dynamics. To overcome these issues, the present study employs a Bayesian framework with Markov Chain Monte Carlo estimation. The Bayesian method not only characterizes the full posterior distribution of parameters and performs well in small- to medium-sized panels, but also better captures uncertainty when results are context-specific. Moreover, by incorporating prior information, Bayesian estimation helps stabilize coefficient estimates and mitigate the adverse effects of multicollinearity, which frequently arise when testing nonlinear specifications [14]. Recent Bayesian applications in related domains, such as Bayesian mixed regression on the globalization - welfare state relationship [15], Bayesian hierarchical modeling of energy impacts on economic growth [16], demonstrate the growing use of Bayesian methods in economic research. Building on this trend, the present study extends Bayesian analysis to investigate nonlinear threshold effects in the globalization - inequality nexus.

The rest of the article is structured into five parts. In section 2, we review relevant theories and literature on the role of globalization in relation to income disparity. The study's methodology and model are detailed in section 3. In section 4, we detail the empirical findings, and section 5 suggests policy recommendations grounded in our findings.

2. Literature Review

2.1. Theoretical role of globalization on income inequality

Dependency theorists have argued that some developing countries experience rapid growth after integrating into the global economy; however, economic growth in these cases can be distorted and inequitable. Multi-national firms have been accused of leveraging economic power to promote oligopolistic marketplaces and hinder egalitarian development [17]. Neoclassical theory contended that trade openness will diminish inequality in developing nations as these nations have comparative advantages in unskilled labor and trade will increase the income of production elements that are largely used by exporters. In contrast, in developed nations where highly skilled workers are the primary beneficiaries, inequality will concurrently rise [18]. Stolper-Samuelson theorem [19] posited that trade-induced changes in product prices increase real returns for factors that are used extensively in the production of exported goods and reduce the profit from other factors. As a result, a country's abundant factors of production benefit from openness, whereas scarce factors suffer. Because capital and skilled labor are relatively abundant in advanced economies, income concentration among the highest earners is expected to rise, generating income gaps among high earners and further widening gaps for those with low incomes.

Income disparity is anticipated to decline in developing countries because economic openness will boost wages for unskilled laborers who are heavily employed in local production. Based on the assumptions of the Heckscher-Ohlin model [20], the effect of globalization on income inequality depends on a country's development level. Migration Selection theory [21] adds that international migration is self-selective, shaped by relative returns to skills in origin and destination countries: lower-skilled workers migrate when origin-country inequality is higher, whereas higher-skilled workers migrate when the destination offers greater returns. Thus, there are theories that debate the impact of globalization on income disparity, but not all of them are coherent. Due to a lack of theoretical consensus, empirical research has been done to assess the influence of globalization on income disparity.

2.2. Literature review

The effect of globalization on income inequality has been the subject of a great deal of empirical study; however, despite the wave of research on this issue, a lack of consensus remains. First, a linear relationship has been demonstrated between globalization and income inequality. Bussmann, Oneal and Soysa [3] used the proportion of FDI in GDP to measure globalization to examine the impact of globalization on inequality in 72 countries in the period 1970-1990, finding no evidence of globalization affecting income inequality. However, when measuring globalization by FDI capital and trade openness, Asteriou, Dimelis and Moudatsou [6] found that trade openness reduces income inequality, whereas FDI has the opposite effect. In contrast, Çelik and Basdas [12] contended that larger FDI inflow improves income equality, whereas trade openness exacerbates income inequality. In addition to trade openness and FDI variables, Munir and Bukhari [5] introduced a technology variable to represent globalization. Applying pooled OLS methods to data from 11 emerging Asian countries from 1980 to 2014, the authors' findings demonstrated that globalization contributes to reducing income inequality significantly.

Kim [7] reached mixed conclusions using trade openness and FDI, replacing the technology variable with the level of democracy and examining South Korean data from 1975 to 2015, applying the 3SLS method. The findings revealed that trade openness has no impact on income inequality, whereas democratic institutions improve it, and FDI exacerbates inequality in income distribution. Dorn, Fuest and Potrafke [4] utilized the KOF index to represent globalization. Despite differences in survey nations, periods, and techniques, both studies indicated that globalization leads to increased income inequality. Tabash, Elsantil, Hamadi and Drachal [9] offer a contrasting perspective. Using the KOF index and 2SLS estimation for 18 developing countries from 1991 to 2021, they found that globalization, particularly through trade openness and FDI, can reduce income inequality. Mukam, Xin and Dorcas [11] explored the impact of international trade on income inequality in Germany from 1990 to 2021. Using a Vector Error Correction Model (VECM), the study examined both short-term and long-term effects and found that increases in exports and imports tend to exacerbate income inequality.

Second, globalization has been found to have a nonlinear impact on income inequality. Figini and Go¨rg [22] demonstrated this in research examining data from 103 countries in the period 1980 - 2002. The results showed that wage inequality in developing countries increases as FDI flows into stocks but gradually decreases as FDI continues to rise. Kaulihowa and Adjasi [23] reached opposite conclusions when investigating data from 16 African countries from 1980 to 2013. The authors revealed a U-shaped effect, demonstrating that FDI reduced inequality in income distribution in the countries surveyed; however, this effect reverses when FDI reaches a certain threshold. Nonlinear effects are also concluded in some studies concerning the impact of trade openness on income inequality. Khan and Nawaz [24] examined data from CIS member countries from 1990 to 2016 using the Sys-GMM method, confirming that income inequality rose due to trade openness and increased demand for skilled labor but gradually declined thereafter, following an inverted U-shaped trajectory. Chigwenembe and Zheng [25] investigated the relationship between international trade and income inequality in the Southern African Development Community (SADC) region over the period 1990-2023. Using the OLS and 2SLS methods, the study found that the impact of trade openness on income inequality varies depending on a country's resource endowment and economic structure.

In particular, resource-rich countries tend to experience rising inequality due to the concentration of resource rents among elites, whereas resource-poor countries benefit from more equitable income distribution through labor-intensive trade expansion. Similarly, the impact of migration on income inequality may change over time and is not necessarily linear. In 2005, McKenzie [26] surveyed 214 Mexican communities and found that income disparity increased during migration's early phases. However, when migration possibilities became available for more people, this effect faded. From a country perspective, Brown and Jimenez [27] compared the impact of migration on income inequality in two countries with different migration experiences, including Fiji (where international migration is an emerging phenomenon) and Tonga (which has experienced more than 40 years of mass migration) in the first half of 2005. The findings revealed that migration increased income inequality in Fiji but decreased it in Tonga. Determining how income inequality is affected by migration depends on countries' migration intensity and specific experience.

