"Impact of climate vulnerability and climate readiness on income inequality: Evidence from developing countries"

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IMPACT OF CLIMATE VULNERABILITY AND CLIMATE READINESS ON INCOME INEQUALITY: EVIDENCE FROM DEVELOPING COUNTRIES

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Abstract

Recognizing the link between climate vulnerability, climate readiness, and income inequality is crucial, as economic disparities can exacerbate climate risks and hinder adaptation, particularly in developing countries. This study analyzes the impact of climate vulnerability and climate readiness on income inequality across 61 developing countries from 1995 to 2022. The Quasi-likelihood under the Independence Model Criterion (QIC) was applied to determine the optimal correlation structure and identify the most relevant covariates. Additionally, Generalized Estimating Equations (GEE), Panel-Corrected Standard Errors (PCSE), and Feasible Generalized Least Squares (FGLS) were employed to ensure robust estimation. To account for measurement uncertainty, 100 multiple imputations of the Gini index from the latest Standardized World Income Inequality Database (SWIID) were used instead of a single point estimate. Empirical results indicate that climate vulnerability significantly ($p < 0.01$) exacerbates income inequality, with estimates ranging from 10.426 to 48.997, whereas climate readiness significantly ($p < 0.01$) mitigates inequality, with elasticity values between –47.259 and –25.764. Control variables, including trade balance, unemployment, and urban population growth, exhibit a strong positive correlation with income inequality, while democracy and natural resource rents are associated with a more equitable income distribution. Economic growth demonstrates a positive and significant effect on inequality, whereas its squared term is negative but generally insignificant, providing only weak support for the Kuznets hypothesis. The findings highlight the pivotal role of climate readiness in mitigating the socio-economic impacts of environmental risks, emphasizing the importance of implementing targeted adaptation policies in highly vulnerable countries.

Keywords inequality, income, climate, vulnerability, readiness, imputation, panel, uncertainty

JEL Classification D31, Q54, O15, C01

INTRODUCTION

Across the globe, governments, cities, and corporations are reevaluating their growth models with an eye toward both short- and long-term sustainability. The recognition that a community's vitality is contingent upon its resilience to climate change has led to a greater emphasis on strategies that strengthen adaptive capacity and promote inclusive growth. This is especially critical in developing countries, where the disproportionate effects of rising temperatures and climate-related disasters are exacerbated by pre-existing vulnerabilities such as weak infrastructure and a reliance on climate-sensitive economic sectors.

These dynamics have placed the relationship between climate change and income inequality at the center of contemporary debates, as socioeconomic disparities both heighten vulnerability and constrain the capacity to adapt effectively. Lower-income groups face greater expo-

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sure to floods, extreme heat, and environmental degradation while possessing fewer resources to mitigate damages or recover from losses. This creates a self-reinforcing cycle in which climate shocks deepen existing disparities, and those disparities in turn amplify sensitivity to future shocks.

This has brought renewed attention to two critical dimensions of the climate–inequality nexus: climate vulnerability and climate readiness. Vulnerability captures the degree to which societies are exposed and sensitive to environmental risks, often amplifying distributive inequalities. Readiness, by contrast, reflects the institutional and structural ability to anticipate, absorb, and adapt to climate shocks, with the potential to buffer or even reverse these inequalities. The scientific problem, therefore, lies in understanding the interaction of these two dimensions. This tension constitutes a central issue for sustainable development, as future inequality will depend not only on the scale of climate risks but also on the capacity of societies to respond to them.

1. LITERATURE REVIEW AND HYPOTHESES

The intersection of climate change and income inequality represents one of the most critical global challenges (Alam et al., 2017; Paglialunga et al., 2022). Climate change exerts a detrimental influence on the global socioeconomic landscape, impeding economic growth and advancement, particularly in less-developed economies (Carleton & Hsiang, 2016; Palagi et al., 2022). However, the degree of vulnerability varies considerably across countries, depending on their economic structure, institutional resilience, infrastructure quality, and adaptive capacity (Barbier & Hochard, 2019; Chancel et al., 2023). Furthermore, the magnitude and nature of climate impacts are influenced by a country's level of economic development, technological advances, and sectoral composition, particularly whether the dominant activities are concentrated in industry, agriculture, or services (Soussane et al., 2023). In this context, increasing attention has been paid to the interaction between climate change and income inequality, particularly given the disproportionate burden borne by developing countries (Diffenbaugh & Burke, 2019; World Bank, 2020). Within this framework, socially vulnerable communities, including those located in coastal zones, economically disadvantaged urban areas, and dispersed rural regions, are confronted with elevated flood risks (Kim et al., 2018; Sayers et al., 2018) while possessing comparatively limited resources to implement effective mitigation strategies.

Research on the impact of climate change on income inequality consistently shows that lower-income populations are disproportionately affected because they are more exposed and vulnerable to its adverse consequences (Hallegatte & Rozenberg, 2017; Diffenbaugh & Burke, 2019; World Bank, 2020). Nonetheless, the magnitude of this impact varies significantly both within and across countries (Hsiang et al., 2019). Climate change is a significant driver of global economic disparity, estimated to increase the income gap between the poorest and richest nations by 25%. This is underscored by projections anticipating a 23% reduction in average global income by 2100 compared to a scenario without climate change, which would further widen global income inequality (Burke et al., 2015).

Empirical evidence from national and cross-country analyses supports this link, suggesting that rising temperatures and climate-related disasters intensify existing disparities by disproportionately affecting low-income populations (Dell et al., 2014; Kotz et al., 2022; Dang et al., 2024). For instance, in the United States, counties reliant on agricultural and labor-intensive sectors experience significant income losses from extreme heat, with each additional day above 30°C reducing per capita income by roughly $20.56, especially on weekdays. These impacts appear to persist over time, with no clear evidence of effective adaptation. Similarly, in global assessments, countries like India have experienced GDP losses exceeding 25% due to rising temperatures, while cooler, wealthier nations such as Norway have benefited economically, thereby highlighting the unequal distribution of climate-induced economic consequences (Deryugina & Hsiang, 2014). Similarly, a large-scale panel study across 43 climate-vulnerable and 39 highly unequal countries demonstrates that increased climate vulnerability, temperature rise, and disaster frequency are significantly associated with widening income gaps (SenGupta & Atal, 2024). The intersection of climate vulnerability and energy poverty further complicates these dynamics. In China, rising temperatures and climate variability have been shown to intensify energy poverty, particularly in rural and inland provinces, where infrastructure deficits and limited energy access exacerbate vulnerability (Wu et al., 2025). These regional and country-specific findings underscore the diverse mechanisms through which climate change affects inequality. For instance, in the context of Vietnam, climate change, measured through mortality rates and economic losses, significantly deepens income inequality, particularly when fiscal governance mechanisms are considered (Huynh & Hoang, 2025).

