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Impact of Climate Change, Human Development and Internet Use on Poverty: Evidence from Panel Quantile Regression

Halim Tatli

(Email: htatli@bingol.edu.tr), Bingöl University, Faculty of Economics and Administrative Sciences, Bingöl, Turkey

Abstract

This paper examines the effects of climate change, human development, internet use and income inequality on poverty using 50 high-, middle and low-income countries between 2004 and 2020. After applying the panel unit root tests, the parameters are estimated using the quantile regression method. The results reveal that climate change has a statistically significant and positive effect on poverty in the selected 50 countries. Also, the impacts of the human development index and internet use are significant and negative. Our findings reveal that income inequality has a positive effect on poverty. The one-way and two-way models, along with the fixed-effect model, also verify the robustness of the results. Finally, the findings are discussed in terms of policy implications. Considering the findings of the study, it is recommended that policies be implemented to reduce the negative effects of climate change, improve human development and increase internet use to reduce poverty.

Keywords: Climate change and poverty, human development and poverty, internet use and poverty

JEL Classification: Q54, Q56, I32

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1. Introduction

This paper investigates the potential impact of climate change on poverty. Increased atmospheric concentrations of greenhouse gases cause global climate change (IPCC, 2007). Climate change poses the greatest threat to the global economy. Also, global poverty has been caused by an increase in climate variability and uncertain climate events. Moreover, concerns have been raised that vulnerable people in poorer countries are more exposed to the negative impacts of climate change (Hallegatte *et al.*, 2017; Chancel *et al.*, 2023). Poor people lack the basic freedoms they need to maintain the lifestyles they value, according to Sen (1999). It is often the poor people who suffer the most from climate change due to their vulnerability, increased exposure and lack of resources to cope with and recover from these shocks (Birkmann *et al.*, 2022). Natural disasters push upwards of 26 million people each year below the international extreme poverty line, according to Hallegatte *et al.* (2017). Climate change impoverishes people by reducing their ability to access resources that are essential for their lives. Poverty, which is at the top of the sustainable development goals (SDGs), is an economic and social phenomenon that needs to be fought all over the world. The SDGs provide a clear road map on which countries can achieve prosperity by providing significant targets for reducing and alleviating the severity of poverty by promoting a sustainable global environment (SDG, 2019). However, the effects of climate change, as well as some other socioeconomic factors, may disrupt the achievement of SGD poverty targets in many countries. Therefore, unless climate change is well assessed and controlled, climate-induced poverty can reverse development gains. Rising temperatures due to climate change can slow economic growth and increase unemployment, particularly in sectors such as agriculture. This can increase income inequality and deepen poverty. In addition, effects such as reduced labour productivity and increased health problems due to temperatures also lead to losses in the economy and can cause more people to fall into poverty (Kotz *et al.*, 2022; Dang *et al.*, 2024). Environment and climate-related shocks directly or indirectly push people into poverty (Hallegatte *et al.*, 2018); shocks related to climate such as drought (Krishna, 2006) and natural disasters (Sen, 2003) increase poverty. Extreme weather events triggered by climate change will increase the proportion of the population living below the poverty line, raising unemployment rates with negative impacts on individual earnings (Deryugina and Hsiang, 2014).

In addition to improving the quality of human capital, education is an important component of human development. Educated human capital can affect environmental quality by contributing to the development of new environmentally friendly technologies (Pata *et al.*, 2023a; Pata *et al.*, 2024). Based on environmental economics literature, human capital plays an important role in combating climate change (Hondroyiannis *et al.*, 2022). Global warming triggered by climate change reduces social welfare and deepens poverty by increasing health problems (Graff Zivin *et al.*, 2018), restricting educational opportunities (Park *et al.*, 2021) and ultimately weakening human capital. In fact, Pata *et al.* (2023a) empirically demonstrated that human capital supports environmental quality. Human capital development helps increase the share of renewable energy (Pata *et al.*, 2023b). Renewable energy investments and technologies also help reduce carbon emissions (Erdogan *et al.,* 2023). In addition, some studies have found that human capital reduces carbon emissions (Mahmood *et al.,* 2022; Pata and Erdogan, 2023; Pata *et al.,* 2024).

Climate change shocks impoverish people by negatively affecting their asset accumulation (Hallegatte *et al.*, 2018). In rural China, Li *et al.* (2024) detected that climate change negatively affects household income, consumption and asset accumulation, which in turn negatively affects household resilience. Also, household income can be affected negatively by climate change effects such as drought, erosion and changes in precipitation, temperature and hydrology (López-Feldman, 2014; Angelsen and Dokken, 2015; Robinson, 2016; Hallegatte *et al.*, 2017; Barbier and Hochard, 2018; Kalli and Jena, 2022; Lankes *et al.*, 2024). While most economic losses from natural disasters such as weather, climate and water extremes caused by climate change from 1970 to 2020 occurred in upper-middle and high-income countries due to greater assets, a disproportionate 82% of all deaths during the same period occurred in low- and lower-middle-income countries (WMO, 2021). In addition, natural disasters greatly affect poor people within developed countries (Bleemer and van der Klaauw, 2017). Unless today's development models change and great reductions in emissions occur, global warming will far exceed the 2015 Paris Agreement targets set at COP21 to "keep temperatures well below 2°C" and "strive to prevent them from exceeding 1.5°C" (IPCC, 2023). With 701 million people living on less than $2.15 a day in 2019, this could further increase the number of extremely poor people. For this reason, the relationship between climate change and poverty needs to be further investigated and poverty reduction strategies need to be implemented.