Overall, the review of previous studies reveals some scientific research gaps. Firstly, while a growing body of literature has explored the impact of globalization on income inequality, most studies have focused on its economic dimensions, such as trade and FDI. In contrast, the social dimension of globalization, particularly international migration, has received limited empirical attention. This neglect is partly due to data constraints, as the UN Population Division's World Population Prospects (WPP) only released migration figures at five-year intervals until 2022, when annual data became available; earlier studies therefore often relied on counterfactual estimates. Secondly, previous studies have predominantly examined the impact of globalization on income inequality using linear models or testing the threshold impact of globalization from the perspective of individual factors, rather than examining the elements of globalization simultaneously. Thirdly, existing research has relied mainly on frequentist methods, which provide limited guidance in nonlinear settings and are more vulnerable to estimation instability. By contrast, the Bayesian framework not only addresses these methodological challenges but also allows the simultaneous estimation of threshold effects for FDI, trade openness, and migration within a unified model. This integrated approach represents a novel contribution

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compared to prior studies, which typically analyzed thresholds separately or focused on a single channel of globalization.

3. Methodology

3.1. Research models

Based on the theories and literature review presented in section 2, this study constructs the following model to analyze how globalization has affected income inequality:

$$GINI_{it} = \alpha_0 + \alpha_1 \times FDI_{it} + \alpha_2 \times FDI2_{it} + \alpha_3 \times TRD_{it} + \alpha_4 \times TRD2_{it} + \alpha_5 \times MIG_{it} + \alpha_6 \times MIG2_{it} + \alpha_7 \times X_{it} + e_{it} \quad (1)$$

To account for potential nonlinear effects of FDI, trade openness, and migration on income inequality, we include the squared terms of these variables in model (1). $FDI2_{it}$: square of FDI; $TRD2_{it}$: square of trade openness; $MIG2_{it}$: square of migration; X_{it}: control variables; and i represents the country and t is the observation time. The variables included in model (1) are described in table 1.

Table 1. Description of Model Variables

Variable type	Variable name (code)	Measure	Expected effect	Referenced research
Dependent variable	Income Inequality (GINI)	GINI coefficient		[7]
Independent variables	FDI	Net FDI/GDP	+/−	[22], [23]
	Trade Openness (TRD)	(Export + Import)/GDP	+/−	[24]
	Migration (MIG)	Net migration/Total population	+/−	[28]
Control variables	Governance Index (GI)	Set of six Worldwide Governance Indicators	+	[7]
	Inflation (INF)	Inflation, consumer prices (annual %)	−	[7]
	Financial Development (PRVT)	Domestic credit to private sector (% of GDP)	+	[22]
	Infrastructure (TEL)	Fixed telephone subscriptions/Total population	−	[5]
	Unemployment (UNE)	Unemployment, total (% of total labor force)	+	[5]
	Remittances (REM)	Personal remittances, received (% of GDP)	−	[28]
	Digitisation (NET)	Individuals using the internet (% of population)	−	[5]
	Government Expenditure (GEG)	General government final consumption expenditure (% of GDP)	+	[7]
	Education (EDU)	School enrollment, primary (% gross)	+	[7]
	Economic growth (GDP)	GDP per capita growth (annual %)	+	[7]

Note: "+" indicates that the expected association with the dependent variable is positive, "–" indicates that the association with the dependent variable is negative. Variables with an expected sign of "+/–" reflect the possibility of a nonlinear relationship, such as a U-shaped or inverted U-shaped association.

This study uses annual data for 36 developing nations from 2010 to 2022 based on data availability. The World Development Indicators (2024) are the primary data source. The study also refers to the World Bank's Standardized World Income Inequality Database (2024) and Solts' World Integrated Trade Solution (2024) to supplement any missing data. The author obtained institutional data from the Worldwide Governance Indicators (2024).

3.2. Research methods

The underlying premise of the Bayesian technique is that the model parameters must be random and the observed data pattern must be fixed. To determine parameters' distribution probabilities, a posterior model, a combination of gathered research data and previous knowledge, is first constructed using Bayesian analysis. The posterior distribution includes the prior distribution, which holds information about the model's parameters that are currently available, and the likelihood function, which provides information about the parameters based on observed data. Part of the posterior

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distribution is the likelihood function, which gives information about the parameters based on observed data, and the prior distribution, which stores information about the model's parameters that is currently accessible.

$$\text{Posterior distribution} \propto \text{Likelihood function x Prior information.}$$

The parameters' posterior distribution is estimated based on the observed sample and the parameters' prior distribution and used to interpret the results. Although the exact posterior distribution is only known in some cases, the general posterior distribution can be estimated using the Markov Chain Monte Carlo (MCMC) method without the need for a large sample approximation. The MCMC technique is frequently used to tune complex models in various fields [29]. In practice, the Bayesian estimation in this study is implemented via Gibbs sampling under the Metropolis-Hastings algorithm, with different prior specifications evaluated through sensitivity analysis. Details of prior selection, Bayes factor comparisons, and diagnostic results are presented in section 4. The overall research process examining the impact of globalization on income inequality is illustrated in figure 1.