The relationship between climate vulnerability and socioeconomic inequality is especially pronounced in developing countries, where limited adaptive capacity exacerbates the adverse impacts of climate change (Adams et al., 2013; IMF, 2021). The established theoretical framework on the relationship between climate change and income inequality posits that inequalities increase the vulnerability of marginalized groups to the effects of climate change through three main channels:

(i) increased exposure to climate risks;

(ii) amplified sensitivity to climate hazards; and

(iii) decreased capacity to control and recover from damage.

The combined effect of these channels creates a vicious cycle where climate-related dangers exacerbate existing disparities (Islam & Winkel, 2017). While heightened vulnerability tends to intensify income disparities, climate readiness, the ability of nations to anticipate, adapt to, and respond to climate risks, can help reduce inequalities (IMF, 2021; Çevik & Jalles, 2023). Empirical evidence consistently shows that increasing climate vulnerability correlates with rising income inequality, particularly in poorer nations, whereas improved climate readiness mitigates this effect in both developed and developing countries. Quantitatively, a 1% rise in climate vulnerability corresponds to a 0.15% increase in income inequality in developing economies, whereas improvements in climate readiness are associated with a 0.11% reduction in inequality across all income groups (Wildowicz-Szumarska & Owsiak, 2024). Moreover, the Notre Dame Global Adaptation Index (ND-GAIN) underscores that countries with low adaptive capacity tend to experience more severe socioeconomic losses from climate events, especially when institutional quality and infrastructure are underdeveloped (Chen et al., 2015). Notably, while climate change vulnerability does not exert a statistically significant effect on income distribution in advanced economies, its impact in developing countries is both highly significant and nearly seven times greater. This divergence is mainly explained by the lower adaptation and mitigation capacity of the poorest countries, which amplifies their exposure to climate-induced economic shocks (Çevik & Jalles, 2023). Although the consequences of global warming are evident across the world, the magnitude of these impacts varies substantially among countries, regions, communities, and individuals. The extent of future economic inequality will be determined, to a significant degree, by the ability of these groups to adapt effectively (Hallegatte & Rozenberg, 2017).

Recent analyses highlight the significant implications of future climate investments on global wealth inequality. Projections suggest that if the private sector alone makes the necessary climate investments by 2050, the private-to-public wealth ratio could increase significantly, potentially from the current 2.3 to 2.7. Moreover, if the richest 1% of global investors controlled all new climate-related assets, their share of total global wealth could increase from 38.5% today to 46% by 2050. These findings underscore the urgency of further interdisciplinary research to explore how climate change mitigation and adaptation efforts can reshape economic inequality globally (Chancel et al., 2024).

In summary, the empirical literature on the relationship between climate vulnerability, climate readiness, and income inequality highlights significant findings while also revealing certain gaps. One notable gap is the limited research that examines these two critical factors jointly, as they are often studied separately. This study addresses this gap by analyzing the effects of climate vulnerability and climate readiness on income inequality

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in 61 developing countries over the period 1995–2022. The following hypotheses were put forward:

H1: *A positive relationship exists between climate change vulnerability and income inequality in developing countries, indicating that higher climate vulnerability leads to increased income inequality.*

H2: *There is a negative relationship between climate change readiness and income inequality in developing countries, suggesting that greater climate readiness is associated with lower income inequality.*

2. METHODS

This study employs an unbalanced annual panel data set of 61 developing countries (see Figure 1) from 1995 to 2022. Income inequality, the dependent variable, is measured using the Gini index from the Standardized World Income Inequality Database (SWIID), version 9.8[1], which includes 100 posterior draws to capture estimation uncertainty[2]. Income inequality is a critical global concern, reflecting the uneven distribution of wealth both within and across countries. Developed nations exhibit varying income levels due to economic policies and labor dynamics, resulting in Gini coefficients typically ranging from 0.3 to 0.4. Conversely, developing nations often experience higher levels of income disparity due to limited access to quality education, healthcare, and employment opportunities. This leads to Gini coefficients exceeding 0.4 in most countries (see Appendix A, Figure A1), exacerbating poverty cycles and social tensions.

For the empirical analysis, the summary Gini index was initially utilized. Subsequently, the model was estimated using the 100 imputations provided by the SWIID dataset to incorporate estimation uncertainty.

Figure 1 presents a pair plot matrix visualizing the distributions and pairwise relationships of four key variables from the study: income inequality (gini_disp), climate vulnerability (VUL), climate readiness (PRE), and GDP per capita (GDP). The diagonal plots show the kernel density estimates for each variable, with the Gini coefficient distribution indicating a concentration of countries in the 40–50 range. The off-diagonal plots illustrate the scatter relationships between each pair of variables. Notably, a clear negative relationship between GDP and income inequality is visible, suggesting that higher GDP is associated with lower income disparity. In contrast, climate vulnerability (VUL) positively correlates with income inequality, indicating that more vulnerable countries tend to have higher Gini coefficients. Similarly, a strong negative relationship is observed between climate readiness (PRE) and climate vulnerability (VUL), highlighting that countries with higher readiness tend to exhibit lower levels of vulnerability.

The key explanatory variables of interest are climate vulnerability and readiness, as measured by the ND-GAIN indices. These indices represent a country's overall exposure to climate-related disturbances and its capacity to manage and adapt to their consequences, respectively[3].

Building on the work of Ponce et al. (2023) and the existing literature, conventional determinants of income inequality were included as control variables. These include gross domestic product (GDP), urban population growth, unemployment, trade balance, and natural resource rents, all sourced from the World Bank's World Development Indicators (WDI) database. In addition, the Rights index, one of four attributes of democracy, was incorporated and obtained from the Institute for Democracy and Electoral Assistance (Tufis & Hudson, 2022). The variable names, descriptions, and sources are provided in Appendix A, Table A1. The dataset used in this study is publicly available online (Chaouech, 2025).

Building on the research objective and existing literature, this study develops a baseline model to investigate the link between income inequality and climate change within an economic framework, as follows:

1 This database adopts a Bayesian method to standardize data gathered from various sources, including the OECD Income Distribution Database, the Socio-Economic Database for Latin America and the Caribbean produced by CEDLAS and the World Bank, Eurostat, the World Bank's PovcalNet, the UN Economic Commission for Latin America and the Caribbean, national statistical offices worldwide, and numerous others. The Luxembourg Income Study data are used as the standard.

2 For any given observation, the variations between these imputations reflect the uncertainty of the estimate (Solt, 2020).

