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Does Income Inequality Endanger Green Growth? Evidence from Selected Countries in Asia and the Global South

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Abstract Income inequality poses a constraint to inclusive growth and development, but whether and how economic inequality affects green growth is relatively understudied in the existing literature. To address this empirical and knowledge gap, the analysis of the paper begins with theoretical perspectives on the diffusion of green growth technologies and how it relates to income inequality. We collected annual data from selected Global South countries from 1991 to 2019 and then used the pooled mean group-autoregressive distribution lag (PMG-ARDL) and the augmented mean group- autoregressive distribution lag (AMG-ARDL) as a benchmark estimation methods and cross-sectional autoregressive distribution lag (CS-ARDL) for robustness checks to investigate the short- and long-run implications for green growth. The results show that higher income inequality is associated with reduced green growth in the long run, whereas the short-run results are mixed. The findings suggest that governments in the Global South should implement effective reforms aimed at lowering inequality while reducing carbon emissions and promoting a green economy.

Keywords: Income Inequality, Green Growth, $C0_2$ Emissions, Climate Change, Global South

JEL Classifications: P46, Q43, Q55

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I. Introduction

The interaction between the environment and the economy has recently garnered much attention (Stern, 2008), which has important implications for inclusive development and poverty reduction in the Global South. These are critical to attaining the Sustainable Development Goals (SDGs) 2030. In the quest to green the economy, inequality is at the centre stage of economic policy debate across the globe. A 'fair share' in income distribution is fundamental to 'going

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green', and efficient production practices (output-input ratio) across countries and businesses can influence productivity levels and Growth (Syverson, 2011). However, developing economies in the global South rely more on exploiting the environment's natural resources. At the same time, these countries are inaccessible to green technologies. This has proven difficult to account for both environment-related inputs (e.g., use of natural resources) and environment-related outputs (e.g., air pollution). Recent studies have linked economic inequalities with environmental problems (Khan et al., 2022; Langnel et al., 2021; Uzar & Eyuboglu, 2019). The Organization for Economic Co-operation and Development (OECD) has estimated a measure of productivity growth that accounts for the generation of a small set of greenhouse gases (GHGs) and criteria air contaminants (CACs) that cause environmental damages from economic activity. Additionally, the works of Brandt et al. (2014), Dang and Mourougane (2014), and Cárdenas Rodríguez et al. (2018) have provided a roadmap that allows environmentally adjusted multifactor productivity (EAMFP) growth to be calculated in a growth accounting framework.

Several theoretical approaches have been presented to question whether green growth, as a policy solution to climate change and environmental concerns, may help to reduce income disparities. For example, government intervention, such as progressive taxes and income transfers, may ameliorate income inequality, and green development can only be realized through public investment in renewable energy and energy efficiency (Duraiappah, 1998). Similarly, O'Neill (2020) contends that the dominance of corporations and the rich, who frequently have a strong interest in sustaining the status quo, can limit government action. Income inequality is caused by unequal distribution of natural resources, according to ecological economists, and green growth can only be attained through a massive overhaul of the market structure, including the adaptation of a green new deal and the progress of alternative forms of ownership, such as microcredit and commons-based peer production (Kallis, 2011). Furthermore, Hickel and Kallis (2020) believe that even under favorable policy conditions, the rate of CO2 emission reductions required to prevent global warming of more than 1.5 °C or 2 °C is highly unlikely. On the other hand, transitioning to green growth has the potential to create 24 million new jobs globally by 2030 if appropriate policies are adopted (ILO, 2018), as well as reduce poverty among low-income households.

Previous empirical research has concentrated on environmental technologies and green Growth (Danish & Ulucak, 2020), technological diffusion and green growth (Wang et al., 2021), environmental entrepreneurship and green development (Wei, Ren, Ullah, & Bozkurt, 2023), innovation technology efficiency and green Growth (Mensah et al., 2019; Zhang & Vigne, 2021; Zhang et al., 2018), and financial development and green Growth (Chen et al., 2023). However, only a few studies focused on economic inequality (Fiorino, 2018; Napolitano et al., 2022; UNEP, 2016). According to a study conducted by the United Nations Environment Programme (UNEP, 2016), green growth can help to reduce economic disparities by creating new green jobs and boosting low-income households' access to clean energy and energy efficiency. Considering all of the preceding points, the extant literature produces mixed results due to their complexity.

Does income inequality endanger green growth? In this paper, data on the EAMFP and environmental innovation were sourced from the OECD database, income inequality from the Standardized World Income Inequality Database (SWIID), financial development from the KOF Swiss database, general government final consumption expenditure from the World Bank's World Development Indicators, and educational attainment from the Barro & Lee database. This paper employs the PMG-ARDL model for the baseline estimation and the CS-ARDL model for robustness checks. A novel battery of tests to examine the cross-dependence, panel unit roots, and cointegration among variables in the sampled group of countries.

We find that rising income inequality is negatively associated with green growth. The results of both the PMG-ARDL and AMG-ARDL models suggest that addressing income inequality is crucial for cutting down carbon emissions and fostering a green economy. Further, the coefficients for environmental innovation are positively and statistically significantly linked to green growth, suggesting that countries in the Global South can develop new solutions and technologies that help mitigate environmental damage by investing in and promoting environmental innovation. In terms of the country-specific models, coefficient estimates show that a 0.1%-point increase in income inequality reduces green growth by 0.002% in Brazil and Costa Rica, 0.001% in Colombia, 0.003% in China, 0.004% in India and South Africa, and 0.005% in Indonesia in the long run. These results are similar to those reported in the robustness checks (CS-ARDL model), and the computed coefficients for the ECT are negative and statistically significant at the 1% level for both model results. Similarly, this paper reveals three possible ways of Granger causation (unidirectional, bidirectional, and no-causality) for the effects of income inequality on green growth.

This paper contributes to the literature on the relationship between income inequality and green growth in the Global South. Several studies have been conducted to investigate whether and how income inequality affects the green economy (Boyce, 1994; Danish & Ulucak, 2020; Fiorino, 2018; Heerink et al., 2001; Mensah et al., 2019; Napolitano et al., 2022; UNEP, 2016; Wang et al., 2021; Zhang et al., 2018), all either concentrated on green technology innovation or the diffusion of technologies in one or a few countries. Others were concerned with environmental entrepreneurship and financial development (Cao et al., 2022; Chen et al., 2023; Wei et al., 2023). Green growth covers additional significant indicators, such as the efficient use of natural resources, that other studies have not yet explored. Further to that, green growth measures the balance between economic development and environmental sustainability (Tawiah et al., 2021). Our measure of green growth is not one-sided, as used in prior studies. This paper distinguishes itself from the others by investigating how income inequality affects green Growth in Global

South economies using the OECD's green growth measurement. Although similar in spirit to the studies of Fiorino (2018) and UNEP (2016), this paper differs in using novel methodological investigation.