Human development is another phenomenon that has a negative and significant impact on poverty today, unlike the impact of climate change (Arimah, 2004). The process of human development involves enhancing people's capabilities and functioning to expand their options and level of well-being (United Nations Development Programme – UNDP, 2000). The HDI (Human Development Index), which measures human development, calculates success in achieving the most basic human capability: living long, becoming knowledgeable and enjoying a decent standard of living (UNDP, 1999). Human development contributes to poverty reduction through education, health and increases in income levels (Tilak, 2002; Anand and Ravallion, 2013; Cremin and Nakabugo, 2012). Interruption and reduction in the increases in these areas may lead to poverty. When societies invest in education, healthcare and economic opportunities, they empower individuals to break free from the cycle of poverty (Anand and Ravallion, 2013). However, unequal access to these resources perpetuates disparities, hindering progress (Anand and Ravallion, 2013; Asadullah *et al.*, 2021). The present study explores the intricate network of interactions described above. The Gini coefficient and internet use are recognized as control variables. The latter is an important social indicator that includes elements such as internet use, access to information and communication, and the Gini coefficient used to measure income distribution is an indicator that reflects economic inequality.

Internet connectivity bridges gaps, enabling information dissemination and social empowerment. In addition, internet use has the potential to lower transaction costs, enhance labour productivity and foster innovation capacity (Paunov and Rollo, 2016; Ma *et al.*, 2018). Poverty is negatively affected by internet use (Beuermann *et al.*, 2012; Yang *et al.*, 2021). The issue of income inequality has been at the forefront of policy debates around the world. However, interest in the importance of the effect of income distribution on poverty is also increasing. Income inequality has a negative impact on increasing poverty (Ravallion, 2000, 2001). According to Ravallion (2005a), income redistribution combined with a public policy can lead to decreased poverty rates.

This study aims to examine the effects of climate change and human development on poverty. Poverty is a complex phenomenon that affects the lives of many people around the world, and this study highlights the role of factors such as climate change and human development to better understand the causes and consequences of poverty. The main hypothesis of this study is that the effects of climate change and human development factors on poverty will be more clearly understood in the presence of control variables such as internet use and the Gini coefficient in a certain context.

This study contributes to the existing literature on poverty reduction by examining the link between climate change and human development with poverty from three perspectives. Firstly, this is the first study to emphasize the link between climate change and human development and poverty. Secondly, the relationships between variables are analysed using the new analysis method, PQR (panel quantile regression), with the latest data and a large panel. Three different models are also estimated, considering three different poverty indicators. Thirdly, the relationship between three global problems – climate change, human development and poverty – is analysed using different methods, over a wider set of variables, by including the use of internet and inequality coefficient control variables, which affect poverty, in the models. The main contribution of the study lies in its comprehensive approach to analysing poverty. By bringing together various factors such as climate change, human development, internet use and income inequality, the study provides a broader understanding of poverty determinants. This multidimensional framework enriches the literature because previous studies often focused on a single factor such as economic growth or education without considering the combined and interdependent effects of these variables. The selection of 50 countries in the high, middle and low-income categories from 2004 to 2020 enables the study to capture global trends and changes in poverty and its determinants in terms of temporal and geographical coverage. Furthermore, including internet use in poverty studies adds a new dimension to the field. While the role of technology in economic growth is well-known, its impact on poverty has been under-researched. The study examines the vital role of digital connectivity in reducing poverty by investigating the relationship between internet use and poverty.

The rest of the study is organized as follows. Section 2 contains a literature review; Section 3 represents the data and methodology; Section 4 gives the results as well as the robustness checks; finally, Section 5 concludes.