3 For more details on these two indices, see the Country Index Technical Report by Chen et al. (2023).

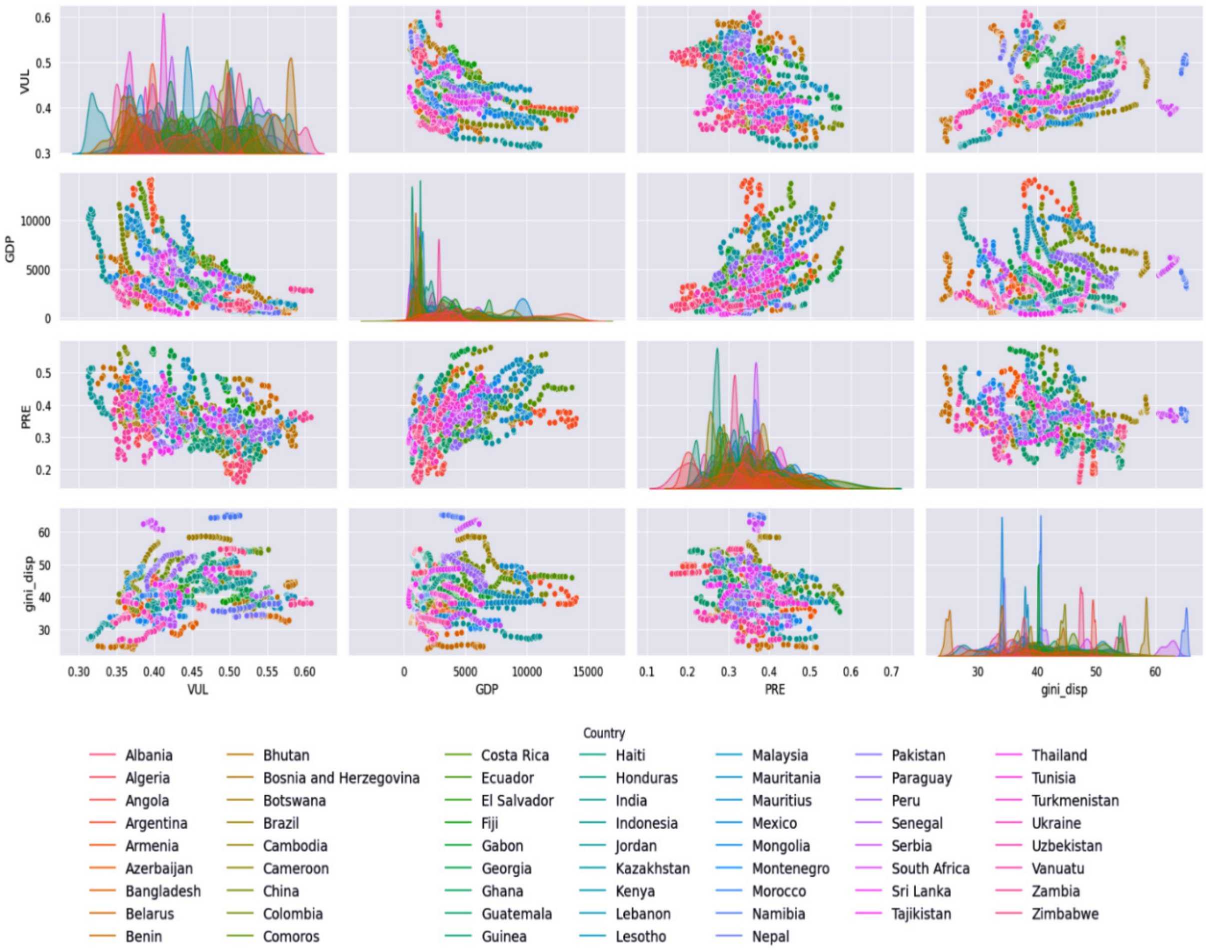

Figure 1. Scatterplot matrix of climate vulnerability, climate readiness, GDP, and Gini index across countries

$$Gini_{it} = \beta_0 + \beta_1 CC_{it} + \beta_j X_{it} + \varepsilon_{it}, \quad (1)$$

where $Gini_{it}$ denotes income inequality, CC_{it} is the measure of climate change vulnerability (VUL) and readiness (RED), X_{it} represents the vector of control variables. ε_{it} is an error term.

To test for the presence of an inverted U-shaped Kuznets curve, both the GDP level and its squared term are included as control variables in Equation (1):

$$Gini_{it} = \beta_0 + \beta_1 CC_{it} + \beta_2 \ln gdpc_{it} + \beta_3 \ln gdpc_{it}^2 + \beta_4 UPG_{it} + \beta_5 UE_{it} + \beta_6 NRR_{it} + \beta_7 Rg_{it} + \beta_8 TB_{it} + \varepsilon_{it}, \quad (2)$$

where ln*gdpc* denotes the logarithm of mean-centered GDP per capita[4], ln*gdpc*^{2} is the ln*gdpc* square, UPG represents Urban Population Growth, *UE* denotes unemployment, *NRR* stands for natural resource rents, *Rg* refers to the rights index, the second of the four democracy attributes, and TB represents the trade balance.

Given the large number of countries and time periods (T and $N > 25$), it is essential to test for cross-sectional dependence (CD) before performing panel data regression, as CD influences the choice of unit root tests. Cross-sectional dependence occurs when panel units are correlated due to common external factors, such as global shocks or economic interdependencies. The Pesaran (2021) CD test was employed to detect this dependence. It is expressed in Equation (3), where T represents the time period, N denotes the panel size, and σ corresponds to the correlation coefficient.

4 To resolve the collinearity issue between GDP and its square, we first take the logarithm of GDP per capita, center it by subtracting the mean, and then square the centered value.

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$$CD_p = \sqrt{\frac{2T}{N(N-1)}}(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\sigma}_{ij}). \quad (3)$$

If no cross-sectional dependence is detected, first-generation panel unit root tests can be applied, including the Levin-Lin-Chu (LLC), Im-Pesaran-Shin (IPS), and Fisher-type tests. However, if cross-sectional dependence is present, second-generation panel unit root tests such as the Cross-sectionally Augmented IPS (CIPS) test developed by Pesaran (2007), are more appropriate. Since the panel data analysis confirmed the presence of cross-sectional dependence, the CIPS test is applied as the unit root test. The general form of the CIPS test equation is as follows:

$$CIPS(N,T) = \frac{\sum_{i=1}^{N} t_i(N,T)}{N}, \quad (4)$$

where N denotes the number of cross-sectional units and T represents the number of time periods in the panel data, t_i refers to the ordinary least squares (OLS), and t-statistics obtained from the Augmented Dickey-Fuller (ADF) regression on the cross-sectional mean (Adeleye et al., 2023).

The long-run relationships were assessed using the second-generation panel cointegration test of Westerlund (2007).

The QIC criterion proposed by Cui (2007) was applied to determine the optimal working correlation structure. Unlike the generalized linear model (GLM), which relies on maximum likelihood estimation, the generalized estimating equation (GEE) approach is based on quasi-likelihood theory. It does not require specification of a full likelihood function. While traditional model selection criteria, such as the Akaike Information Criterion (AIC), are not directly applicable to GEE, the QIC provides a robust alternative for selecting the most appropriate model and correlation structure (Cui, 2007). The QIC formula, originally proposed by Pan (2001), is given as follows:

$$QIC = -2Q(\mu; I) + 2trace(\Omega_I^{-1} V_R) \quad (5)$$

where I represents the independent covariance structure used to compute quasilikelihood, V_R are derived from a general working covariance structure R, Ω_I is a variance estimator assuming an independent correlation structure, and

$$\mu = g^{-1}(X\beta) \quad (6)$$

where $g^{-1}()$ is the inverse link function, β and the robust variance estimator.