Given the lack of consensus among theoretical and empirical studies on the relationship between income inequality and green growth, this paper contributes to a better understanding of these complex issues. The transition to a green economy is about more than just lowering carbon emissions and safeguarding the environment; it is about providing inclusive economic opportunities and encouraging energy independence. Green energy accessibility and consumption are very unequally distributed across the Global South, with low-income households meeting their energy demands using firewood and charcoal and facing an increasing price of some of these green energies. This condition has hindered some consumers from transitioning to cleaner energy and increases the risk of increasing inequality. Green growth policies can have either negative or positive societal consequences depending on how they are designed and implemented. For example, when a policy gives economic support to lower-income households, lowering poverty benefits higher-income households even more by allowing them to take advantage of the direct benefits of green growth policy incentives more easily, widening the wealth gap. Finally, this paper discusses policy implications for Global South policymakers and private-sector enterprises. The findings could help them focus more on appropriate climate financing measures, equal access to resources and opportunities, green incentives for the private sector, enabling access to education, and considering progressive tax policies, all of which are important factors in the race to a green economy.

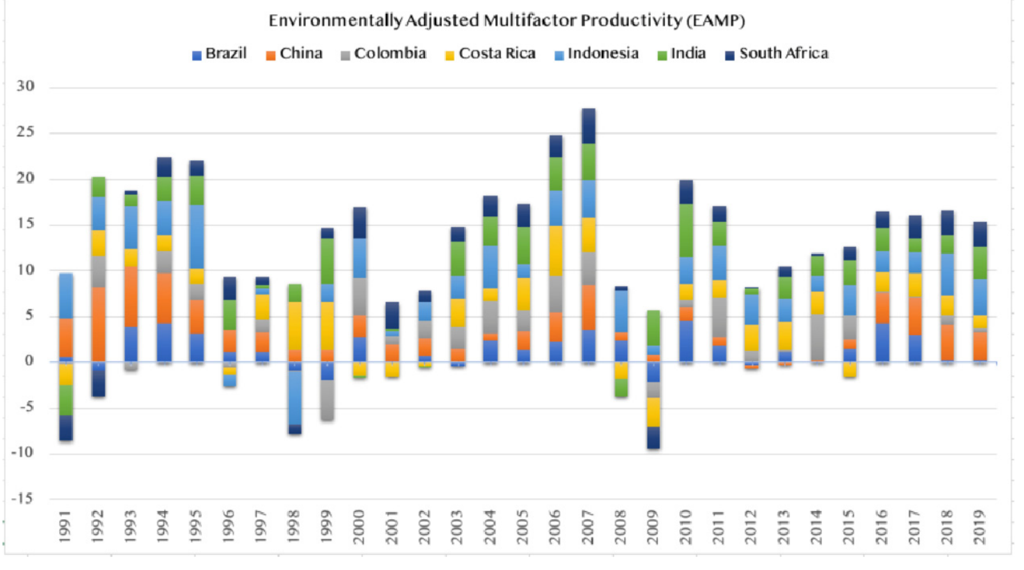
The following is a reminder of this paper. Section 2 presents the background to income inequality and green growth. Section 3 discusses theoretical perspectives and related empirical literature. Section 4 describes the data sources, summary descriptions, and econometric specifications. Section 5 presents the results and discussions. Section 6 concludes with policy implications.

II. Background to Inequality and Green Growth

The EAMFP measures a country's ability to produce more income using a given set of inputs, such as domestic natural resources while accounting for the undesirable by-products of pollution (Cárdenas Rodríguez et al., 2018). According to the OECD (2023), EAMFP compares multifactor productivity (MFP) more accurately in measuring and evaluating an economy's growth quality, as natural resources and the environment become a harder constraint on economic growth. Several factors, such as technological improvements-oriented production of good outputs and transitioning towards cleaner technologies, human capital enhancement, strong and efficient institutions, and comparative advantage of economies of scale, can play a huge role in productivity. However, the undesirable outputs consist of emissions of greenhouse gases (GHGs), which induce climate change and constitute environmental problems.

Figure 1 presents EAMFP growth in seven Global South economies (Brazil, China, Colombia, Costa Rica, Indonesia, India, and South Africa) from 1991 to 2019 using the OECD database. Compared to the rest of the countries, China has consistently assessed an economy's productivity performance while considering the effects of environmental degradation. However, China was responsible for 32.9% of global CO2 emissions (EU, 2021).

Figure 1. Trend of Environmentally Adjusted Multifactor Productivity Growth (EAMFP) in selected global South countries (1991-2019)



(Source) Author's calculation based on OECD (2023) database

Despite global attempts to lift millions out of poverty, the gap between the "*haves*" and "*have-nots*" is growing. Inequalities in the Global South have many faces when compared to the Global North, such as lack of access to opportunities, healthcare, Education, water, food, and basic infrastructure-all of which render poorer households more vulnerable to natural disasters and climate change. For example, 40% of the poorest South Africans' annual salary is less than US$1,000 per person, compared to US$39,000 per person income for the Global North's top 10% in 2017 (Gradin et al., 2021). Regarding income inequality, as shown in Figure 2, the percentage of poor individuals has decreased in Brazil and India during the last decade. China, Indonesia, and South Africa, on the other hand, are steadily declining. Income inequality can have a negative impact on green growth by limiting poorer households' access to resources and opportunities. Low-income households, for example, may lack the financial ability to invest in environmentally beneficial technologies such as renewable energy systems or energy-efficient appliances. As a result, these households' ability to engage in a low-carbon and green economy is limited.