2. Literature Review

In this study, four different study areas are debated. The literature on the impact of climate, human development, internet use and income inequality on poverty is examined, respectively. Table 1 lists some of the most prominent papers. The studies given in table 1 are classified based on the variables used in the study model. Climate change negatively affects the environment and causes poverty by reducing the production capacity and per capita income of countries. There are empirical studies in the literature that analyse the relationship between climate change and poverty. Studies investigating the impact of climate change on poverty are mostly based on samples of less developed countries (Bui *et al.,* 2014; González *et al.,* 2022; Dang *et al.,* 2023). Studies have shown that natural disasters related to climate change negatively affect poverty in different geographic areas, especially in poorer sub-Saharan Africa (Azzarri and Signorelli, 2020). Developing and developed economies are both adversely affected by climate change (Dang *et al.,* 2024). Studies in the literature reveal that there is a positive and significant relationship between poverty and climate change. For example, Masron and Subramaniam (2019) pointed out that environmental degradation is a possible determinant of poverty. As a result of the causality analysis carried out by Awad and Warsame (2022), they found that the global panel and the African panel showed a bidirectional causal relationship between poverty and the ecological footprint. Bolarinwa and Simatele (2024) found that climate change has a positive effect on poverty in both low- and middle-income countries, although this effect is only significant for extreme poverty in low-income countries. Similar to this study, Baloch *et al.* (2020) and Koçak and Çelik (2022) also found that climate change has a positive effect on poverty. Zhao *et al.* (2021) and Eichsteller *et al.* (2022) observed a negative relationship between poverty and environmental degradation in country-level analyses. However, Barbier and Hochard (2018) conducted a spatial analysis and found no evidence that environmental factors have a direct impact on changes in poverty in 83 developing countries.

Since poverty is a multidimensional phenomenon, its severity cannot be reduced by a one-dimensional factor such as income increase. Improving education and health conditions at individual and social levels, as well as income, emerges as an important strategy in the fight against poverty. The impact of this strategy can be seen by examining the relationship between poverty and the HDI, a three-dimensional indicator of income, health and education. As Bloom and Canning (2000) noted, productivity, education, investments in physical capital and demographic dividends all have the potential to contribute to income growth. The relationship between poverty and HDI has not received much attention in previous studies due to its theoretical ambiguity, complexity and lack of a clear relationship. Most studies have focused on the relationship between HDI dimensions and poverty. For example, Arimah (2004) analysed data for thirty African countries for 1990 and 2001 by employing ordinary least-squares regression methodology. Inter-country differences in poverty levels can be explained by factors associated with different aspects of human development, according to the tests. They include public expenditures on education, enrolment in primary schools, female enrolment in education, health expenditures and good governance. According to DeNavas-Walt *et al.* (2015), education levels have a significant impact on poverty in the USA. According to Sofilda *et al.* (2013), HDI has a substantial link with poverty in 34 provinces in Indonesia and significantly reduces poverty. Singh (2012) also found that HDI and the growth of per capita income are strongly linked to poverty, leading to the conclusion that HDI decreases poverty. El Hasanah *et al.* (2022) found that increased HDI was linked with lower poverty. As per a case study conducted on HDI, poverty and crime, HDI promotes the objective of crime and poverty alleviation (Jamaliah and Elyta, 2022). Also, Ahmad *et al.* (2019) found that HDI and its education dimension reduce poverty.

Household surveys have recently examined the relationship between poverty and internet use (Mora-Rivera and García-Mora, 2021; Phan, 2023; Xie *et al.,* 2023). From a theoretical perspective, the internet can be an important tool in reducing poverty, because it is a leading tool that allows individuals to access information cheaply. Zhu *et al.* (2022) and

Yang *et al.* (2021) found that internet use negatively affects poverty incidence across Chinese provinces. Similarly, Yang *et al.* (2021) found that internet use has a significant and negative impact on multidimensional poverty in China. Mora-Rivera and García-Mora (2021) observed that internet access was a strong driver of eliminating rural and urban poverty in Mexico. Also, Phan (2023) disclosed that internet use assists rural households, including the poor ones, in fostering their livelihoods in Vietnam. Expanding internet use can be used as an important tool in reducing poverty as it will support access to information, increase labour productivity and strengthen social capital and human capital (Nguyen *et al.*, 2022).

In the development economics literature, effects of income inequality on poverty have been the subject of ever-extending debate (Ahluwalia, 1976; Robinson, 1976); it has produced many studies on the subject (Datt and Ravallion, 1992; Kakwani, 1993; Ali and Thorbecke, 2000; Adams, 2004; Bergstrom, 2022). There is complex and controversial empirical evidence on the links between poverty and income inequality. For instance, Bergstrom (2022) found that the impact of income inequality on poverty is negative. However, Besley and Burgess (2003) and Honohan (2004) found a positive association between inequality and poverty. Ravallion (2005b) found a positive relationship between the rate of change in income inequality and the rate of change in poverty rates, using the Gini coefficient to measure income inequality. This is similar to the findings of Fosu (2010a). Khan *et al.* (2014) argued that poverty can be a self-reinforcing phenomenon due to its impact on economic growth and inequality. Apergis *et al.* (2011) found that poverty and inequality influence each other mutually.

As a result of the above literature review, it can be seen that studies have been conducted on the relationship between climate change, human development and poverty. The findings of these studies generally show that climate change increases poverty, while human development reduces poverty.