The model was first estimated using the Generalized Estimating Equation (GEE) approach with three correlation structures: independence, first-order, and exchangeable correlations. The QIC program was subsequently employed to determine the best-fitting model and the optimal correlation structure. The correlation structure associated with the smallest QIC value was selected, and the model with the lowest QIC_u value was considered the best-fitting specification. Finally, given the presence of cross-sectional dependence in the data and the cointegration among variables, panel-corrected standard errors (PCSE) were applied to estimate all models, thereby addressing heteroscedasticity and serial correlation. However, PCSE performs optimally in estimating standard errors without sacrificing efficiency only when the number of periods is close to the number of groups ($T \approx N$). When $T > N$, it is common to encounter practical research situations where the PCSE estimator entails a substantial loss of efficiency (Reed & Webb, 2010). To ensure robustness, the feasible generalized least squares (FGLS) method was also employed.

Both Panel-Corrected Standard Errors (PCSE) and Feasible Generalized Least Squares (FGLS) estimate the conditional mean of the dependent variable while adjusting for issues like heteroskedasticity and serial correlation in the error terms. However, they do not explicitly model the full distribution of uncertainty in the data (such as higher moments beyond the mean, like variance or skewness). Accordingly, the newly available SWIID dataset was utilized, providing 100 draws of the Gini coefficient to capture variability in income inequality measurements. Rather than relying on a single estimate, this approach directly incorporates uncertainty into the analysis. To account for this variability, the models were estimated using MI-compatible Generalized Estimating Equations (MI-GEE), specifically designed to analyze multiply imputed data. This method ensured that uncertainty across imputations was properly integrated, resulting in more robust and reliable statistical inferences.

3. RESULTS

Table 1 presents the summary statistics for all variables using untransformed values. The mean values of the Gini Index, Climate Vulnerability Index, and Climate Readiness Index are 42.092, 0.449, and 0.353, respectively. The minimum and maximum values range from 23.9 to 65.2 for the Gini Index, 0.312 to 0.608 for the Climate Vulnerability Index, and 0.161 to 0.577 for the Climate Readiness Index.

Table 1. Summary statistics

Variable	Obs.	Mean	Std. dev	Min	Max
Gini	1,451	42.092	7.940	23.9	65.2
VUL	1,451	0.449	0.065	0.312	0.608
RED	1,451	0.353	0.071	0.161	0.577
GDP	1,451	3,739.202	2,824.376	369.934	14,040.62
UPG	1,451	2.305	1.579	–4.200	10.516
UE	1,451	8.793	5.908	0.249	31.84
NRR	1,425	5.961	8.775	0.001	75.365
Rg	1,451	0.470	0.118	0.153	0.835
TB	1,430	–6.919	12.944	–69.368	42.309

Table 2 displays the correlation matrix and statistical significance. The results of the collinearity test confirm the absence of multicollinearity, supporting the validity of the regression models. These findings indicate that no perfect linear relationships exist among the variables.

Table 2. Correlation statistics

Variance ratio (VUL)

Coefficient (p-value)	VUL	Lngdpc	Lngdpc2	UPG	UE	NRR	Rg	TB
VUL	1.000	–	–	–	–	–	–	–
Lngdpc	–0.647	1.000	–	–	–	–	–	–
	(0.000)							
Lngdpc2	0.107	–0.152	1.000	–	–	–	–	–
	(0.000)	(0.000)						
UPG	0.511	–0.299	0.053	1.000	–	–	–	–
	(0.000)	(0.000)	(0.040)					
UE	–0.239	0.125	–0.113	–0.167	1.000	–	–	–
	(0.000)	(0.000)	(0.000)	(0.000)				
NRR	–0.074	–0.020	–0.072	0.211	0.073	1.000	–	–
	(0.005)	0.439	(0.006)	(0.000)	(0.005)			
Rg	–0.103	0.390	–0.003	–0.180	0.304	–0.263	1.000	–
	(0.000)	0.000	(0.897)	(0.000)	(0.000)	(0.000)		
TB	–0.179	0.319	0.036	0.114	–0.126	0.387	–0.042	1.000
	(0.000)	(0.000)	(0.165)	(0.000)	(0.000)	(0.000)	(0.111)	

Variance ratio (RED)

Coefficient (p-value)	PRE	Lngdpc	Lngdpc^2	UPG	UE	NRR	Rg	TB
RED	1.000	–	–	–	–	–	–	–
Lngdpc	0.515	1.000	–	–	–	–	–	–
	(0.000)							
Lngdpc^2	0.017	–0.152	1.000	–	–	–	–	–
	(0.5)	(0.000)						
UPG	–0.319	–0.299	0.053	1.000	–	–	–	–
	(0.000)	(0.000)	(0.040)					
UE	0.023	0.125	–0.113	–0.167	1.000	–	–	–
	(0.364)	(0.000)	(0.000)	(0.000)				
NRR	–0.243	–0.020	–0.072	0.211	0.073	1.000	–	–
	(0.000)	(0.439)	(0.006)	(0.000)	(0.005)			
Rg	0.430	0.390	–0.003	–0.180	0.304	–0.263	1.000	–
	(0.000)	(0.000)	(0.897)	(0.000)	(0.000)	(0.000)		
TB	0.102	0.319	0.036	0.114	–0.126	0.387	–0.042	1.000
	(0.000)	(0.000)	(0.165)	(0.000)	(0.000)	(0.000)	(0.111)	

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Table 3. CD, panel unit root, and cointegration test

Variables	CD test	CIPS test			
		Without trend		With trend	
	Coefficient	Level	1st Diff	Level	1st Diff
Gini	32.024***	8.583	–9.768***	4.489	–10.346***
VUL	105.634***	4.361	–20.930***	0.306	–17.773***
RED	36.543***	–0.186	–18.284***	0.832	–15.059***
Lngdpc	155.92***	4.728	–13.673***	6.561	–11.790***
$Lngdpc^2$	2.564***	–2.263***	–13.673***	3.137	–11.790***
UPG	20.595***	3.201	–11.400***	4.779	–9.310***
UE	6.848***	0.181	–15.710***	3.791	–12.295***
NRR	51.007***	–2.173***	–18.959***	–0.720	–15.738***
Rg	22.549***	–1.103	–19.066***	1.864	–15.618***
TB	10.299***	–2.673***	N/A	–1.333**	N/A
Westerlund (2007) cointegration test					
Variance ratio (VUL) = 3.3578*** Variance ratio (PRE) = 2.350***					

Note: *** $p < 0.01$, ** $p < 0.005$, * $p < 0.1$; *p*-value in (), NA not applicable.

Table 3 reports the results of the cross-sectional dependence (CD) test. The null hypothesis of cross-sectional independence is rejected, indicating the presence of cross-sectional dependence. This finding justifies the use of the panel-corrected standard errors (PCSE) method, which adjusts for interdependencies and improves estimation accuracy. Due to the detected dependence, second-generation panel unit root tests were conducted. Pesaran's (2007) CIPS test results reveal that all variables, except trade balance, are stationary at first difference. Additionally, the Westerlund (2007) cointegration test supports the presence of a long-run equilibrium relationship among the variables.