Figure 2. Trends in income inequality in selected global South countries

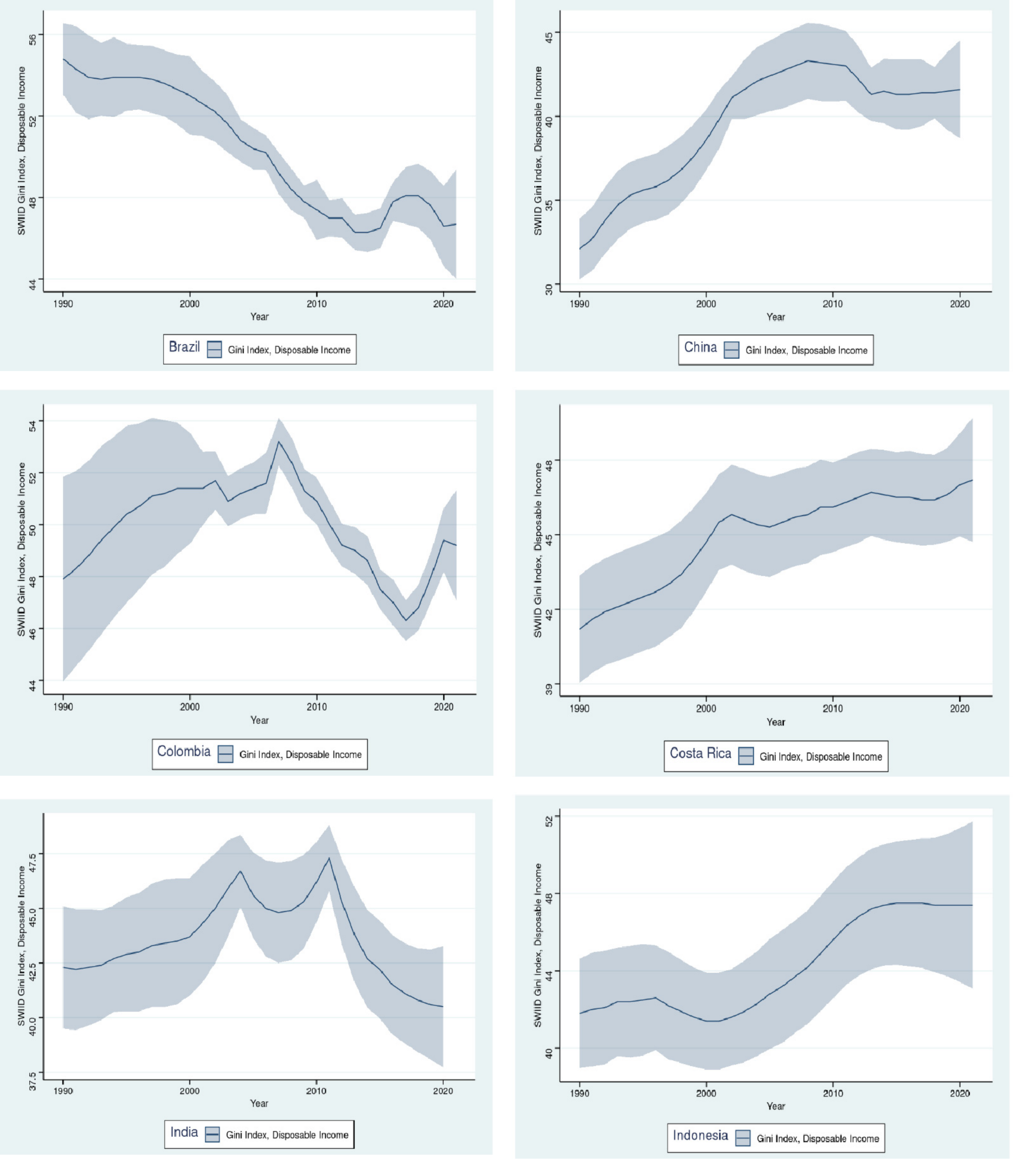
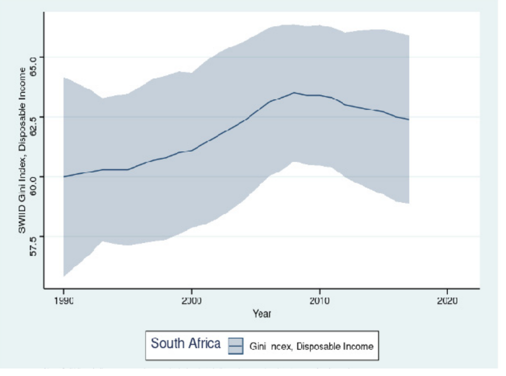


Figure 2. Continued



(Source) Authors' calculation based on Solt (2020)
Note. Solid lines indicate mean estimations; shaded regions indicate the associated 95% uncertainty intervals

III. Review of Literature and Hypothesis Development

Green Growth, or the green economy, has dominated development and environmental economics in recent years. This was the biggest concern of the 2012 Rio+20 Conference on Sustainable Development. Many governments worldwide consider green growth as an overwhelmingly dominant policy response to increasingly urgent warnings about climate change and ecological concerns (Dale et al., 2016). However, few studies link income inequality to green growth. This linkage is also understudied in other parts of the world, with most studies focusing on environmental sustainability. This section provides a brief theoretical basis and related empirical literature and tests two hypotheses.

A. Theoretical Explanation

Green Growth is synonymous with a low-carbon or green economy that is both environmentally sustainable and socially inclusive. The OECD (2001) defines green growth as "fostering economic growth and development while ensuring that natural assets continue to provide the resources and environmental services on which our well-being relies" (p.18). There have been several theories put forward to explain these two concepts. Academia has shaped theoretical views on the link between income inequality and green growth, including neoclassical, Keynesian, and ecological economics. Income inequality is caused by market forces, according to neoclassical economists, and green growth can only be achieved by market-based solutions such as carbon tax and carbon trading (Stiglitz, 2012). According to this theory, markets can absorb environmental costs and drive businesses to implement more sustainability measures, reducing economic disparities. However, O'Neill (2020) argues that market-based systems cause environmental degradation because they benefit the wealthy at the expense of the poor.

Conversely, Keynesians believe that government intervention, such as progressive taxation and income transfers, may alleviate income inequality and that green development can only be realised by public spending on renewable energy and energy efficiency (Duraiappah, 1998). This school of view claims that government intervention can help produce a more equitable income distribution and that public investment can help overcome market failures and provide the infrastructure needed for green growth. Some critics, however, argue that the influence of corporations and the wealthy, frequently vested in maintaining the status quo, can constrain government action (O'Neill, 2020). Income inequality, according to ecological economists, is caused by the unequal distribution of natural resources, and green growth can only be achieved through a significant overhaul of the market structure, including the adoption of a green new deal and the advancement of alternative forms of ownership, such as microfinance institutions and commons-based peer production (Kallis, 2011). They believe that the current economic system, based on the extraction of natural resources and the accumulation of private wealth, is the fundamental cause of income inequality and environmental degradation. The economic system must be significantly restructured to achieve green development and eradicate wealth disparities.

From institutional viewpoints (the OECD, the United Nations Environment Programme (UNEP), and the World Bank), technological change and substitution advances will increase the economy's ecological efficiency, and government should accelerate the formulation of appropriate regulations and incentives. Transitioning to green growth could generate 24 million new employment globally by 2030 if the appropriate policies are implemented (ILO, 2018) and reduce poverty among low-income households. Although China and India have experienced relative decoupling (Wiedmann et al., 2015), there is little indication of persistent absolute decoupling of GDP in South Africa (Hickel & Kallis, 2020). One persistent debate is that green growth necessitates a shift toward cleaner, more sustainable energy systems—a type of decoupling of economic growth from resource use and its negative environmental consequences. Because economic progress in the form of GDP is compatible with the planet's ecology, green growth theorists assume absolute decoupling of GDP growth from resource utilization and carbon emissions at a rate sufficient to prevent climate change and other ecological concerns (see Solow, 1973). To that end, Stern's (2008) seminar work has consistently made a case for incorporating environmental problems into economic activity, arguing that firm and timely actions can avoid the economic costs of delaying decisions on climate change and environmental challenges.