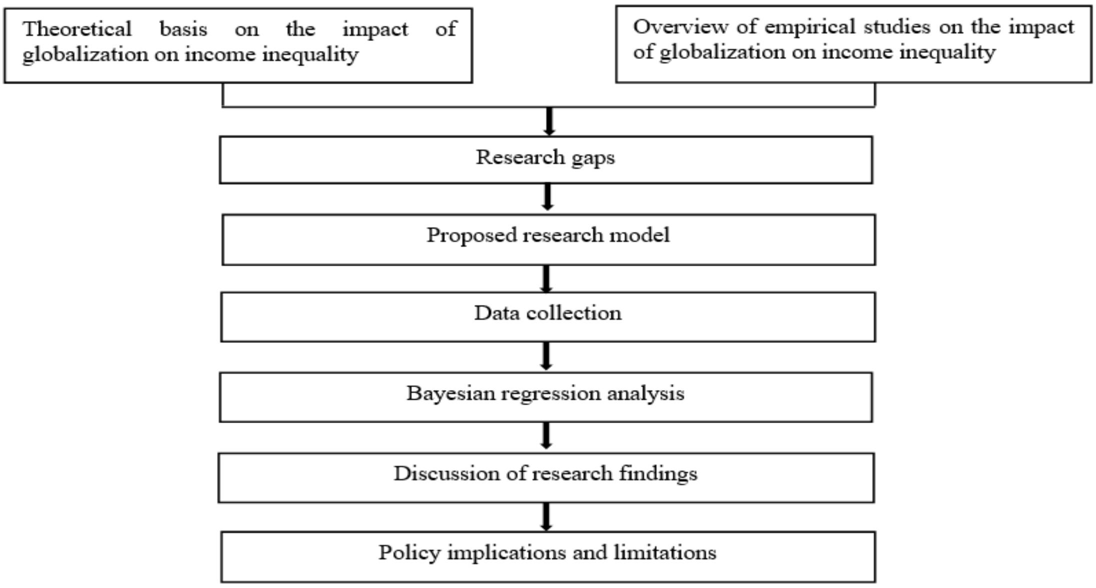

Figure 1. Research flowchart

4. Results and Discussion

This work employs the Metropolis-Hastings method via Gibbs sampling, utilizing an MCMC chain of 10,000 for Bayesian analysis. Previous studies predominantly employed the frequency method, resulting in a lack of prior information. In this context, Block, Joern, Peter Jaskiewicz and Danny Miller [30] suggested establishing standard Gaussian distributions for various prior information and performing Bayesian factor analysis to identify the most appropriate prior. To ensure the validity of inference in the absence of reliable prior knowledge, this study conducts a prior sensitivity analysis by simulating five alternative normal priors N () with {1, 10, 100, 1000, 10000}. These values span a continuum from relatively informative () to highly diffuse (). Smaller variances constrain the prior distribution tightly around zero, while larger values approximate noninformative priors. This range enables the assessment of robustness across different levels of prior informativeness. Overly diffuse priors may fail to capture the underlying data structure, whereas overly tight priors may introduce bias if prior beliefs diverge from empirical evidence. The study then applies Bayesian factor analysis and Bayes test models to select the most appropriate prior distribution.

The prior information simulation with the highest average log ML and avg log BF is chosen based on Bayes factor analysis. As shown in table 2, simulation 1 achieves the largest avg log ML = 540.8286. Its Bayes factor value is not reported because simulation 1 is designated as the baseline prior, a necessary reference point against which all other specifications are compared. According to the Bayes test model results in column 6 of table 2, simulation 1 also attains the highest P(M|y), confirming its superiority; therefore, simulation 1 is selected.

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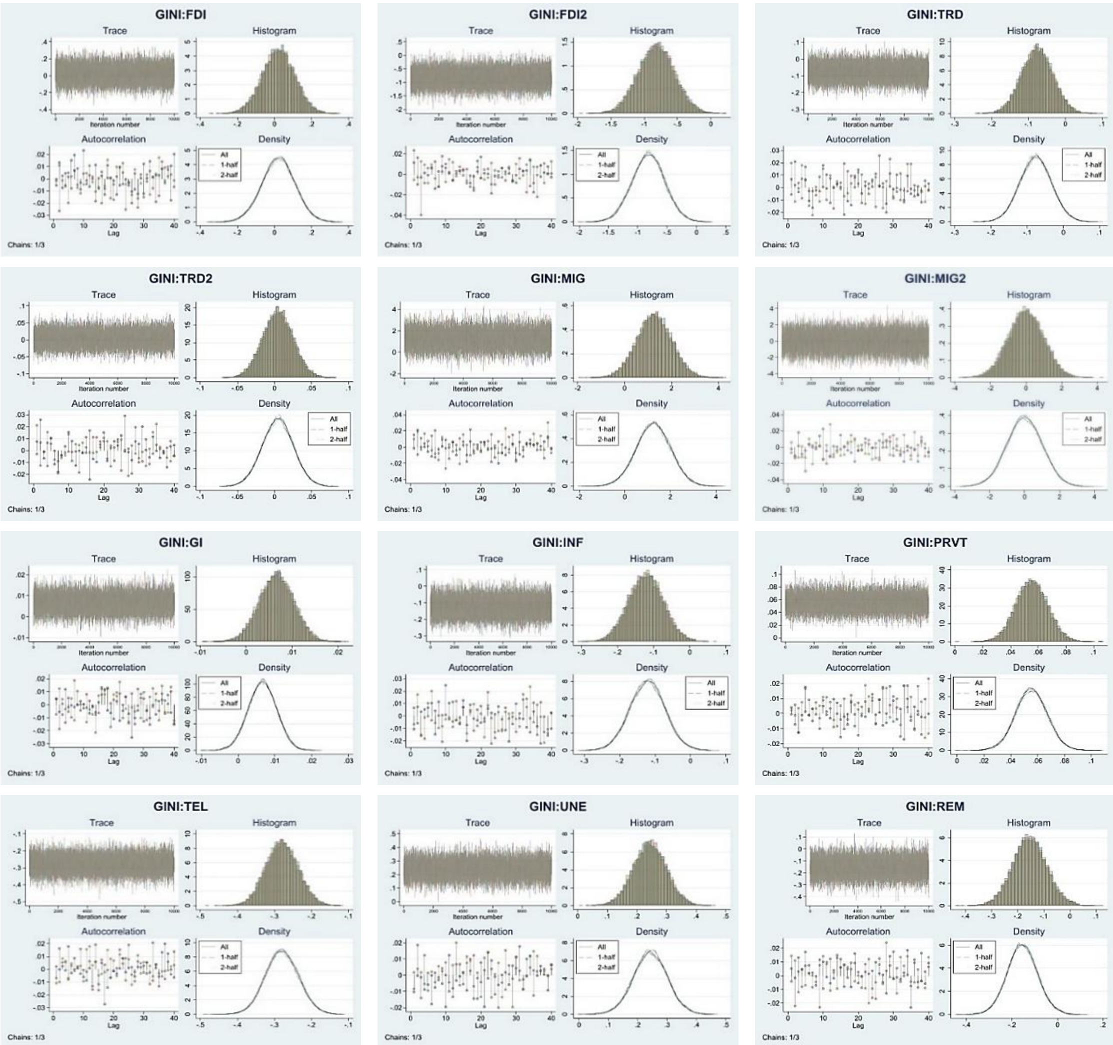
Table 2. Results of the Bayes Factor Analysis and the Bayes Test Model