The QIC (Quasi-likelihood under the Independence model Criterion) program was applied to identify the best-fitting model. Following the approach of Hardin and Hilbe (2003), the process began with selecting the optimal working correlation structure. Given that the Gini index is a continuous variable, the normal distribution with identity link function was used. QIC and QIC_u values were computed for the three correlation structures. As shown in Table 4, the independence structure yielded the lowest QIC, making it the preferred specification.

Under this correlation structure, multiple model specifications were tested using different subsets of covariates. The full model produced the lowest QIC and QIC_u values (highlighted in Table 4) and was selected as the best-fitting model.

Tables 5, 6, and 7 report the GEE, PCSE, and FGLS estimation results, respectively. The findings show that climate vulnerability significantly increas-

Table 4. QIC for model selection under normal distribution

Correlation	Variables	Trace	P	QIC	QIC_u
Independent	Gini VUL lngdpc lngdpc2 UPG UE NRR Rg TB	145.745	0	60,843.214	60,552.538
Exchangeable	Gini VUL lngdpc lngdpc2 UPG UE NRR Rg TB	80.263	0	81,717.034	81,557.323
Autoregressive	Gini VUL lngdpc lngdpc2 UPG UE NRR Rg TB	36.991	0	85,607.790	85,534.621
Independent	Gini VUL lngdpc lngdpc2 UPG UE NRR	123.360	0	63,517.409	63,271.503
Independent	Gini VUL UPG UE NRR	116.124	0	64,603.027	64,371.592
Independent	Gini VUL UPG UE NRR TB	108.348	0	64,666.274	64,450.392
Independent	Gini RED lngdpc lngdpc2 UPG UE NRR Rg TB	137.564	0	55,701.265	55,426.949
Exchangeable	Gini RED lngdpc lngdpc2 UPG UE NRR Rg TB	73.390	0	87,618.414	87,472.448
Autoregressive	Gini RED lngdpc lngdpc2 UPG UE NRR Rg TB	40.882	0	87,684.774	87,603.823
Independent	Gini RED UPG UE NRR Rg TB	107.746	0	58,842.035	58,627.356
Independent	Gini RED lngdpc lngdpc2 UPG UE NRR	115.937	0	59,262.165	59,031.105
Independent	Gini RED UPG UE NRR TB	100.627	0	60,533.371	60,332.931

es income inequality across all models. The coefficient is positive and significant at the 1% level, with estimates ranging from 10.426 to 48.997, offering strong support for hypothesis 1 (H1) and confirming that heightened climate vulnerability exacerbates inequality.

In contrast, climate readiness negatively and statistically significantly affects income inequality across all models ($p < 0.01$). This result provides strong support for hypothesis 2 (H2), confirming that greater adaptive capacity mitigates the adverse distributional effects of climate shocks and reduces inequality.

Table 5. GEE results (Dep Var: Gini)

Variables	GEE results							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
VUL	43.335***	41.311***	14.955***	19.423***	–	–	–	–
	(0.000)	(0.000)	(0.000)	(0.000)				
RED	–	–	–	–	−46.549***	−37.825***	−42.859***	−30.729***
					(0.000)	(0.000)	(0.000)	(0.000)
Lngdpc	3.098***	3.085***	–	–	2.412***	–	3.148***	–
	(0.000)	(0.000)			(0.000)		(0.000)	
Lngdpc^2	−0.501**	−0.319	–	–	−0.309	–	−0.017	–
	(0.060)	(0.228)			(0.225)		(0.944)	
UPG	1.709***	1.778***	1.897***	1.814***	2.038***	1.821***	2.138***	1.851***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
UE	0.437***	0.388***	0.384***	0.429***	0.303***	0.333***	0.323***	–
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
NRR	−0.234***	−0.170***	−0.193***	−0.263***	−0.320***	−0.313***	−0.286***	−0.345***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rg	−5.277***	–	–	–	7.476***	11.159***	–	–
	(0.004)				(0.000)	(0.000)		
TB	0.079***	–	–	0.125***	0.094***	0.140***	–	0.144***
	(0.000)			(0.000)	(0.000)	(0.000)		(0.000)
Constant	19.506***	17.250***	28.764***	27.765***	50.333***	45.844***	51.209***	48.114***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,404	1,425	1,425	1,404	1,404	1,404	1,425	1,404
Countries	61	61	61	61	61	61	61	61
Wald statistic	644.87	601.80	447.64	520.95	834.34	712.15	747.39	652.32

Note: *** $p < 0.01$, ** $p < 0.005$, * $p < 0.1$; p-value in ().

Table 6. PCSE results (Dep Var: Gini)

Variables	PCSE, Main Analysis							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
VUL	43.335***	41.311***	14.955***	19.423***	–	–	–	–
	(0.000)	(0.000)	(0.000)	(0.000)				
RED	–	–	–	–	−46.549	−37.825	−42.859	−30.729
					(0.000)	(0.000)	(0.000)	(0.000)
Lngdpc	3.098***	3.085***	–	–	2.412	–	3.148	–
	(0.000)	(0.000)			(0.000)		(0.000)	
Lngdpc^2	−0.501***	−0.319	–	–	−0.309	–	−0.017	–
	(0.032)	(0.166)			(0.166)		(0.934)	
UPG	1.709***	1.778***	1.897***	1.814***	2.038	1.821	2.138	1.851
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
UE	0.437***	0.388***	0.384***	0.429***	0.303	0.333	0.323	0.403
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NRR	−0.234***	−0.170***	−0.193***	−0.263***	−0.320	−0.313	−0.286	−0.345
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

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Table 6 (cont.). PCSE results (Dep Var: Gini)

Variables	PCSE, Main Analysis							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Rg	−5.277***	–	–	–	7.476	11.159	–	–
	(0.000)				(0.000)	(0.000)		
TB	0.079***	–	–	0.125***	0.094	0.140	–	0.144
	(0.000)			(0.000)	(0.000)	(0.000)		(0.000)
Constant	19.506***	17.250***	28.764***	27.765***	50.333	45.844	51.209	48.114
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,404	1,425	1,425	1,404	1,404	1,404	1,425	1,404
R-squared	0.314	0.296	0.239	0.270	0.372	0.336	0.344	0.317
Countries	61	61	61	61	61	61	61	61
Wald statistic	580.36	537.94	342.30	440.08	891.27	748.75	762.36	677.48

Note: *** $p < 0.01$, ** $p < 0.005$, * $p < 0.1$; *p*-value in ().