Table 1: Empirical studies

Author(s)	Sample and period	Method	Key findings
		Poverty and climate	
Bui *et al*. (2014)	Household Living Standard Survey in Vietnam, 2008	Fixed-effects regression	It is estimated that if households had not been exposed to natural disasters, poverty would have decreased by 2.7 percent.
Arouri *et al.* (2015)	Household Living Standard Surveys in Vietnam, 2004, 2006, 2008 and 2010	Fixed-effects regression	Storms, floods and droughts due to climate change have negative impacts on household income and spending. Found that households affected by floods have an increased probability of poverty.
Azzarri and Signorelli (2020)	Household Surveys in 24 African countries, 2002–2014	Pooled-OLS, spatial auto-correlation	Poverty is negatively associated with humid regions, while poverty is positively associated with hotter regions.
González *et al*. (2022)	Argentina, 1970–2010	Pooled-OLS	Natural disasters due to climate change have significantly increased multidimensional poverty.
Dang *et al.* (2023).	134 countries, 2010–2019	Fixed-effects regression	Both higher and lower temperatures have strong and statistically significant effects on poverty worldwide.
		Poverty and HDI	
Arimah (2004)	North and South Africa Countries, 1995–2002	Pooled-OLS	Variables reflecting different aspects of human development can explain cross-country differences in poverty levels.
Carter *et al.* (2007)	Ethiopia, 1996–2003	Pooled-OLS, Tobit approach	Climate-related shocks such as hurricanes and droughts negatively affect the welfare of poor individuals.
Ahmad *et al*. (2019)	Southeast Sulawesi in Indonesia, 2010–2018	Partial least squares	Found that human development index has a negative and significant effect on poverty.
El Hasanah *et al.* (2022)	232 regencies and cities in Eastern Indonesia, 2017	Multiple linear regression	Increasing HDI is linked to lower poverty.
		Poverty and internet use	
May *et al.* (2011)	Household surveys in East Africa 2007–2010	OLS with matched sample	A household's poverty status improves by 2.5% when they have access to ICTs and this effect is larger for poorer households.
Mora-Rivera and García-Mora (2021)	National Household Income and Expenditure Survey in Mexico, 2016	Propensity score matching approach	In rural areas, internet access has a greater impact on reducing extreme income poverty and extreme multidimensional poverty than in urban areas.
Nguyen *et al.* (2022)	Provinces in Thailand, 2016–2017	Heteroscedasticity-based instrumental variable regression, unconditional quantile regression	Internet use for productive activities increases household income and higher-income households use the internet more frequently than lower-income households.
Afzal *et al.* (2022)	86 countries across the globe, 2005–2020	Two-step systematic generalized method of moments	Technology penetration, measured using the percentage of internet users, the percentage of fixed broadband internet subscribers and the percentage of mobile phone subscribers, was found to have a negative impact on poverty.

Xie *et al.* (2023)	China, 2020	Probit model	Farmer poverty is significantly reduced by internet use.
Phan (2023)	Access to Resources Household Survey in Vietnam	Generalized method of moments, propensity score matching	Internet use was found to help rural households, including the poor, improve their livelihoods. Internet access increases average annual household income per capita and reduces the likelihood of being poor.
		Poverty and income inequality	
Fosu (2010b)	Global sample, 1980–2004	Random-effects and fixed-effects methods	Poverty is found to be less sensitive to income as inequality increases. Significant regional and cross-country differences exist in the relative impact of inequality on poverty.
Apergis *et al.* (2011)	50 US states, 1980–2004	Panel cointegration test, fully modified OLS	A bidirectional relationship exists between poverty and income inequality in both the short and long term. In the short term, income inequality and the unemployment rate positively influence poverty.
Ibrahim and Uchechi (2020)	Nigeria, 1986–2018	Autoregressive distributed lag	Nigeria's poverty rate increased by 75% as a result of income inequality.
Marrero and Servén (2022)	A panel of 158 countries, 1960–2010	Pooled-OLS, within-group estimates, generalized method of moments	Inequality has a consistently negative impact on growth due to its strong association with poverty.
Amponsah *et al.* (2023)	35 sub-Saharan Africa countries, 1990–2018	Two-step instrumental variables generalized method of moments	Poverty and inclusive growth are adversely affected by income inequality.

Source: Author's own elaboration

2.1 Literature gap

Climate change has recently generated noticeable adverse effects globally across various disciplines and has become one of the top priorities in international policy and academic research. Specifically, the natural disasters and ecosystem disruptions triggered by climate change increase social vulnerability, exacerbating the cycle of poverty and hindering development efforts. Therefore, empirically analysing these issues is of great importance. Analyses of the impact of climate change on poverty are often conducted at the regional or provincial level within countries. However, analysing the effects of climate change on poverty solely within specific countries or regions may not fully capture its significant global impact. Consequently, most previous studies have not investigated the global effects of climate change on poverty. This study aims to contribute to filling this gap and focuses on conducting an analysis of the global impacts of climate change on poverty. It does so by combining various economic variables, which are considered to have significant effects on poverty in light of the impacts of climate change, based on available data. The study analyses the effects of climate change on poverty using a comprehensive set of variables, along with current data and methodologies. To measure the extent or prevalence of poverty in different countries, an indicator of the proportion of the population living below the poverty line in each country is required. This indicator is derived from two distinct datasets. The first dataset reports the proportion of a country's population living below the national or official poverty line.