B. Empirical Literature

Following the theoretical views, many previous studies have used empirical data to focus on environmental technologies and green Growth (Danish & Ulucak, 2020), technological diffusion and green Growth (Wang et al., 2021), environmental entrepreneurship and green development (Wei et al., 2023), innovation technology efficiency and green growth (Mensah et al., 2019; Zhang & Vigne, 2021; Zhang et al., 2018) and financial development and green Growth (Cao et al., 2022; Chen et al., 2023), but few have looked at inequality and environment (Boyce, 1994; Heerink et al., 2001), green innovation and inequality (Napolitano et al., 2022), and green economy and inequality (Fiorino, 2018; UNEP, 2016). Green Growth, for example, might assist in reducing economic disparities by creating new green jobs and boosting low-income households' access to clean energy and energy efficiency, according to a study conducted by the United Nations Environment Programme (UNEP, 2016). Greener societies are more economically equitable, but excessive economic inequality fosters social mistrust and isolation, undermining the ability to collectively value public assets (Fiorino, 2018). In Nigeria, Haruna and Alhassan (2022) employ Auto-regressive Distributed Lags (ARDL) on data from 1991 to 2018 and show that even high amounts of informality can promote income inequality in the short run.

In contrast, using parametric modelling on a panel sample of 57 countries between 1970-2010, Napolitano et al. (2022) show that inequality harms countries' ability to create complex green technology. Excessive economic inequality can impede green growth by reducing the market for environmentally sustainable goods and limiting authorities' opportunity to invest in renewable energy and energy efficiency. Similarly, large income disparities may reduce the purchasing power of low-income households, restricting them from spending on renewable energy and energy-efficient technologies. Using OLS and IV approaches, Aghion et al. (2019) conducted an empirical study using data from 1980 to 2005 and confirm a similar finding by looking at the distribution of labour and firm owners and the rate of technology innovation. They observe that technological innovation promotes entrepreneurship while increasing income inequality. They use ordinary least squares and instrumental variables in the commuting zone data of the U.S.

Additionally, high levels of economic inequality may impede political will to invest in sustainable innovation because the wealthy and businesses hold more power over government policy and are more inclined to resist government intervention. As a result, there is a trade-off between increased social expenses of green growth and poverty-reduction growth (Dercon, 2012), and the government should evaluate environmental policies and huge promises of obvious benefits at little or no cost (Schmalensee, 2012). Understanding the potential trade-off between sustainability and social fairness in fostering green growth in the Global South is important. Although existing studies provide some insight into green growth and income inequality, they failed to consider the Global South, where these issues are more relevant. Also, none of them captured both short-term and long-term relationships, as done in this current paper.

The relationship between income inequality and green growth is complex. While different theoretical perspectives provide different approaches, it is widely accepted that reducing economic inequality and boosting green growth are complementary and interrelated goals that must be addressed simultaneously to ensure sustainable development.

Based on the preceding literature review, we put forward the following hypothesis.

H1. An increase in income inequality reduces green growth

IV. Data and Methodology

A. Data Sources and Descriptive Statistics

This study uses panel data from seven Global South countries (China, Colombia, Costa Rica, India, Indonesia, and South Africa). Based on data availability, these countries were carefully selected. Data on the EAMFP (measured as green growth) were obtained from the OECD (2023) database, Income Inequality (as measured by the Gini index) from the Standardized World Income Inequality Database (SWIID), Environmental Innovation (as measured by the development of environment-related technologies) from the OECD database, Financial Development from the KOF Swiss database, General Government Final Consumption Expenditure from the World Bank's World Development Indicators, and Educational Attainment from the Barro & Lee database.

Table 1 shows the descriptive statistics for the model's dependent and explanatory variables, which were used to investigate whether income inequality harms green growth in the Global South's economies. These variables came from various sources. Green Growth in this study has an average value of 7.8%, with the maximum value being 14.2% and the minimum value being 0.3%, with a standard deviation of 2%. The Gini index, on the other hand, has a mean value of 13%, with maximum and minimum values of 47.5% and 0.30%, respectively. The average value of environmental innovation is 10.4%, with a maximum of 42.9%, a minimum of 2.3%, and a standard deviation of 10.4%. Furthermore, the pairwise correlation matrix is shown in Table A6 (online appendix), and this study ensures that it does not exceed generally utilized standards (0.7). The variable definitions and descriptive statistics are listed below.

Table 1. *Variable Definitions and Descriptive Statistics*

Variables	Definitions	Mean	Std. Dev.	Min	Max	Sources
GG	Environmentally adjusted multifactor productivity	7.86	2.09	0.38	14.20	OECD
GN	Income inequality	13.44	19.55	0.30	47.50	SWIID
EI	Development of environment-related technologies (% of all technologies)	10.42	5.20	2.32	42.92	OECD
FD	Financial globalization index	45.28	11.60	16.84	76.42	KOF Swiss
GovSpend	General government final consumption expenditure (% of GDP)	14.45	3.72	5.69	22.16	WDI
EDU	Educational attainment	24.30	11.28	1.88	63.76	Barro & Lee

Note. OECD computed EAMFP as a percentage change over time by comparing the performance of different nations.

B. Econometric Model

From a theoretical standpoint, income inequality could have a negative or positive effect on green growth, depending on the trade-off between sustainable environmental policies and addressing the issues of social inequities (Hickel & Kallis, 2020; O'Neill, 2020). Following Sun (2022) and Kousar et al. (2022), the model is expressed as follows:

$$GG_{it} = \beta_0 + \beta_1 GINI_{it} + \beta_2 EI_{it} + \beta_3 FD_{it} + \beta_4 GovSpend_{it} + \beta_5 Edu_{it} + \epsilon_{it} \tag{1}$$

where GG_{it} is the dependent variable; $GINI_{it}$ represents income inequality; EI_{it} denotes environmental innovation; FD_{it} is the financial development; $GovSpend_{it}$ and Edu_{it} represent government spending and educational attainment, respectively; and ϵ_{it} is the error term. Equation (1) presents only the long-run estimates.

To capture both the long-run and short-run estimates, the PMG-ARDL model introduced by Pesaran et al. (1999) is specified as follows in error correction form:

$$\begin{aligned}\Delta GG_{it} = \beta_0 &+ \sum_{i=1}^{p} \pi_{1k} \Delta GG_{it-i} + \sum_{i=1}^{p} \pi_{1k} \Delta GINI_{it-i} + \sum_{i=1}^{p} \pi_{1k} \Delta EI_{it-i} \\ &+ \sum_{i=1}^{p} \pi_{1k} \Delta FD_{it-i} + \sum_{i=1}^{p} \pi_{1k} \Delta GovSpend_{it-i} + \sum_{i=1}^{p} \pi_{1k} \Delta Edu_{it-i} + \beta_1 GINI_{it-1} \\ &+ \beta_2 EI_{it-1} + \beta_3 FD_{it-1} + \beta_4 GovSpend_{it-1} + \beta_5 Edu_{it-1} + \eta . ECM_{t-1} + \epsilon_{it} \end{aligned} \tag{2}$$