Table 7. FGLS results (Dep Var: Gini)

Variables	FGLS, Robustness							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
VUL	48.997***	42.366***	10.426***	17.636***	–	–	–	–
	(0.000)	(0.000)	(0.000)	(0.000)				
RED	–	–	–	–	−47.259***	−30.973***	−44.913	−25.764***
					(0.000)	(0.000)	(0.000)	(0.000)
Lngdpc	3.325***	2.924***	–	–	2.803***	–	3.097***	–
	(0.000)	(0.000)			(0.000)		(0.000)	
Lngdpc^2	−0.425****	−0.439***	–	–	0.002	–	0.488***	–
	0.002	0.001			(0.988)		(0.000)	
UPG	1.615***	1.711***	1.843***	1.698***	1.431***	1.280***	1.536***	1.368***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
UE	0.392***	0.356***	0.317***	0.371***	0.172***	0.239***	0.198***	0.298***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NRR	−0.189***	−0.142***	−0.169***	−0.219***	−0.246***	−0.256***	−0.257***	−0.268***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rg	−7.546***	–	–	–	3.764***	5.415***	–	–
	(0.000)				(0.000)	(0.000)		
TB	0.056***	–	–	0.097***	0.049***	0.119***	–	0.114***
	(0.000)			(0.000)	(0.000)	(0.000)		(0.000)
Constant	17.898***	16.768***	31.019***	28.371***	53.881***	47.497***	53.883***	47.588***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,404	1,425	1,425	1,404	1,404	1,404	1,425	1,404
Countries	61	61	61	61	61	61	61	61
Wald statistic	1757.33	1562.86	1469.04	1121.41	1609.65	1114.53	1953.50	1262.63

Note: *** $p < 0.01$, ** $p < 0.005$, * $p < 0.1$; *p*-value in ().

Furthermore, the positive association between climate vulnerability and inequality (H1), as well as the negative association between climate readiness and inequality (H2), remain robust even after incorporating 100 multiple imputations of the Gini index from the latest SWIID.

The trade balance variable is positively associated with income inequality and highly significant, suggesting that greater openness to trade may increase disparities. Conversely, the Rights Index has a negative and statistically significant effect, indicating that stronger civil liberties and social protections are associated with lower inequality. The impact of unemployment on income inequality is positive and statistically significant. Similarly, urban population growth shows a positive association with inequality.

Interestingly, natural resource rents (NRR) are negatively associated with income inequality and statistically significant at the 1% level across all models.

Table 8. Multiple-imputation estimates, GEE results (Dep Var: Gini)

Variables	Multiple-imputation estimates, GEE results							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
VUL	45.238***	42.091***	14.085***	18.438***	–	–	–	–
	(0.000)	(0.000)	(0.014)	(0.002)				
RED	–	–	–	–	−46.222***	−36.535***	−43.011***	−29.912***
					(0.000)	(0.000)	(0.000)	(0.000)
Lngdpc	3.471***	3.277***	–	–	2.678***	–	3.314***	–
	(0.000)	(0.000)			(0.000)		(0.000)	
Lngdpc²	−0.546	−0.347	–	–	−0.360	–	−0.045	–
	(0.154)	(0.344)			(0.337)		(0.900)	
UPG	1.656***	1.741***	1.867***	1.777***	2.017***	1.776***	2.112***	1.804***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
UE	0.451***	0.401***	0.396***	0.438***	0.315***	0.348***	0.334***	0.413***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NRR	−0.233***	−0.168***	−0.193***	−0.262***	−0.320***	−0.312***	−0.286***	−0.342***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rg	−6.616***	–	–	–	6.327**	10.417***	–	–
	(0.014)				0.033	(0.000)		
TB	0.074***	–	–	0.125***	0.089***	0.141***	–	0.144***
	(0.006)			(0.000)	(0.001)	(0.000)		(0.000)
Constant	18.966***	16.594***	28.824***	27.911***	50.404***	45.406***	50.947***	47.526***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,404	1,425	1,425	1,404	1,404	1,404	1,425	1,404
Countries	61	61	61	61	61	61	61	61
F statistic	28.75	33.54	35.60	32.65	35.21	37.55	42.07	41.02

Note: *** $p < 0.01$, ** $p < 0.005$, * $p < 0.1$; *p*-value in ().

The GDP coefficient is positive and significant, whereas the squared term (Lngdpc²) is negative but generally insignificant or only marginally significant. These results provide limited empirical support for the Kuznets' inverted U-shaped relationship between economic development and income inequality.

Finally, the robustness of the findings is confirmed by the use of Multiple Imputation (MI) and the Generalized Estimating Equations (GEE) approach, which incorporates estimation uncertainty (see Table 8). All variables remain significant across specifications, except for the squared GDP per capita term (Lngdpc²), which does not retain statistical significance.

4. DISCUSSION

The empirical findings of this study provide significant insights into the factors influencing the relationship between climate vulnerability, climate readiness, and income inequality within developing countries. The results show both alignment with and deviation from previous studies, while also uncovering novel trends pertinent to this specific context.

The finding that climate vulnerability significantly exacerbates income inequality is strongly consistent with the general scientific consensus reported by Çevik and Jalles (2023), Diffenbaugh and Burke (2019), and the World Bank (2020), all of whom have consistently identified that climate shocks disproportionately affect low-income populations and developing countries. Similarly, the finding that enhanced climate readiness mitigates income inequality is in strong agreement with the general scientific consensus formed by Çevik and Jalles (2023) and Wildowicz-Szumarska and Owsiak (2024), all of whom emphasize the crucial role of proactive adaptation in reducing climate-induced economic disparities. This body of research highlights that institutional quality, robust infrastructure, and effective governance, core components of climate readiness, are vital for resilience against climate shocks. In developing countries, where climate vulnerability is most pronounced, a high level of

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readiness allows for a more equitable distribution of resources for disaster relief and recovery, while also enabling the implementation of preventative measures that protect vulnerable populations from financial hardship.

These results confirm that investments in adaptive capacity are essential to strengthen both climate resilience and socioeconomic equality. This study advances prior research by providing a more rigorous methodological approach that explicitly accounts for the uncertainty inherent in the data.

Beyond climate-related factors, the influence of several other key variables was confirmed within this sample of developing countries. The study identifies a non-linear relationship between economic growth and income inequality, offering only limited empirical support for Kuznets' (1955) hypothesis[5], a result consistent with the findings of Pattnaik et al. (2025).

The highly significant and positive association between the trade balance and income inequality aligns with the findings of Cheong and Jung (2021) and Bhuyan and Oh (2021), emphasizing that greater trade openness can contribute to rising inequality. In contrast, the Rights index negatively and significantly affects income inequality, indicating that stronger legal protections and civil liberties foster a more equitable income distribution (Apergis & Cooray, 2020; Román-Aso et al., 2025). However, when climate vulnerability was replaced by climate readiness, the relationship reversed, revealing a positive association with inequality in some models. This contrast suggests that while rights help reduce inequality in vulnerable contexts, they may amplify disparities in more prepared economies, where well-positioned groups disproportionately capture greater benefits from adaptation opportunities.

The empirical evidence indicates a positive association between unemployment and income inequality, implying that elevated unemployment rates constitute a significant determinant of distributive disparities. This finding aligns with the results of Ponce et al. (2023). Similarly, urban population growth is positively associated with rising income inequality. This finding is consistent with Kuznets' (1955) hypothesis that urbanization leads to pronounced income disparities both between and within rural and urban areas.