However, as each country establishes its poverty threshold based on its specific socio-economic conditions, this can introduce challenges to the reliability of cross-country poverty comparisons. The second dataset captures the percentage of individuals living on less than \$2.15, \$3.65 or \$6.85 per day, facilitating a standardized measure of poverty across countries. In this study, the possible effects of climate change and human development on poverty in a wide geographical area are analysed with a new dataset using these poverty lines. Unlike previous studies, the present study jointly examines the effects of climate change, human development measured through poverty-related factors such as education, health and income, the internet as a source of access to information and income inequality on poverty.

3. Data and Methodology

This study investigates the relationship between poverty, climate, HDI, internet use and the Gini coefficient for 50 countries of the world from 2004 to 2020. The selection of 50 countries for this study was primarily driven by data availability across key variables such as poverty headcount ratio, Human Development Index (HDI), climate data, internet use and the Gini coefficient. Since the analysis covers the period from 2004 to 2020, only countries with complete and consistent data for these variables were included in the final sample. Additionally, these 50 countries represent a balanced mix of high-, middle- and low-income countries, ensuring diversity and coverage of different socioeconomic contexts. This selection process is aimed at maintaining the integrity of empirical analysis while balancing the need for representativeness and data completeness. The poverty headcount ratio data are drawn from the World Bank (WB, 2023). Based on 2017 prices, the international poverty line is \$2.15 per person per day, which means anyone living on less than \$2.15 a day lives in extreme poverty (WB, 2024). To facilitate cross-country comparisons of poverty rates, standardized poverty thresholds are exploited to ensure consistency in assessing living standards across diverse socioeconomic contexts. These thresholds, such as the \$2.15 per day extreme poverty line, are calibrated to reflect comparable levels of deprivation across countries, with additional benchmarks set at \$3.65 per day for lower-middle-income countries and \$6.85 per day for upper-middle-income countries, as described by the World Bank.

The surface temperature change is a proxy of climate measured as degrees Celsius and the data are drawn from the International Monetary Fund (IMF, 2023). The United Nations Development Programme (UNDP) describes the HDI as a measure of overall achievement in key areas of human development. It encompasses three elements: longevity, education and standard of living, with data sourced from UNDP (2023). The Gini index measures inequality in income or consumption distribution within an economy, its data are drawn from WB (2023). Internet users are defined as individuals who have accessed the internet (from any location) within the last 3 months, as a percentage of the population. This variable was included in the study as a proxy for individuals' access to information. Table 2 provides further details about the dataset.

Table 2: Variables, description, symbols and sources

Variables	Description	Symbols	Source
Poverty headcount ratio at $2.15	Proportion of the population living below the $2.15 per day poverty line, adjusted for 2017 PPP (% of population)	*POV*1	WDI
Poverty headcount ratio at $3.65	Proportion of the population living below the $3.65 per day poverty line, adjusted for 2017 PPP (% of population)	*POV*2	WDI
Poverty headcount ratio $6.85	Proportion of the population living below the $6.85 per day poverty line, adjusted for 2017 PPP (% of population)	*POV*3	WDI
Surface temperature change	Temperature change with respect to a baseline climatology	*STC*	IMF
Human Development Index	Human Development Index	*HDI*	UNDP
Individuals using the internet	Internet users are defined as individuals who have accessed the internet from any location within the past three months, expressed as a percentage of the population	*INET*	WB/WDI
Gini inequality coefficient	The Gini index measures inequality in income or consumption distribution within an economy.	*GINI*	WB/WDI

Source: Author's own elaboration

A summary of descriptive statistics for all the variables is presented in table 3. The mean values of *POV*1, *POV*2, *POV*3, *STC*, *HDI*, *INET* and *GINI* are 2.25, 6.31, 16.91, 1.31, 0.82, 57.77 and 35.80, respectively. The mean values are with a minimum of −0.34 in *STC* and a maximum of 0.95 in *HDI*. Also, the standard deviation values are with a minimum of 0.0902 in *HDI* and a maximum of 26.6485 in *INET*. Based on the Jarque–Bera statistics, it is deduced that the variables do not follow a normal distribution (Jarque and Bera, 1980). The *p*-values of the Jarque–Bera test are less than 0.05, which also shows that the dataset is not normally distributed. Due to the non-normal distribution of all the variables, applying ordinary least squares (OLS)-based regression can induce unreliable estimates. In addition, if the series is not normally distributed, applying such as OLS may lead to biased estimates, inefficient results and incorrect inferences, especially at the tails, where outliers or skews may be more prominent. Quantile approaches allow understanding the impact of covariates not only on the median but also on other quantiles (*e.g.*, the 10th or 90th percentiles), making them particularly useful when dealing with non-normal distributions (Yu *et al*., 2003). Therefore, the non-normal distribution of the mentioned variables requires using the PQR approach.