In addition to the panel PMG-ARDL model, the CS-ARDL model proposed by Chudik and Pesaran (2015) is used as a robustness check. In comparison to standard approaches such as random effect and pooled ordinary least squares, the CS-ARDL approach addresses slope homogeneity and cross-sectional dependence concerns, as well as multicollinearity, autocorrelation, and endogeneity. The augmented ARDL model captures cross-sectional correlation in the error term by using a linear combination of cross-sectional averages and all regressors. As in Chudik and Pesaran (2015), the CS-ARDL is estimated using both mean group (MG) and PMG-ARDL estimators. The following is the model's specification:

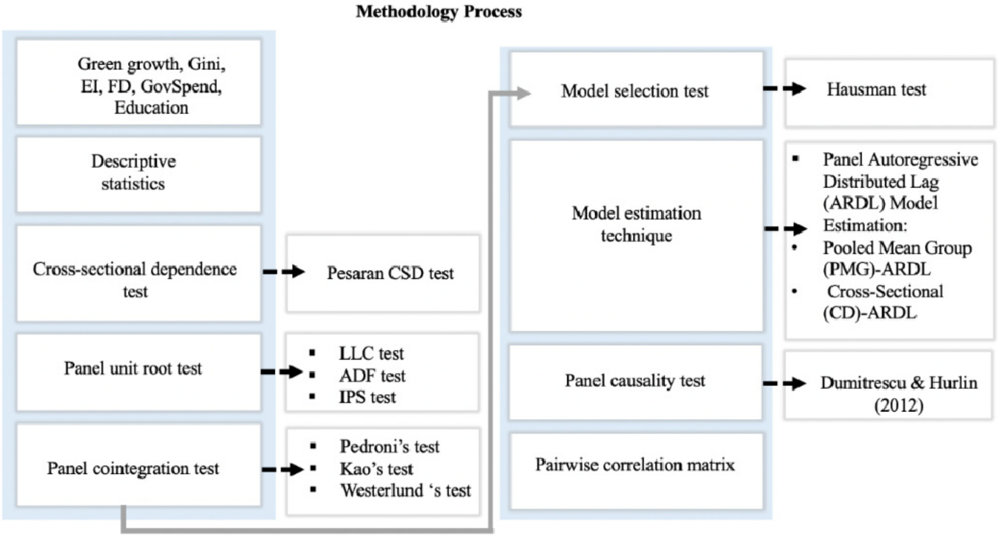
$$\begin{aligned}\Delta GG_{it} = \phi_0 + \gamma_{it}\left(GG_{it-1} - \beta_i X_{it-1} - Y_i C_{it-1} - \phi_{1i} GG_{it-1} - \vartheta_2 \overline{X}_{it-1} - \rho_2 \overline{C}_{it-1}\right) \\ + \sum_{j=1}^{p-1} \phi_{ij} \Delta GG_{it-j} + \sum_{i=1}^{q-0} \varsigma_{ij} \Delta X_{it-j} + \sum_{i=1}^{q-1} \pi_{1k} \Delta C_{it-J} + \omega_{1it} \Delta GG_{it} \\ + \omega_{2it} \Delta \overline{X}_{it} + \omega_{3it} \Delta \overline{C}_{it} + \epsilon_{it}\end{aligned} \tag{3}$$

where $\overline{X}$ and $\overline{C}$ are the cross-section average of GG_{it} and X_{it}. The CS-ARDL assists in jointly handling the dynamics, heterogeneity, and cross-sectional dependency in data that requires the estimation of heterogeneous coefficients (see Eberhardt & Presbitero, 2015; McNabb, 2018).

It is critical to emphasize that the time dimension (T) must be large enough to allow the model to be assessed across every cross-country unit, and a considerable number of lagged cross-section averages may be added to validate the estimators. These estimators have been used in various empirical growth studies due to their consistency and effectiveness (De V. Cavalcanti et al., 2015; Samargandi et al., 2015).

The first step in the panel ARDL approach is determining whether the variables have a long-run correlation. Specifically, the null hypothesis of no cointegration (H_0 : $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$) is assessed using an F-test against the alternative hypothesis (H_0 : $\beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq 0$) using an F-test. After that, the computed F-statistics are compared to two sets of critical values: upper and lower (Pesaran et al., 2001). The null hypothesis can be rejected if the computed F-statistics are more than (less than) the upper (lower) critical value, confirming the existence (absence) of the long-run relationship. For this reason, this study investigates the time series properties of the order of integration. This is required to determine whether the variables are stationary at order $I(0)$, $I(1)$, or both. Following that, the Hausmann test was used to choose an ARDL model based on the model selection criteria used to estimate the short- and long-run models. The panel ARDL evaluates both short- and long-run impacts at the same time. The long-run effects are derived from β_2 - β_5, by normalizing β_1, but the short-run effects in Equation (2) are established by first-differenced signs, as this technique considers endogeneity and serial correlation. The methodological approaches used in this investigation are shown in Figure 3.

Figure 3. Methodological framework in this study



(Source) Author's construction

V. Results and Discussion

A. Preliminary Tests

Some preliminary tests, such as cross-sectional dependence, unit root, and cointegration, are crucial to be performed before proceeding with panel model estimation (Pedroni, 2019; Pesaran, 2021). The results of the proposed cross-sectional dependence test are presented in Table 2 (Pesaran, 2015). The estimates show that the variables are interdependent and statistically significant at the 1% level. Consequently, the null hypothesis of no cointegration is rejected. Any shocks in one economy will almost surely affect the others in the sampled group. The unit root tests are then run, and the results are displayed in Table 3. This study employs the Levin, Lin, and Chu (LLC), Augmented Dickey-Fuller (ADF), and Im, Pesaran, and Shin (IPS) tests. For example, the LLC unit root test results demonstrate that Green Growth, ENVINNO, FINDEV, GOVSpend, and Education are stationary at order $I(0)$, whereas Gini is stationary at order $I(1)$. However, ADF and IPS follow the same pattern of Green Growth and GOVSpend stationarity at the order $I(0)$, whereas Gini, ENVINNO, and FINDEV are stationary at $I(1)$.

Furthermore, after assessing the data series' stationarity properties, the LLC, ADF, and IPS are utilized to test the long-run cointegration relationship between green growth and its drivers. Table 4 (Panel1-3) shows the results of the panel cointegration tests, demonstrating that the null hypothesis is rejected and that long-run cointegration exists among some of the variables in the model. The findings of the Westerlund panel cointegration test with constant and trend, for example, show evidence of rejecting the null hypothesis for G_t, P_t, and P_a tests statistics, indicating a cointegration relationship in at least a few cross-sectional units (i.e., in at least one group) (Westerlund, 2007). Because there are indications of mixed order of integration, the findings highlight an important conclusion for adopting the approach to assess cointegrating relationships. This investigation considers a second-generation cointegration test with mixed and strict integration orders. Given the cross-sectional dependency and unit root results, the next step is to focus on and analyze the long-run model using a robust estimator that can accommodate cross-sectional dependency, given the variables' stationarity.