Finally, natural resource rents (NRR) negatively affect income inequality across all model specifications. This statistically significant result suggests that revenues from natural resources can serve as a tool for economic equalization if effectively managed in developing nations.

CONCLUSION

The purpose of this study is to examine the impact of climate vulnerability and climate readiness on income inequality in 61 developing countries from 1995 to 2022.

The empirical analysis yields four principal conclusions that enhance the understanding of the determinants of income inequality in developing nations. The results consistently reveal a strong, statistically significant positive relationship between climate vulnerability and income inequality across all model specifications. In contrast, enhanced climate readiness substantially reduces income inequality, exhibiting significant and robust negative effects. These findings remain consistent even after accounting for control variables, including GDP per capita, urban population growth, unemployment, natural resource rents, the Rights index, and trade balance. Overall, the results support the hypothesis that higher climate readiness mitigates the adverse effects of climate vulnerability on income inequality. Additionally, the Rights index is significantly negatively correlated with inequality, indicating that stronger legal protections and civil liberties promote a more equitable income distribution. Similarly, natural resource rents significantly reduce income inequality, suggesting a potential redistributive role of resource wealth in developing countries.

5 According to this theory, income inequality rises during the early stages of economic development and gradually declines once income levels surpass a certain threshold.

These findings yield numerous important implications for climate policy and sustainable development in the developing world. First, enhancing climate readiness emerges as one of the most effective strategies to mitigate climate-induced inequality, particularly in highly vulnerable countries. Second, climate readiness initiatives are insufficient on their own and must be complemented by comprehensive governance reforms that strengthen legal protections and civil liberties. Third, the potential for natural resource wealth to reduce inequality must be leveraged through strategic, transparent, and equitable management policies. Finally, the persistent relationship between climate and inequality highlights the urgent need for holistic strategies that address both environmental and socioeconomic challenges.

Future research should address various limitations and investigate new aspects of the climate-inequality nexus. Including more recent information, as it becomes available, would expand the temporal scope of the study and shed light on post-2022 trends. Incorporating institutional quality indices, innovative policy measures, and detailed demographic variables would provide a more comprehensive understanding of the drivers of inequality. Advanced nonlinear modelling techniques may also reveal threshold effects and complex dynamics.

AUTHOR CONTRIBUTIONS

Conceptualization: Olfa Chaouech.
Data curation: Olfa Chaouech.
Formal analysis: Olfa Chaouech.
Investigation: Olfa Chaouech.
Methodology: Olfa Chaouech.
Software: Olfa Chaouech.
Validation: Olfa Chaouech.
Writing – original draft: Olfa Chaouech.
Writing – review & editing: Olfa Chaouech.

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APPENDIX A

Table A1. Variables description with measurements and source

Variables and symbols	Description	Measurement	Data source
Dependent variable			
Gini Index (Gini)	A measure of income inequality where values closer to 0 indicate greater equality, and values closer to 100 represent higher inequality	Index	SWIID database
Independent variable			
VUL	A value close to 0 indicates low climate change vulnerability, whereas a value approaching 1 signifies high vulnerability to the impacts of climate change	Index	ND-GAIN
RED	A high value (close to 1) indicates that a country excels in its institutional framework, culture of innovation, business practices, and education level	Index	ND-GAIN
Control variables			
GDP	This measure reflects the total economic output of a country, adjusted for taxes and subsidies	GDP per capita (constant 2015 thousand USD)	WD
TB	Sum of exports and imports of goods and services, expressed as a share of GDP	% del GDP	WD
UPG	Percentage of the total population living in areas designated as urban, according to classifications by national statistical offices	% Annual growth	–
UE	The active population that is without work but actively seeking and available for employment	total (% of total labor force)	–
NRR	Total income generated from oil, natural gas, coal (both hard and soft), minerals, and forests	% of GDP	–
Rg	The rights index is the second of the four attributes of democracy indices. This attribute comprises four subattributes: Access to Justice, Civil Liberties, Basic Welfare, and Political Equality which were aggregated into the Rights Index using the BFA method	Index	International IDEA

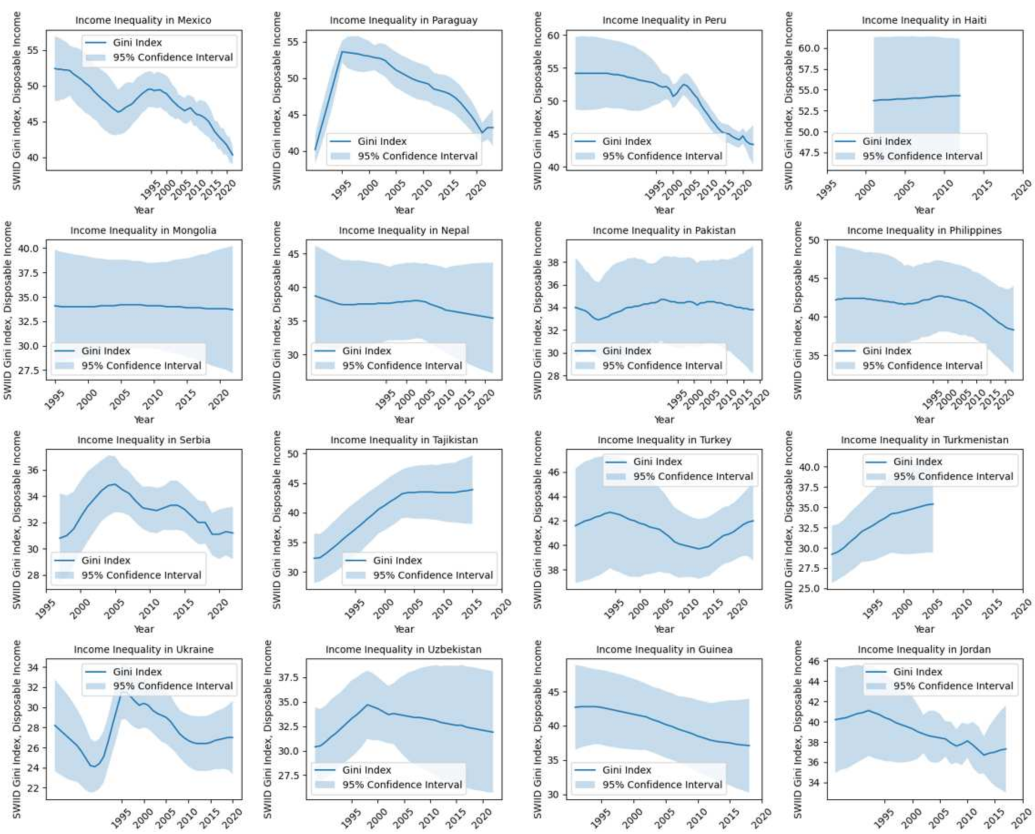

Figure A1. Plots SWIID gini_disp estimates with Confidence Intervals for the 61 countries of our sample