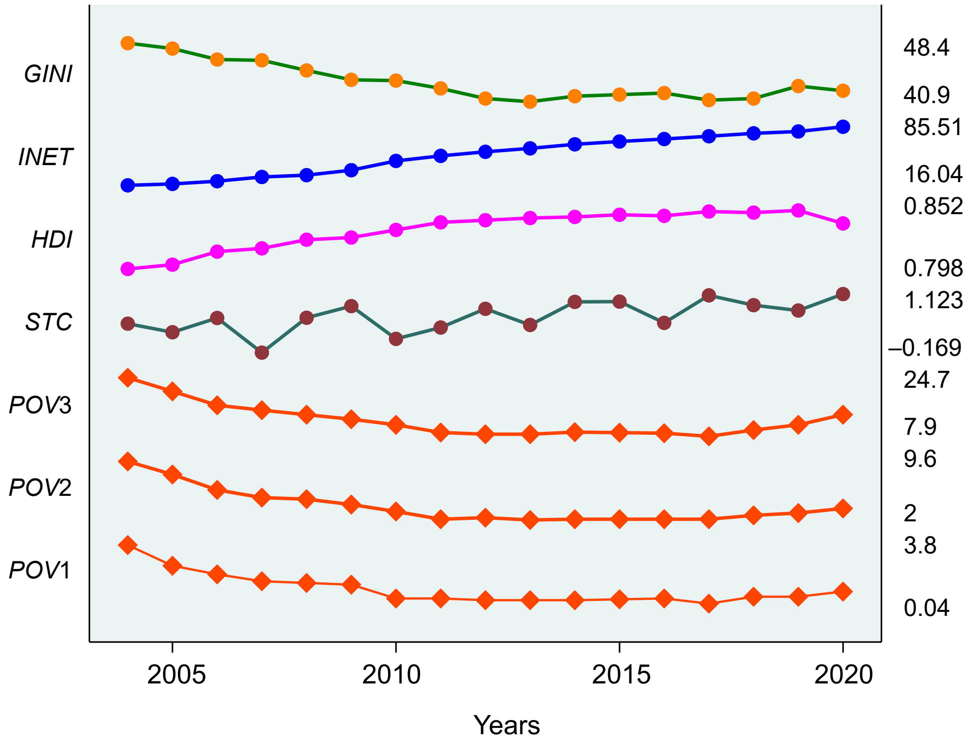
Table 3: Descriptive statistics

Variable	Mean	Std. dev.	Median	Min	Max	Skewness	Kurtosis	Jarque–Bera
***POV*1**	2.2568	4.1966	0.500	0.00	30.60	2.9599	13.3844	5,060.3***
***POV*2**	6.3158	10.4741	1.200	0.00	68.10	2.4585	10.1637	2,673.8***
***POV*3**	16.9120	21.8198	4.800	0.00	91.40	1.3435	3.7947	278.1***
STC	1.3074	0.6534	1.234	−0.34	3.69	0.5514	3.0811	43.3***
HDI	0.8222	0.0902	0.843	0.57	0.96	−0.5550	2.2946	61.3***
INET	57.7417	26.6485	63.635	2.60	98.46	−0.4579	2.0368	62.6***
GINI	35.8000	8.2999	33.850	21.40	59.50	0.7698	2.7018	87.1***

Note: *** denotes statistical significance at 1% levels.
Source: Author's own calculations

In Figure 1, the three poverty lines (2.15, 3.65 and 6.85) are in a general downward trend except in 2020. It can be seen that the *STC* value in the panel shows an increase and a decrease over the years. The *HDI* variable appears to be in a general increasing trend over the years except in 2020. On the other hand, the *INET* variable in the panel shows an increasing trend over the years. While there was a decrease in *GINI* values between 2004 and 2013, it showed a tendency to increase and decrease at low levels in other years.

Figure 1: Graphical representation of variables



Note: The secondary y-axis is used solely for scaling purposes to visualize variables with different magnitudes and does not represent poverty thresholds or descriptive statistics.

Source: Author's own elaboration

Correlations among the study variables are given in table 4. *STC*, *HDI* and *INET* indicate a negative correlation (with all the poverty lines) while *GINI* shows a positive correlation. A high and negative correlation coefficient of 0.8514 is observed between *HDI* and *POV*3, suggesting that these two variables are strongly correlated. In the case of this model, there are relatively low correlation coefficients among the independent variables, ensuring that the multicollinearity problem is not a constraint.