Table 2. *Cross-Sectional Dependence*

Variables	GG	GN	EI	FD	GS	ED
Pesaran (2004) test	3.99***	4.160***	6.912***	4.736***	3.36***	5.173***
Prob.	0.000	0.000	0.000	0.000	0.001	0.000
Off-diagonal elements	0.202	0.357	0.478	0.306	0.353	0.416

Note. ***p<0.01; **p<0.05; *p<0.1

Table 3. *Panel Unit Root Test*

Variables	LLC		Decision	ADF		Decision	IPS		Decision
	I(0)	I(1)		I(0)	I(1)		I(0)	I(1)	
Green Growth	-6.670***		I(0)	-8.532***		I(0)	-7.842***		I(0)
Gini	4.020	-3.522***	I(1)	3.583	-4.850***	I(1)	4.387	-4.411***	I(1)
ENVINNO	-1.567*		I(0)	-0.514	-6.224***	I(1)	-0.545	-5.89***	I(1)
FINDEV	-2.878***		I(0)	-1.106	-6.362***	I(1)	-1.056	-5.717***	I(1)
GOVSpend	-1.972**		I(0)	-1.501*		I(0)	-1.400*		I(0)
Education	-2.124**		I(0)	3.601	-3.524**	I(1)	2.561	-2.574***	I(1)

Note. ***p<0.01; **p<0.05; *p<0.1

Table 4. *Panel Cointegration Tests*

Panel A: Pedroni (2004)'s Estimates

CG = f(GG, GN, EI, FD, GS, EDU)	Statistics	Prob.
Modified Phillips-Perron t	1.848**	0.032[b]
Phillips-Perron t	-5.415***	0.000[a]
Augmented Dickey-Fuller t	-5.391***	0.000[a]

Table 4. *Continued*

Panel B: Kao's Estimates

CG = f(GG, GN, EI, FD, GS, EDU)	Statistics	Prob.
Modified Dickey-Fuller t	-6.524***	0.000[a]
Dickey-Fuller t	-7.504***	0.000[a]
Augmented Dickey-Fuller t	-6.665***	0.000[a]
Unadjusted modified Dickey-Fuller t	-15.947***	0.000[a]
Unadjusted Dickey-Fuller t	-9.761***	0.000[a]

Note. In both panels, Pedroni and Kao procedures are estimated, ***p<0.01; **p<0.05; *p<0.1 (a, and b) show a significance level of 1% and 5%, respectively.

Panel C: Westerlund panel cointegration test

Statistics	Gt	Ga	Pt	Pa
Value	-4.383***	-15.765	-12.554***	-18.021**
z-value	-4.822	-0.254	-5.806	-2.129
P-value	0.000	0.400	0.000	0.017

Note. ***p<0.01; **p<0.05; *p<0.1

B. Empirical Results

Table 5 presents the estimation results for the PMG-ARDL, AMG-ARDL, and CS-ARDL models. The long-run estimates based on the PMG-ARDL model in column 1 indicate that the coefficient on the error correction term (ECT) is statistically significant at the 1% level. This conclusion suggests that following a shock, the system regresses to its long-run values, showing that some variables are cointegrated. The main focus of this analysis is income inequality. According to the findings, rising income inequality reduces green growth. The coefficient is statistically significant at the 1% level, implying that every 0.1-point increase in income inequality reduces green growth by 0.038%. These findings are consistent with Hallegatte et al. (2012) and Kim et al. (2014).

Furthermore, environmental innovation is positively and statistically significantly associated with green growth at the 1% level, implying that a 0.1% increase in environmental innovation boosts green growth by 0.143%. These findings corroborate prior empirical work by Mensah et al. (2019), Zhang et al. (2018), and Danish and Ulucak (2020). In the long run, government spending and educational attainment have a positive and statistically significant impact on green growth at the 1% level, respectively. This means that long-term investment in research and development can lead to increased green growth. However, the short-run estimate gives mixed findings. However, utilizing the third lag, income inequality continues to have a negative impact on green growth. High levels of income inequality can limit low-income households' purchasing power, as they may lack the funds for investment in renewable energy and energy-efficient technologies.

Next, we present the estimated results for the AMG-ARDL in column 2 of Table 5. The coefficient is statistically negative at the 1% level in the long-run estimates. More specifically, a 0.1-point increase in income inequality reduces green growth by -0.038% in the countries under study. This suggests that as income inequality rises, countries' potential to be environmentally sustainable decreases. Similarly, we observed a positive correlation between environmental innovation (0.024%, financial development (0.508%), government spending (0.304%), education (0.123%), and green growth. The short-run estimated results are similar to those obtained in column 1 (PMG-ARDL). The estimated results are robust as indicated by a negative and statistically ECT.

Table 5. *Panel Estimation of Green Growth*

Variables	(1) Basic model PMG-ARDL		(2) AMG-ARDL		(3) Robustness model CS-ARDL	
	Coefficient	t-Stat	Coefficient	z-Stat	Coefficient	z-Stat
Long-Run Equation						
GINI	-0.038***	-6.139	-0.041**	-2.34	-0.002*	-1.97
ENVINNO	0.143***	3.662	0.123**	2.37	0.017	1.50
FINDEV	0.963	0.912	0.508	-1.98	-5.509	-1.01
GOVSpend	0.969***	5.364	0.304***	1.94	-0.134	-0.60
Education	0.077***	2.798	0.024***	2.13	0.145	0.56
Short-Run Equation						
⊿(GINI)	0.012	1.245	0.019	0.40	-0.001	-0.60
⊿(GINI(-1))	0.002*	1.672	0.014*	1.26	-0.004***	-3.74
⊿(GINI(-2))	-0.003**	-2.143	-0.023**	-2.35		
⊿(ENVINNO)	-0.019	-1.219	-0.843	0.08	0.002	0.36
⊿(ENVINNO(-1))	-0.018	-0.928	-0.843	-1.36	0.018	1.52
⊿(ENVINNO(-2))	-0.012*	-1.804	-0.043	0.48		
⊿(FINDEV)	0.967	0.146	0.608*	0.45	-5.935	-0.99
⊿(FINDEV(-1))	5.854*	1.775	1.538*	1.63		
⊿(FINDEV(-2))	-1.486	-0.400	-0.641	-1.06		
⊿(GOVSpend)	-0.710*	-1.831	-0.020*	-1.78	-0.158	-0.56
⊿(GOVSpend(-1))	-0.171	-0.238	-0.070	0.17		
⊿(GOVSpend(-2))	-1.348*	-1.772	-0.150*	-1.24		
⊿(Education)	-0.153	-0.302	-0.043	-0.57	0.176	0.49
⊿(Education(-1))	-0.080	-0.147	-0.069	-0.81		
⊿(Education(-2))	0.715	0.796	0.072	1.46		
C	3.677***	2.706	2.874***	1.224	2.362***	-12.59
ECM(-1)	-0.868***	-4.66	-0.826***	-3.52	-0.381***	-5.12

Note. Column (1) indicates the estimation of PMG-ARDL, while column (2) provides the estimation of CS-ARDL. ***p<0.01; **p<0.05; *p<0.1

Moving on to the robustness checks in column 3, the estimates of the CS-ARDL model confirm the results reported from the baseline model in column 1. The computed coefficients for the ECT are negative and statistically significant at the 1% level. According to this specification, income inequality has a negative and significant impact on green growth at the 10% level, demonstrating the CS-ARDL consistency in detecting the cross-sectional correlation in the error term Chudik and Pesaran (2015). The findings show that a 0.1-point increase in income inequality leads to a decline in green growth in the sampled Global South countries in the long run.