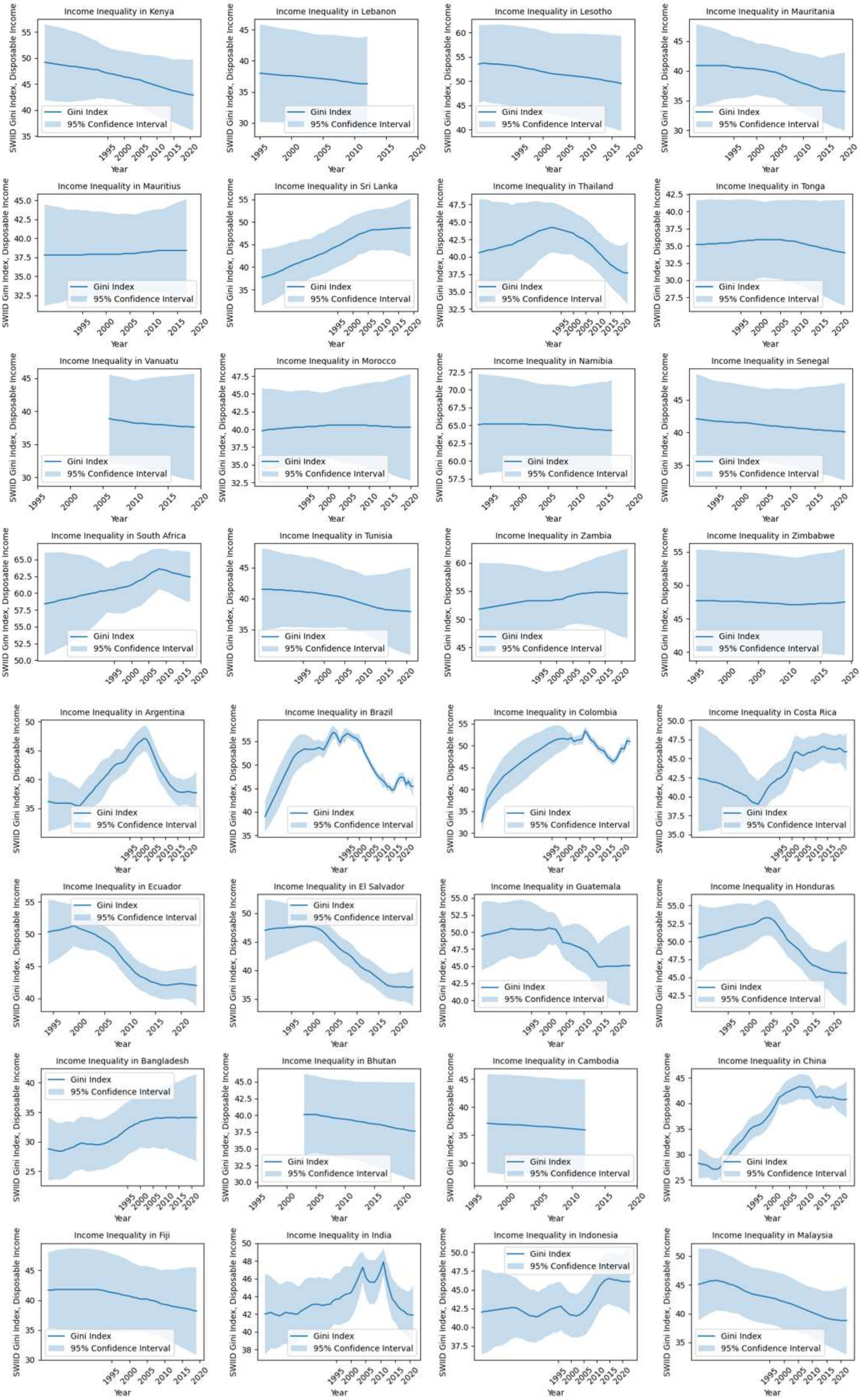

Figure A1 (cont.). Plots SWIID gini_disp estimates with Confidence Intervals for the 61 countries of our sample

http://dx.doi.org/10.21511/ee.16(3).2025.06

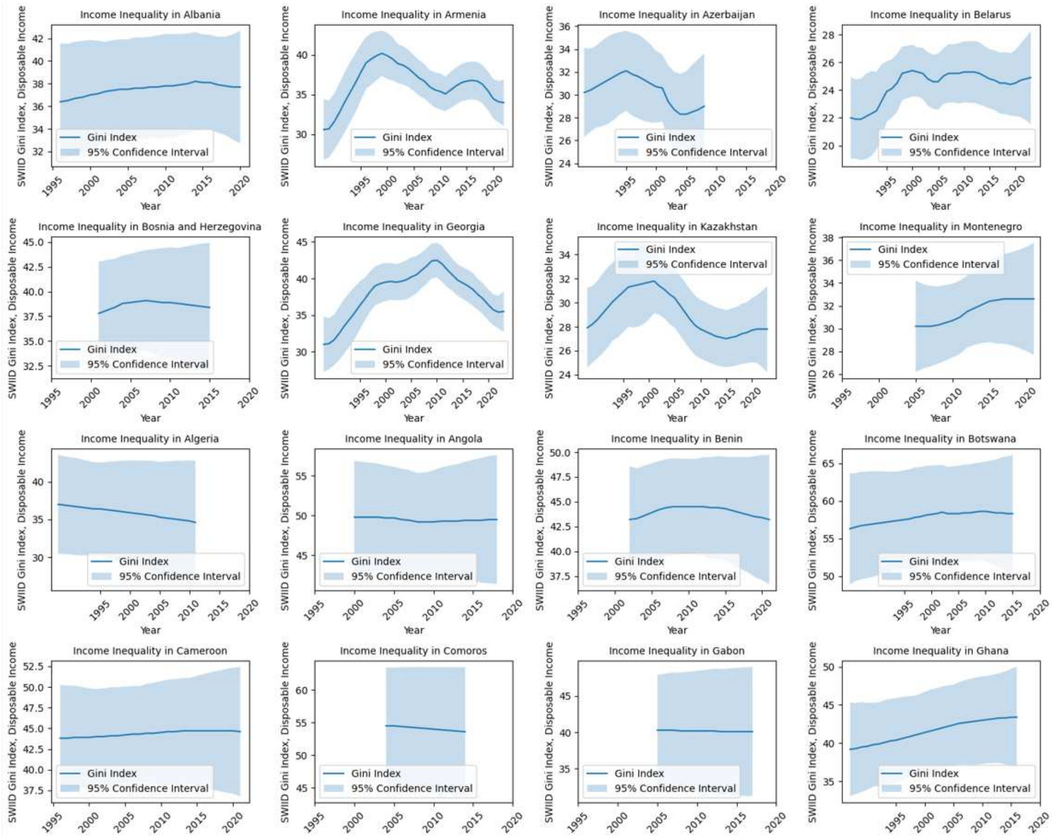

Figure A1 (cont.). Plots SWIID gini_disp estimates with Confidence Intervals for the 61 countries of our sample