Simulation	Chain	Average log marginal likelihood (avg log ML)	Bayes factor log average (avg log BF)	P(M)	P(M|y)
1~N (0,1)	3	540.8286	.	0.2000	1.0000
2~N (0,10)	3	524.6802	−16.1484	0.2000	0.0000
3~N (0,100)	3	506.6481	−34.1805	0.2000	0.0000
4~N (0,1000)	3	488.3014	−52.5272	0.2000	0.0000
5~N (0,10000)	3	469.9940	−70.8346	0.2000	0.0000

This study simulates Bayesian regression using MCMC, which must converge to ensure robustness, which is verified using visual diagnostic graphs. Figure 2 presents the convergence diagnostics for all posterior estimates from the Bayesian regression using MCMC simulation. For each parameter, the trace plots (top-left) show that MCMC fluctuates stably around a constant mean without visible trends, suggesting stationarity. The density plots (bottom-right) exhibit smooth and unimodal distributions, while the autocorrelation plots (bottom-left) indicate low lag correlation across iterations. Collectively, these diagnostic graphs confirm that the Bayesian sampler has adequately converged, ensuring the robustness of posterior inferences.



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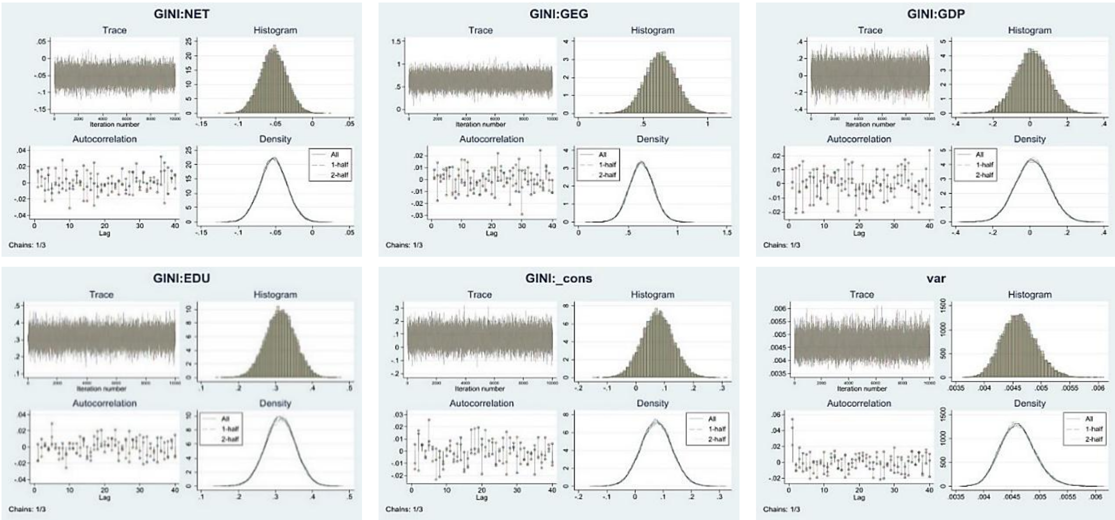

Figure 2. Convergent Diagnosis

The results of table 3 indicate that the maximum Gelman-Rubin Rc is only 1; therefore, it can be deduced that the coefficients'Rc values are less than or equal to 1, which meets the requirement of being less than 1.1, and the MCMC series meets the convergence requirement. Column 2 in table 3 shows the change in the dependent variable GINI when an average change in each independent variable in the model occurs. Column 3 in table 3 indicates the probability of the direction of each variable's effect, with the average probability for all variables exceeding 50%.

Table 3. Bayesian Regression Results

	Average value	**Average posterior probability**
FDI	0.21844	59.85%
FDI2	−0.81489	99.83%
TRD	−0.07669	99.16%
TRD2	0.04601	58.98%
MIG	0.01258	95.26%
MIG2	−0.49297	50.19%
GI	0.00660	95.86%
INF	−0.12168	99.30%
PRVT	0.05551	100.00%
TEL	−0.27942	100.00%
UNE	0.24241	100.00%
REM	−0.15419	99.11%
NET	−0.05256	99.84%
GEG	0.63426	100.00%
GDP	0.01270	55.47%
EDU	0.31272	100.00%
_cons	−0.07607	
var	0.00462	
Average acceptance rate	1.00000	
Minimum average effectiveness	0.93190	
Gelman–Rubin Rc max	1.00000	

Examining the impact of globalization from a financial perspective (as measured by FDI) indicates that this impact increases income inequality with a 59.85% probability. The FDI2 variable is negative, with a 99.83% probability,

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demonstrating a probability of an inverted U-shaped relationship between FDI and income inequality. According to the regression results in table 3, the estimated coefficients for FDI ($\alpha_1 = 0.21844$) and FDI2 ($\alpha_2 = -0.81489$) allow us to calculate the turning point of this nonlinear effect. Following the standard approach, the threshold is obtained by solving the first-order condition of the quadratic specification, where the marginal effect $\frac{\partial \text{GINI}}{\partial \text{FDI}} = \alpha_1 + 2 \times \alpha_2 \times \text{FDI}$ is set equal to zero. This yields the formula threshold of FDI = $-\frac{\alpha_1}{2\times\alpha_2}$. Substituting the coefficients from table 3 gives threshold of FDI $= -\frac{0.21844}{2\times -0.81489}$ = 0.134. Thus, when net FDI exceeds 13.4% of GDP, the marginal effect of FDI on inequality becomes negative, implying that inequality will decline beyond this point. This finding is consistent with Figini and Go¨rg [22], who determined that FDI benefits highly skill-intensive sectors and increases income inequality in developing countries, but this effect gradually decreases as FDI continues to rise.

From the perspective of trade globalization, the findings demonstrate that reduced income inequality from trade openness in developing countries has a fairly high probability of 99.16%, reaching the extreme threshold with a high probability of 58.98%. This indicates that trade openness affects income inequality in a U-shaped trajectory. According to the regression results in table 3, the estimated coefficients for trade openness TRD ($\alpha_3 = -0.07669$) and TRD2 ($\alpha_4 = 0.04601$) allow us to determine the turning point of this nonlinear effect. Following the standard procedure, the threshold is calculated by solving the first-order condition of the quadratic specification, where the marginal effect $\frac{\partial \text{GINI}}{\partial \text{TRD}} = \alpha_3 + 2 \times \alpha_4 \times \text{TRD}$ is set equal to zero. Solving this yields the formula threshold of TRD = $-\frac{\alpha_3}{2\times\alpha_4}$. Substituting the coefficients from table 3 gives the TRD threshold = $-\frac{-0.07669}{2\times 0.04601}$ = 0.8335. This means that when total trade accounts for less than 83.35% of GDP, trade openness narrows the income gap, but once this threshold is exceeded, further trade liberalization promotes income inequality. This result contradicts previous research by Khan and Nawaz [24]. It can be argued that the rationale for this result is that expanding foreign trade will increase unskilled workers' wages, which is consistent with the Stolper-Samuelson theorem [19] in the early stages of trade openness. However, when these countries no longer have the advantage of cheap labor or resources, they will tend to be trapped in the 'race to the bottom' to maintain cost competitiveness [31]. One approach for this is paying low wages to workers, which leads to increased income inequality.