Table 6 then presents the country-specific models. The PMG-ARDL model is the main model employed in this estimation. The negative sign linked with the ECT coefficient estimations indicates the convergence towards stability at the 1% level. The findings show that income inequality has a negative and statistically significant long-run impact on green growth in all of the selected countries of the Global South (at the 1%, 5%, and 10% levels). The coefficient estimates prove that a 0.1% increase in income inequality reduces green growth by 0.002% in Brazil and Costa Rica, 0.001% in Colombia, 0.003% in China, 0.004% in India and South Africa, and 0.005% in Indonesia in the long run. Similarly, the coefficient estimates in environmental innovation are positive and statistically significant (at the 1%, 5%, and 10% levels), implying that a 0.1%-point rise in environmental innovation enhances green growth by 0.003% in Brazil, 0.001% in China, 0.013 % in Colombia, 0.296% in Costa Rica, 0.012 % in India, 0.010% in Indonesia, and 0.010% in South Africa. As previously stated, these findings appear to give strong evidence of investment in environmental-related technologies that promote the green economy. This finding is consistent with Cao et al. (2022). The coefficients for control variables, notably financial development, government spending, and education, are somewhat comparable to those obtained in Table 5.

The short-run findings show a mixed result among the sampled countries. For example, even at different lagged levels, both the coefficients for environmental innovation, financial development, government spending, and Education are positive and statistically significant (at the 1%, 5%, and 10% levels) on green growth. The estimated results, particularly for Indonesia, have been consistent. One likely reason is that the Indonesian government significantly reduced poverty by 10% in 2019 (World Bank, 2022) and moved toward net-zero emissions at a reduced cost (IRENA, 2018). Finally, the F-statistics coefficient estimates and the ECT corroborate the long-run cointegration relationship among the variables in all models of the selected group of Global South countries. Furthermore, in this investigation, the Ramsey and CUSUM tests confirm the model's exact specification and stability.

Table 7 estimated the statistical significance of the W-statistics and Z-bar-statistics using the pairwise Dumitrescu and Hurlin (2012) panel causality test. The W-statistic is primarily based on linear hypotheses integrating the average Wald statistics for independent variable coefficients for Granger causality. On the other hand, the Wald test's Z-bar depicts the standardized statistics under the Wald test's premise that they are separately and identically distributed among individuals. The findings reveal three different directions of Granger causation (unidirectional, bidirectional, and no-

Table 6. *Country-Specific Estimates of Green Growth*

Variables	Brazil		China		Colombia		Costa Rica		India		Indonesia		South Africa	
	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
Long-Run Equation														
GINI	-0.002*	-2.043	-0.003**	-3.530	-0.001**	-2.631	-0.002*	-1.607	-0.004*	-1.516	-0.005***	-4.621	-0.004*	-3.509
ENVINNO	0.003**	2.762	0.001***	4.681	0.013**	3.710	0.296*	2.330	0.012*	0.420	0.010**	2.939	0.022**	1.682
FINDEV	3.093*	2.017	2.092	3.882	-0.847	1.513	0.099	0.015	0.666	0.032	1.739***	5.257	0.016*	2.115
GOVSpend	0.417*	1.093	0.578*	2.194	0.446**	2.238	1.288*	2.283	0.880*	2.107	0.682**	3.008	1.096*	3.750
Education	0.354***	5.152	0.435**	3.430	0.025	1.228	2.403**	3.752	1.639**	2.203	2.094***	4.941	0.018	0.408
Short-Run Equation														
Δ(GINI)	-0.005***	-6.223	0.013**	3.324	0.079*	4.024	0.003	1.261	-0.028**	1.783	0.015**	3.799	0.009**	3.529
Δ(GINI(-1))	0.001	1.392	0.024*	2.411	1.049	3.236	-0.003	-1.583	0.020*	-1.203	0.007*	2.340	0.002	2.675
Δ(ENVINNO)	0.004***	3.614	0.243***	4.960	0.106**	3.984	0.019	0.136	0.007**	0.402	0.015*	1.282	0.020**	1.466
Δ(ENVINNO(-1))	-0.002	-1.176	0.180**	3.520	0.110*	2.452	-0.041	-0.412	-0.041	-0.412	-0.056	-1.573	0.017**	2.745
Δ(FINDEV)	0.367*	1.146	2.378**	3.990	1.264**	3.590	1.782	3.757	1.430	2.757	0.291**	2.334	0.979**	1.787
Δ(FINDEV(-1))	0.654*	1.775	1.193*	2.922	0.302*	1.712	0.429	2.305			1.529*	2.501		
Δ(GOVSpend)	1.824***	3.952	0.091	0.341	0.231	1.631	1.076**	3.149	0.328***	3.583	2.540**	1.639	0.848*	1.931
Δ(GOVSpend(-1))	0.613**	4.103	0.719*	2.552	0.023*	3.110	1.033	3.642	0.518**	3.902			0.460	1.527
Δ(Education)	0.354***	1.785	0.475*	2.193	0.136*	2.710	0.478*	2.571	0.950***	1.692	0.898**	3.955	0.187	1.890
Δ(Education(-1))			0.300	0.434										
C	4.151*	1.588	2.362***	7.049*	3.924***	2.049*	1.478***	3.049*	3.682***	2.418*	1.478***	3.049*	3.682***	2.418*
Diagnostics														
F-test	6.129***		7.075***		5.751***		11.943***		8.848***		9.316***		5.271***	
ECM(-1)	-1.470***	6.31	-0.771***	5.12	-1.666***	6.23	-1.106***	5.33	-0.780***	4.82	-1.966***	6.04	-0.674**	7.24
LM	0.357		0.408		0.376		0.363		0.446		0.598		0.682	
RESET	0.414		0.229		0.125		0.407		0.294		0.281		0.378	
CUSUM	S		S		S		S		S		S		S	
CUSUM-sq	S		S		S		S		S		S		S	

causality) for the effects of income disparity on green growth. The model estimation demonstrates that Gini and environmental innovation have a unidirectional causal effect on green growth; the financial development granger caused Gini unidirectionally; the government spending granger caused Gini bi-directionally; and Gini, financial development, and Education granger caused environmental innovation unidirectionally. Therefore, the mixed findings are especially useful for policymakers in the Global South who are trying approaches to boost the green economy.