Table 4: Correlation test

	*POV*1	*POV*2	*POV*3	*STC*	*HDI*	*INET*	*GINI*
***POV*1**	1.0000	–	–	–	–	–	–
***POV*2**	0.9348***	1.0000	–	–	–	–	–
***POV*3**	0.7692***	0.9171***	1.0000	–	–	–	–
STC	−0.3147***	−0.3105***	−0.2920***	1.0000	–	–	–
HDI	−0.6853***	−0.7559***	−0.8514***	0.3283***	1.0000	–	–
INET	−0.5996***	−0.6701***	−0.7489***	0.4429***	0.8426	1.0000	–
GINI	0.5906***	0.5161***	0.4792***	−0.4017***	−0.6054***	−0.5051***	1.0000

Note: *** denotes statistical significance at 1% levels.
Source: Author's own calculations

The study uses three models to analyse poverty. The first model exploits the poverty headcount ratio at $2.15 as a dependent variable, while in the second and third models, the poverty headcount ratio at $3.65 and the poverty headcount ratio at $6.85 are taken as dependent variables respectively. The three models are compared to determine how the impact of climate change will vary if the poverty line rises. The following three models are specified:

$$POV1_{it} = \theta_i + \beta_1 STC_{it} + \beta_2 HDI_{it} + \beta_3 INET_{it} + \beta_4 GINI_{it} + \varepsilon_{it} \tag{1}$$

$$POV2_{it} = \theta_i + \beta_1 STC_{it} + \beta_2 HDI_{it} + \beta_3 INET_{it} + \beta_4 GINI_{it} + \varepsilon_{it} \tag{2}$$

$$POV3_{it} = \theta_i + \beta_1 STC_{it} + \beta_2 HDI_{it} + \beta_3 INET_{it} + \beta_4 GINI_{it} + \varepsilon_{it} \tag{3}$$

Based on existing empirical literature, the control variables, internet use and inequality coefficient are chosen. For example, the most recent studies used internet use (Phan, 2023; Zhu *et al.*, 2022) and inequality coefficient (Khan *et al.*, 2014; Bergstrom, 2022). As poverty affects income inequality and human development, income inequality affects human development as well (Qasim *et al.*, 2020). For this reason, the functional relationships *GINI* = *f*(*POV*1, *STC*, *HDI*, *INET*) and *HDI* = *f*(*POV*1, *STC*, *GINI*, *INET*) are analysed with the PQR method. Since these analyses would take the article beyond accepted scientific length criteria, the results are not given in the article[1].

1 The results are available upon request.

3.1 Estimation technique and procedures

Regression is one of the important analysis methods used to analyse the relationship between variables. There are different regression methods based on certain assumptions. The multiple regression method is generally a method that examines the relationship between the average value of the dependent variable and various values of the independent variable. Therefore, when you want to analyse a relationship between different percentages and an average based on the median instead of the arithmetic mean, the multiple regression method may be insufficient (Engle and Manganelli, 2004; Abrevaya and Dahl, 2008). In such a case, the PQR approach can be used instead of traditional regression approaches (Koenker, 2004). This method better explains the relationship in the dependent variable on the median instead of the conditional mean at different percentages (Koenker and Bassett, 1982). The PQR method developed by Koenker and Bassett (1978) has three advantages. These advantages can be expressed as follows: (i) it is capable of addressing the issue of outliers as well as providing robust results (Wen *et al.*, 2022; Anwar *et al.*, 2022; Liu *et al.*, 2023); (ii) no assumptions are made regarding the moment function (Chien *et al.*, 2021; Liu *et al.*, 2022); and (iii) there is no assumption that PQR depends on identical distributions (Liu *et al.*, 2023). It calculates the coefficients of estimators for each quantile. Equation 4 shows the PQR approach for different quantiles of y_{it} given x_{it} (Koenker, 2004).

$$y_{it} = \psi_i + x_{it} + \varepsilon_{it} \tag{4}$$

where y_{it} is the dependent variable, ψ_i is the individual fixed effects, x_{it} is the independent variables and ε_{it} is the error term. For the λ-conditional quantile function, the coefficient estimator will be as follows:

$$Q_{y_{it}}(\lambda \backslash\ \psi_i, x_{it}) = \psi_i + x'_{it}\theta(\lambda) + (\lambda)\ \varepsilon_t,\ i = 1, \ldots, N;\ t = 1, \ldots, T \tag{5}$$

where i symbolizes the individual and t denotes time. N stands for the number of observations in the country i and T denotes the time observation in a specific time t. The parameters of the estimates' will be derived through the subsequent equation:

$$\min_{(\theta,\psi)} = \sum_{n=1}^{n} \sum_{i=1}^{N} \sum_{T=1}^{T} v_w \rho_w (y_{it} - \psi_i \text{-} \mathrm{x}_{\mathrm{it}}^{'} \theta(\lambda) + (\lambda)\varepsilon_t) \tag{6}$$