From the perspective of social globalization/migration, the results reveal that migration has a positive impact on income inequality with a probability of 95.26%. Yet, the negative sign of the squared migration term with a 50.19% probability indicates a nonlinear pattern, suggesting that the effect will eventually reverse. Based on the coefficients reported in table 3 ($\alpha_5 = 0.01258$; $\alpha_6 = -0.49297$) , the turning point can be derived by solving for the critical value of the quadratic form, where the marginal effect of migration on inequality equals zero. Applying the formula threshold of MIG = $-\frac{\alpha_5}{2\times\alpha_6} = -\frac{0{,}01258}{2\times -0.49297}$ = 0.01276. This implies that when net migration reaches 1.276% of the total population, its impact shifts from increasing to reducing inequality. The rationale for this finding is that migration costs are high in communities that lack migration experience, making migration a choice that is only available to families with relatively high incomes, and these families benefit from remittances, causing the income gap between households with migrants and those without migrants to become even wider. However, as migration continues, communities that have already migrated can provide information and support to future migrants from their home countries, reducing the costs of migration and many people in low-income families will have more opportunities to migrate, which reduces income inequality. This aligns with the experimental research of McKenzie [26], Shen, Docquier and Rapoport [28].

Table 4 reports the average levels of FDI, trade openness, and net migration for 36 developing countries during 2010-2022. These averages are benchmarked against the threshold values identified by the Bayesian model (FDI: 13.4% of GDP; TRD: 83.35% of GDP; MIG: 1.276% of population). The results indicate that all countries remain below the FDI and migration thresholds, suggesting that these channels continue to operate within the inequality-increasing range. By contrast, 13 countries (Bulgaria, Croatia, Georgia, Honduras, Hungary, Kyrgyz, Mongolia, North Macedonia, Poland, Serbia, Thailand, Ukraine, Vietnam) exceed the trade openness threshold, placing them in a regime where further openness is associated with rising inequality, while the remaining countries lie below the threshold, where trade openness contributes to narrowing income disparities.

Table 4. Bayesian Regression Results

No	Country	Avg of FDI	Avg of TRD	Avg of MIG	No	Country	Avg of FDI	Avg of TRD	Avg of MIG
1	Albania	0.07862	0.75073	0.00827	19	Indonesia	0.01351	0.44588	0.00052
2	Argentina	0.01521	0.30761	-0.00038	20	Kazakhstan	0.04632	0.67401	-0.00009
3	Armenia	0.03581	0.74479	0.00331	21	Kyrgyz	0.05254	1.18988	0.00237
4	Bolivia	0.01978	0.69306	0.00104	22	Mali	0.03169	0.60518	0.00234
5	Brazil	0.02814	0.26009	0.00003	23	Mexico	0.01840	0.68638	0.00069
6	Bulgaria	0.03892	1.20326	0.00052	24	Mongolia	0.12676	1.11447	0.00002
7	Chile	0.02572	0.64164	-0.00313	25	N.Macedonia	0.03011	1.15084	0.00041
8	China	0.01401	0.43555	0.00017	26	Pakistan	0.00910	0.30123	0.00084
9	Colombia	0.02561	0.36939	-0.00095	27	Peru	0.03612	0.49280	0.00176
10	Croatia	0.02627	0.86655	0.00459	28	Poland	0.01826	0.93650	0.00046
11	Dominican	0.03855	0.53762	0.00303	29	Romania	0.02369	0.78847	0.00261
12	Ecuador	0.00879	0.52617	-0.00058	30	Russian	-0.00333	0.48536	-0.00159
13	Egypt	0.02190	0.44225	0.00019	31	Serbia	0.05657	0.92220	0.00021
14	El Salvador	0.01864	0.75421	0.00728	32	South Africa	0.00541	0.55421	-0.00321
15	Georgia	0.07028	0.95625	0.00358	33	Thailand	-0.00462	1.24794	-0.00024
16	Honduras	0.04582	1.08529	0.00075	34	Turkiye	0.01174	0.53688	-0.00319
17	Hungary	0.01671	1.61728	-0.00123	35	Ukraine	0.02901	0.97364	-0.00063
18	India	0.01373	0.46709	0.00053	36	Vietnam	0.04822	1.75939	0.00097

The results of table 3 also support the initial hypotheses regarding the effects of the control variables on income inequality, demonstrating that GI, PVRT, UNE, GEG, GDP, and EDU have positive effects, whereas INF, TEL, REM, and NET have negative effects.

The GI exerts a statistically significant positive effect on GINI, suggesting that stronger institutional environments may paradoxically increase inequality. This is likely due to the selective attraction of high-quality FDI inflows that favor skilled workers with higher earnings, thereby widening the income gap - a finding consistent with Xu, Han, Dossou and Bekun [32] and Nguyen [33]. INF, with a 99.30% probability, is negatively associated with inequality in our sample, indicating that moderate inflation tends to narrow income gaps. This aligns with studies such as Monnin [34] and Siami-Namini and Hudson [35], which emphasize that the effect of inflation on inequality is sensitive to context and may not be strictly linear. PRVT shows a 100% probability of increasing inequality, as greater financial depth, while potentially improving productivity and human capital, can also lead to exclusion for vulnerable groups lacking access to credit-mirroring the findings of Sethi, Bhattacharjee, Chakrabarti and Tiwari [36].