Table 7. *Pairwise Dumitrescu and Hurlin (2012) Panel Causality Test Results*

Null hypothesis	W-Stat.	Zbar-Stat.	*p*-value	Direction of causality
GINI ≈ Green Growth	6.288	11.321	0.016	GINI ⇨ Green Growth
Green growth ≈ GINI	4.891	7.279	0.263	
ENVINNO ≈ Green growth	3.328	4.035	0.042	ENVINNO ⇨ Green Growth
Green growth ≈ ENVINNO	4.524	5.735	0.462	
FINDEV ≈ Green growth	3.128	5.165	0.243	Green growth ≠ FINDEV
Green growth ≈ FINDEV	3.646	4.573	0.115	
GOVSpend ≈ Green growth	5.163	3.039	0.168	Green growth ≠ GOVSpend
Green growth ≈ GOVSpend	3.044	4.169	0.265	
Education ≈ Green growth	4.456	5.808	0.218	Education ≠ Green growth
Green growth ≈ Education	5.605	4.646	0.117	
ENVINNO ≈ GINI	3.476	3.388	0.165	GINI ⇨ ENVINNO
GINI ≈ ENVINNO	5.162	3.222	0.001	
FINDEV ≈ GINI	3.908	3.858	0.053	FINDEV ⇨ GINI
GINI ≈ FINDEV	3.376	4.279	0.200	
GOVSpend ≈ GINI	3.912	3.862	0.052	GINI ⇆ GOVSpend
GINI ≈ GOVSpend	4.511	3.515	0.011	
Education ≈ GINI	7.071	5.299	0.351	GINI ≠ Education
GINI ≈ Education	4.081	3.128	0.297	
FINDEV ≈ ENVINNO	5.403	4.221	0.054	ENVINNO ⇨ FINDEV
ENVINNO ≈ FINDEV	4.652	3.683	0.092	
GOVSpend ≈ ENVINNO	6.908	11.317	0.012	ENVINNO ⇨ GOVSpend
ENVINNO ≈ GOVSpend	4.867	3.813	0.069	
Education ≈ ENVINNO	5.893	4.842	0.055	Education ⇨ ENVINNO
ENVINNO ≈ Education	4.621	3.629	0.129	
GOVSpend ≈ FINDEV	4.340	4.153	0.218	FINDEV ⇨ GOVSpend
FINDEV ≈ GOVSpend	7.983	3.940	0.052	
Education ≈ FINDEV	4.633	3.647	0.008	Education ⇨ FINDEV
FINDEV ≈ Education	3.514	4.430	0.152	
Education ≈ GOVSpend	6.58465	4.769	0.206	GOVSpend ⇨ Education
GOVSpend ≈ Education	5.87211	3.818	0.058	

Notes. (≈, ⇆, ⇨ and ≉) denotes null hypothesis, bidirectional, unidirectional causality and no causality. ***$p<0.01$; **$p<0.05$; *$p<0.1$

VI. Conclusion and Policy Implications

This paper infuses various theories and related empirical studies into a cohesive analysis framework that helps better understand the role of income disparity in reducing greenhouse gas emissions. We focus our analysis on a sample of seven countries from the Global South (Brazil, China, Colombia, Costa Rica, India, Indonesia, and South Africa) from the period 1991-2019, moved away from overly concentrated studies on the contributors to environmental sustainability to fill a gap in the extant literature on green growth. Therefore, our primary contribution to this investigation is to account for the short- and long-run implications of income inequality on green growth. This paper employs a novel battery of tests to examine the cross-dependence, panel unit roots, and cointegration among variables in the sampled countries. Two estimation techniques were used to overcome the cross-dependence and slope heterogeneity concerns: PMG-ARDL and AMG-ARDL for the baseline models, and CS-ARDL model estimations as robustness checks.

The empirical results show that the parameters tested exhibit long-run cointegration relationships. Both the PMG-ARDL and AMG-ARDL models show that rising income inequality negatively and significantly affects green growth. For this reason, addressing income inequality is crucial for reducing carbon emissions and fostering a green economy. Further, the coefficients for environmental innovation are positively and statistically significantly linked to green growth, suggesting that countries in the Global South can develop new solutions and technologies that help mitigate environmental damage by investing in and promoting environmental innovation. This, in turn, can potentially increase economic prosperity and alleviate poverty among low-income households. Government spending and educational attainment, on the other hand, have a positive and statistically significant impact on green growth. This also suggests that long-term government investment in R&D, particularly in human capital development, might increase green growth.

We conducted a robustness check for the CS-ARDL model; the findings show that income inequality significantly negatively affects green growth at the 10% level, demonstrating the CS-ARDL consistency in capturing the cross-sectional correlation in the error term Chudik and Pesaran (2015). These results are similar to those reported in the baseline model, and the computed coefficients for the ECT are negative and statistically significant at the 1% level for both model results. Similarly, this paper reveals three possible ways of Granger causation (unidirectional, bidirectional, and no-causality) for the effects of income inequality on green growth. In terms of the country-specific models, coefficient estimates show that a 0.1%-point rise in income inequality lowers green growth by 0.002 % in Brazil and Costa Rica, 0.001 percent in Colombia, 0.003 % in China, 0.004 % in India and South Africa, and 0.005 % in Indonesia in the long run.

This paper offers different practical ways of minimizing the effects of income inequality on green growth based on empirical findings. First, the government may consider implementing progressive tax policies and enabling access to education and equality of opportunity to help reduce income disparity and ensure increased access to resources and opportunities that ensure more equitable wealth distribution. Second, the governments of the Global South need to promote more development in environmental-related technologies. The efficacy of environmental innovation in supporting green growth, however, is dependent on government investment in R&D as well as providing incentives to private sector stakeholders to contribute to inclusive green growth. With more private sector participation, the cost of buying renewable energy-saving appliances for low-income households might be reduced, lowering carbon emissions. Finally, this paper suggests that the government focus resources on sectors crucial to encouraging green growth. These include renewable energy, energy efficiency, environmental protection, sustainable transportation, and agriculture. Investing in such areas may create the conditions for a thriving green economy.

Future research might look at how green growth policies affect income inequality at the household level, bearing in mind individual purchasing power to transition to renewable energy usage. This entails investigating the micro-level effects of green growth policies on various socioeconomic cohorts. This could assist in offering more insight into the distributional implications of green growth policies, which could be used to design more effective and inclusive policy measures. Second, the private sector's involvement as a driver of green finance is critical to greening the economy, particularly the incentives and constraints that impact the behaviour of private sector stakeholders and how they might contribute to inclusive green growth. Finally, the relevance of government policies and institutions in enabling inclusive green growth should be considered. This could contribute to a better understanding of the increasingly interconnected nature of these issues and the development of appropriate policy measures that promote both environmental sustainability and social fairness.

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