In contrast, Technological Infrastructure (TEL) and Digitalization (NET) significantly reduce inequality, with impact probabilities of 100% and 99.84%, respectively, emphasizing the role of inclusive technological access in narrowing income gaps, consistent with Calderón and Chong [37] and Mohd Daud, Ahmad and Ngah [38]. UNE is associated with a 100% probability of increasing inequality, as job losses disproportionately impact lower-income individuals whose benefits often fall below prior wages, as noted by Zulfiu Alili and Adnett [39]. Conversely, REM are highly likely (99.11%) to reduce inequality by improving household welfare and stimulating economic activity through consumption and investment, in line with Acosta, Calderón, Fajnzylber and Lopez [40], Portes [41], and Akobeng [42]. GEG is found to positively influence inequality with full certainty, implying that in many developing nations, public spending often benefits politically connected or middle-income groups rather than the poor, as discussed by Alderson, Beckfield and Nielsen [43]. Similarly, EDU, measured by primary enrollment, is positively correlated with inequality. This may reflect uneven access and quality, where wealthier groups disproportionately benefit from educational expansion. The result contrasts with Lin, Kim, and Wu [44] but is consistent with Xu, Han, Dossou and Bekun [32], Zulfiu Alili and Adnett [39], and Abdullah, Doucouliagos and Manning [45]. Finally, GDP shows a modest positive effect on inequality (55.47% probability), supporting Kuznets' (1955) hypothesis that inequality tends to rise in the early stages of economic development, a pattern also observed by Kim [7].

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5. Conclusion

This study examines the effects of trade openness, financial openness and social globalization on income disparity in developing nations. The estimated findings from a panel data sample of 36 developing nations from 2010 to 2022 using the MCMC simulation method and a Bayesian approach reveal a threshold effect of globalization on income disparity in developing economies. Trade openness has a U-shaped influence on income inequality, with a threshold of 83.35% of GDP, while migration and FDI have an inverted U-shaped effect with thresholds of 1.276% of the population and 13.4% of GDP, respectively. The threshold effects uncovered in this study carry important and practical implications for policymakers in developing economies, highlighting the need for differentiated policy responses depending on a country's position relative to the turning points of globalization's influence on income inequality. Beyond policy relevance, these findings also contribute to the theoretical literature by revealing that globalization's effects are nonlinear and context-dependent, thereby challenging the notion of a uniform or one-directional relationship as often implied in traditional globalization-inequality frameworks.

Accordingly, the following policy implications are proposed based on the study's key findings. First, trade openness shows a U-shaped link with inequality. Countries below the 83.35% of GDP threshold should pursue further liberalization to narrow income gaps, coupled with vocational training, better transport and logistics for small exporters, and rural credit access. For those above the threshold, additional liberalization risks worsening inequality; thus, it should be paired with redistributive taxes, targeted cash transfers, and worker retraining programs. Second, FDI has an inverted U-shaped effect. Where FDI is below 13.4% of GDP, further inflows may initially heighten inequality; these countries should strengthen labor standards, negotiate local content requirements, and avoid enclave investments before deepening openness. Above the threshold, governments can leverage FDI for inclusive growth by streamlining approvals, incentivizing skill transfer, and fostering linkages with domestic SMEs. Third, social globalization, measured by migration, also follows an inverted U-shape. Since all sampled countries remain below the 1.276% threshold, policy should focus on mitigating the inequality-increasing effects of early-stage migration. Key measures include reducing remittance transfer costs, expanding bilateral labor agreements to protect low-skilled workers, and improving access to safe migration channels and pre-departure training. These steps can help broaden the benefits of migration and prevent its initial inequality-widening impact.

The paper only examines a sample of 36 developing nations between 2010 and 2022 due to access issues that make it difficult to get balanced panel data for use in quantitative regression techniques. Although the study still meets the representativeness requirements for implementation with this sample size, increasing the sample size and research duration in future research is needed for more accurate results. Another limitation concerns potential endogeneity, particularly the risk of reverse causality between inequality and globalization measures (e.g., inequality influencing FDI inflows or migration flows). While the Bayesian framework mitigates some concerns by incorporating prior information and uncertainty, future studies could apply identification strategies such as instrumental variables or dynamic panel methods to address this issue more directly.

6. Declarations

6.1. Author Contributions

Author Contributions: Conceptualization, P.D.V., D.T.N.L., and D.L.K.O.; Methodology, P.D.V. and D.L.K.O.; Software, D.L.K.O. and D.T.N.L.; Validation, D.T.N.L. and D.L.K.O.; Formal Analysis, P.D.V.; Investigation, D.L.K.O. and D.T.N.L.; Resources, D.T.N.L. and D.L.K.O.; Data Curation, D.L.K.O.; Writing—Original Draft Preparation, P.D.V.; Writing—Review and Editing, D.T.N.L. and D.L.K.O.; Visualization, D.L.K.O. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

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

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6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] R. Breunig and O. Majeed, “Inequality, poverty and economic growth,” *International Economics,* vol. 161, pp. 83–99, May. 2020, doi: 10.1016/j.inteco.2019.11.005.

[2] M. Bask and M. Bask, “Cumulative (Dis)Advantage and the Matthew Effect in Life-Course Analysis,” *PLOS ONE*, vol. 10, no. 11, art. e0142447, Nov. 2015, doi: 10.1371/journal.pone.0142447.

[3] M. Bussmann, J. Oneal, and I. de Soysa, “The Effect of Globalization on National Income Inequality,” *Comparative Sociology*, vol. 4, no. 3–4, pp. 285–312, Jan. 2005, doi: 10.1163/156913305775010089.

[4] F. Dorn, C. Fuest, and N. Potrafke, “Trade openness and income inequality: New empirical evidence,” *Economic Inquiry*, vol. 60, no. 1, pp. 202–223, 2022, doi: 10.1111/ecin.13018.

[5] K. Munir and M. Bukhari, “Impact of globalization on income inequality in Asian emerging economies,” *International Journal of Sociology and Social Policy*, vol. 40, no. 1/2, pp. 44–57, Jan. 2019, doi: 10.1108/IJSSP-08-2019-0167.

[6] D. Asteriou, S. Dimelis, and A. Moudatsou, “Globalization and income inequality: A panel data econometric approach for the EU27 countries,” *Economic Modelling*, vol. 36, pp. 592–599, Jan. 2014, doi: 10.1016/j.econmod.2013.09.051.

[7] H. Kim, “The Effects of Globalization and Democratization on Inequality in South Korea The Effects of Globalization and Democratization on Inequality in South Korea,” *Korea Observer - Institute of Korean Studies*, vol. 53, no 3, pp. 471-494, Sep. 2022, doi: 10.29152/KOIKS.2022.53.3.471.

[8] L. Zhou, B. Biswas, T. Bowles, and P. J. Saunders, “Impact of Globalization on Income Distribution Inequality in 60 Countries,” *Glob. Econ. J*., vol. 11, no. 1, pp. 1-16, art. 1850216, Mar. 2011, doi: 10.2202/1524-5861.1628.

[9] M. I. Tabash, Y. Elsantil, A. Hamadi, and K. Drachal, “Globalization and Income Inequality in Developing Economies: A Comprehensive Analysis,” *Economies*, vol. 12, no. 1, pp. 23-39, Jan. 2024, doi: 10.3390/economies12010023.

[10] P. Van Phan, “Does Globalization Affect Inequality?: An Analysis of Vietnamese Data,” *Journal of Southeast Asian Economies*, vol. 39, no. 1, pp. 96–108, 2022, doi: 10.1355/ac39-1f.

[11] U. D. F. Mukam, W. Xin, and B. M. Dorcas, “The Impact of International Trade on Income Inequality: The Case of Germany,” *Market Forces*, vol. 19, no. 1, pp. 153-176, Jul. 2024, doi: 10.51153/mf.v19i1.655.

[12] Çelik and Basdas, “How Does Globalization Affect Income Inequality? A Panel Data Analysis | SpringerLink,” *Int Adv Econ Res*, vol. 16, pp. 358–370, 2010, doi: 10.1007/s11294-010-9281-0.

[13] C. J. Albers, H. A. L. Kiers, and D. van Ravenzwaaij, “Credible Confidence: A Pragmatic View on the Frequentist vs Bayesian Debate,” *Collabra: Psychology*, vol. 4, no. 1, art. 31, Aug. 2018, doi: 10.1525/collabra.149.

[14] M. H. Pesaran and R. P. Smith, “A Bayesian analysis of linear regression models with highly collinear regressors,” *Econometrics and Statistics*, vol. 11, pp. 1–21, Jul. 2019, doi: 10.1016/j.ecosta.2018.10.001.

[15] N. T. N. Nga and N. N. Thach, “Reexamining the economic globalization-welfare state nexus: a Bayesian mixed approach to linear and non-linear dynamics,” *Cogent Economics and Finance*, vol. 12, no. 1, art. 2416987, Dec. 2024, doi: 10.1080/23322039.2024.2416987.

[16] N. Ngoc Thach, “Bayesian Hierarchical Modeling of Individual Effects: Renewables and Non-Renewables on Global Economic Growth,” *SAGE Open*, vol. 14, no. 3, pp. 1-18, art. 21582440241268739, Jul. 2024, doi: 10.1177/21582440241268739.

[17] A. Tausch, “Globalisation and development: the relevance of classical ‘dependency’ theory for the world today,” *International Social Science Journal*, vol. 68, no. 227–228, pp. 79–99, 2018, doi: 10.1111/issj.12190.

[18] R. M. Solow, “Chapter 9 Neoclassical growth theory,” in *Handbook of Macroeconomics*, vol. 1, Elsevier, 1999, pp. 637–667, doi: 10.1016/S1574-0048(99)01012-5.

[19] W. F. Stolper and P. A. Samuelson, “Protection and Real Wages,” *The Review of Economic Studies*, vol. 9, no. 1, pp. 58–73, Nov. 1941, doi: 10.2307/2967638.

[20] B. Ohlin, Interregional and International Trade: Revised Edition, Revised edition. Harvard University Press, 1967.

[21] G. J. Borjas, “Self-Selection and the Earnings of Immigrants: Reply,” *The American Economic Review*, vol. 80, no. 1, pp. 305–308, 1990.

[22] P. Figini and H. Go¨rg, “Does Foreign Direct Investment Affect Wage Inequality? An Empirical Investigation,” *The World Economy*, vol. 34, no. 9, pp. 1455–1475, 2011, doi: 10.1111/j.1467-9701.2011.01397.x.

[23] T. Kaulihowa and C. Adjasi, “FDI and income inequality in Africa,” *Oxford Development Studies*, vol. 46, no. 2, pp. 250–265, Apr. 2018, doi: 10.1080/13600818.2017.1381233.

[24] I. Khan and Z. Nawaz, “Trade, FDI and income inequality: empirical evidence from CIS,” *International Journal of Development Issues*, vol. 18, no. 1, pp. 88–108, Jan. 2019, doi: 10.1108/IJDI-07-2018-0107.

[25] N. C. Chigwenembe and W. Zheng, “The Impact of International Trade on Income Inequality in the SADC Region,” *Modern Economy*, vol. 16, no. 3, 399-418, Art. no. 3, Mar. 2025, doi: 10.4236/me.2025.163019.

[26] McKenzie, D., “Beyond Remittances: The Effects of Migration on Mexican Households,” in *International migration, Remittances, and the Brain Drain, World Bank Publications*, 2006, pp. 123–147.

[27] R. P. C. Brown and E. Jimenez, “Estimating the net effects of migration and remittances on poverty and inequality: comparison of Fiji and Tonga,” *Journal of International Development*, vol. 20, no. 4, pp. 547–571, 2008, doi: 10.1002/jid.1474.

[28] I.-L. Shen, F. Docquier, and H. Rapoport, “Remittances and inequality: a dynamic migration model,” *J Econ Inequal*, vol. 8, no. 2, pp. 197–220, Jun. 2010, doi: 10.1007/s10888-009-9110-y.

[29] J.-H. Yang, H.-F. Lam, and Y.-H. An, “Development of a two-phase adaptive MCMC method for efficient Bayesian model updating of complex dynamic systems,” *Engineering Structures*, vol. 270, art. 114836, Nov. 2022, doi: 10.1016/j.engstruct.2022.114836.

[30] J. H. Block, P. Jaskiewicz, and D. Miller, “Ownership versus management effects on performance in family and founder companies: A Bayesian reconciliation,” *Journal of Family Business Strategy*, vol. 2, no. 4, pp. 232–245, Dec. 2011, doi: 10.1016/j.jfbs.2011.10.001.

[31] Shou, H., “Race to the bottom or move to the middle? Globalization and welfare regime transformation in the developing world,” *Dissertations and Theses, University of Illinois at Urbana-Champaign*, 2010. Accessed: Jul. 21, 2023.

[32] C. Xu, M. Han, T. A. M. Dossou, and F. V. Bekun, “Trade openness, FDI, and income inequality: Evidence from sub-Saharan Africa,” *African Development Review*, vol. 33, no. 1, pp. 193–203, 2021, doi: 10.1111/1467-8268.12511.

[33] V. B. Nguyen, “The difference in the FDI inflows – Income inequality relationship between developed and developing countries,” *The Journal of International Trade and Economic Development*, vol. 30, no. 8, pp. 1123–1137, Nov. 2021, doi: 10.1080/09638199.2021.1925331.

[34] P. Monnin, “Inflation and Income Inequality in Developed Economies,” in *Council on economic policies (CEP), Rochester*, NY, Jun. 2014. Doi: 10.2139/ssrn.2444710.

[35] S. Siami-Namini and D. Hudson, “Inflation and income inequality in developed and developing countries,” *Journal of Economic Studies*, vol. 46, no. 3, pp. 611–632, Jan. 2019, doi: 10.1108/JES-02-2018-0045.

[36] P. Sethi, S. Bhattacharjee, D. Chakrabarti, and C. Tiwari, “The impact of globalization and financial development on India’s income inequality,” *Journal of Policy Modeling*, vol. 43, no. 3, pp. 639–656, May 2021, doi: 10.1016/j.jpolmod.2021.01.002.

[37] C. Calderón and A. Chong, “External sector and income inequality in interdependent economies using a dynamic panel data approach,” *Economics Letters*, vol. 71, no. 2, pp. 225–231, May 2001, doi: 10.1016/S0165-1765(01)00374-3.

[38] S. N. Mohd Daud, A. H. Ahmad, and W. A. S. W. Ngah, “Financialization, digital technology and income inequality,” *Applied Economics Letters*, vol. 28, no. 16, pp. 1339–1343, Sep. 2021, doi: 10.1080/13504851.2020.1808165.

[39] M. Zulfiu Alili and N. Adnett, “Did FDI increase wage inequality in transition economies?,” *International Journal of Social Economics*, vol. 45, no. 9, pp. 1283–1304, Jan. 2018, doi: 10.1108/IJSE-09-2017-0373.

[40] P. Acosta, C. Calderón, P. Fajnzylber, and H. Lopez, "What is the Impact of International Remittances on Poverty and Inequality in Latin America?," *World Development*, vol. 36, no. 1, pp. 89–114, Jan. 2008, doi: 10.1016/j.worlddev.2007.02.016.

[41] L. S. V. Portes, "Remittances, poverty and inequality," *Journal of Economic Development*, vol. 34, no. 1, pp. 127–140, Jun. 2009, doi: 10.35866/CAUJED.2009.34.1.008.

[42] E. Akobeng, "Out of inequality and poverty: Evidence for the effectiveness of remittances in Sub-Saharan Africa," *The Quarterly Review of Economics and Finance*, vol. 60, pp. 207–223, May 2016, doi: 10.1016/j.qref.2015.10.008.

[43] A. S. Alderson, J. Beckfield, and F. Nielsen, "Exactly How Has Income Inequality Changed?: Patterns of Distributional Change in Core Societies," *International Journal of Comparative Sociology*, vol. 46, no. 5–6, pp. 405–423, Dec. 2005.

[44] Lin S et al., "Foreign direct investment and income inequality: Human capital matters," *Journal of Regional Science,* vol. 53, no. 5, pp. 874–896, 2013.

[45] A. Abdullah, H. Doucouliagos, and E. Manning, "Does Education Reduce Income Inequality? A Meta-Regression Analysis," *Journal of Economic Surveys*, vol. 29, no. 2, pp. 301–316, 2015.

Appendix 1: Bayesian Regression Results

	Mean	Std. Dev.	MCSE	Median	Equal-tailed [95% Cred. Interval]	
FDI	0.21844	0.08841	0.00051	0.22450	-0.15165	0.29535
FDI2	-0.81489	0.27751	0.00160	-0.81358	-1.35887	-0.27231
TRD	-0.07669	0.04334	0.00025	-0.07694	-0.16085	0.00822
TRD2	0.04601	0.02083	0.00012	0.04682	-0.03634	0.04625
MIG	0.01258	0.07534	0.00435	0.01257	-0.22401	0.27347
MIG2	-0.49297	0.10063	0.00581	-0.50432	-0.49701	0.19766
GI	0.00660	0.00379	0.00002	0.00659	-0.00077	0.01403
INF	-0.12168	0.04886	0.00028	-0.12182	-0.21768	-0.02614
PRVT	0.05551	0.01161	0.00007	0.05541	0.03277	0.07838
TEL	-0.27942	0.04429	0.00026	-0.27927	-0.36647	-0.19194
UNE	0.24241	0.05666	0.00033	0.24275	0.13171	0.35320
REM	-0.15419	0.06555	0.00038	-0.15420	-0.28371	-0.02739
NET	-0.05256	0.01796	0.00010	-0.05257	-0.08758	-0.01735
GEG	0.63426	0.12010	0.00070	0.63387	0.40081	0.87174
GDP	0.01270	0.09110	0.00053	0.01261	-0.16635	0.19119
EDU	0.31272	0.04028	0.00023	0.31281	0.23355	0.39111
_cons	0.07607	0.05452	0.00032	0.07604	-0.03008	0.18361
var	0.00462	0.00031	0.00000	0.00460	0.00404	0.00525

Appendix 2: Posterior Probabilities

	Mean	Std. Dev.	MCSE
prob1 : {GINI:FDI} > 0	0.5985	0.4902	0.0028
prob1 : {GINI:FDI2} < 0	0.9983	0.0412	0.0002
prob1 : {GINI:TRD} < 0	0.9916	0.1919	0.0011
prob1 : {GINI:TRD2} > 0	0.5898	0.4919	0.0029
prob1 : {GINI:MIG} > 0	0.9526	0.2125	0.0012
prob1 : {GINI:MIG2} < 0	0.5019	0.5000	0.0029
prob1 : {GINI:GI} > 0	0.9586	0.1991	0.0011
prob1 : {GINI:INF} < 0	0.9930	0.0836	0.0005
prob1 : {GINI:PRVT} > 0	1.0000	0.0000	0.0000
prob1 : {GINI:TEL} < 0	1.0000	0.0000	0.0000
prob1 : {GINI:UNE} > 0	1.0000	0.0000	0.0000
prob1 : {GINI:REM} < 0	0.9911	0.0941	0.0005
prob1 : {GINI:NET} < 0	0.9984	0.0404	0.0002
prob1 : {GINI:GEG} > 0	1.0000	0.0000	0.0000
prob1 : {GINI:GDP} > 0	0.5547	0.4970	0.0029
prob1 : {GINI:EDU} > 0	1.0000	0.0000	0.0000