In the above equation, v_w and ρ_w are the function and check the relative effect of the n quantiles. The quantile of relevance θ and ψ is the fixed effect term. The effects of climate, *HDI*, internet use and the Gini coefficient on poverty are also examined in the study. The structure of Model 1 is captured by equations (7) through (9):

$$Q_{POV1_{it}}(\lambda|\psi_i, x_{it}) = \lambda\psi_i + \lambda\beta_1 STC_{it} + \lambda\beta_2 HDI_{it} + \lambda\beta_3 INET_{it} + \lambda\beta_4 GINI_{it} + \varepsilon_{it} \quad (7)$$

$$Q_{POV2_{it}}(\lambda|\psi_i, x_{it}) = \lambda\psi_i + \lambda\beta_1 STC_{it} + \lambda\beta_2 HDI_{it} + \lambda\beta_3 INET_{it} + \lambda\beta_4 GINI_{it} + \varepsilon_{it} \quad (8)$$

$$Q_{POV3_{it}}(\lambda|\psi_i, x_{it}) = \lambda\psi_i + \lambda\beta_1 STC_{it} + \lambda\beta_2 HDI_{it} + \lambda\beta_3 INET_{it} + \lambda\beta_4 GINI_{it} + \varepsilon_{it} \quad (9)$$

In order to achieve robust parameter estimates, this study uses PQR to account for normality, stationarity and slope heterogeneity. The cross-section dependence (CD) test suggested by Pesaran (2004) is used to reveal the cross-sectional dependence in variables, the CIPS and CADF unit root tests are applied to check unit roots, the delta test proposed by Pesaran and Yamagata (2007) is utilized to examine homogeneity/heterogeneity, and the CD_{LM1}, CD_{LM2} and CD_{LMAdj} tests are employed to determine cross-sectional dependence in the model. The fixed effects (FE) model is also performed for robustness to control the PQR results.

4. Results and Discussion

The CD test suggested by Pesaran (2004) is used to reveal the CD, which is the spreading effect of a shock from one cross-section to another. The results of the CD test are presented in table 5. Based on the results of the CD test, the *p*-values for all the variables in the model are below 0.01, rejecting the null hypothesis of no cross-sectional dependence and confirming the presence of cross-sectional dependence among the variables.

Table 5: CD test

Variable	CD test
***POV*1**	22.58***
***POV*2**	27.81***
***POV*3**	38.11***
STC	63.10***
HDI	138.12***
INET	132.00***
GINI	21.45***

Note: *** denotes statistical significance at 1% levels.

Source: Author’s own calculations

To check the unit roots in the variables, the CIPS and CADF unit root tests are applied after verifying the cross-sectional dependence between the variables. Tests such as CIPS and CADF cover cross-sectional dependence as second-generation unit root tests. CIPS and CADF results are shown in table 6. According to the results, in the case of CIPS, all the variables except *INET* are stationary at level, while *INET* is stationary at first difference. On the other hand, in the case of CADF, it is observed that *POV*1, *POV*2, *STC*, *HDI*, *INET* and *GINI* are stationary at level, while *POV*3 is stationary at first difference.

Table 6: Unit root test

	CIPS		CADF	
	I(0)	I(1)	I(0)	I(1)
***POV*1**	–2.980***	–4.311***	–2.736***	–3.396***
***POV*2**	–2.503***	–3.962***	–2.329***	–2.827***
***POV*3**	–2.074*	–3.541***	–1.853	–2.263***
STC	–3.530***	–4.859***	–2.850***	–4.298***
HDI	–2.192**	–3.567***	–2.087**	–2.463***
INET	–1.951	–3.533***	–2.129**	–2.700***
GINI	–2.177**	–3.992***	–2.193**	–2.724***

Notes: I(0) indicates series at level, while I(1) refers to series at first difference. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. The critical values for the CIPS test at the 1%, 5% and 10% significance levels are –2.25, –2.11 and –2.03, respectively. Similarly, the critical values for the CADF test are –2.250, –2.210 and –2.030 at the 1%, 5% and 10% levels, respectively.

Source: Author's own calculations

To choose the most appropriate method for the relationship between the dependent variable and the independent variables, the homogeneity/heterogeneity status of the models must be tested as well as their cross-sectional dependence. Accordingly, the Delta Tilde and Delta Tilde$_{adj}$ tests developed by Pesaran and Yamagata (2008) are used to examine homogeneity/heterogeneity and the CD_{LM1}, CD_{LM2} and $CD_{LM\text{-}Adj}$ tests are applied to test CD. The results of these tests are presented in table 7. The results demonstrate that the panel time-series data exhibit cross-sectional dependency. Using the delta test created by Pesaran and Yamagata (2008), it is determined whether the slope coefficient is homogeneous. The results indicate that the series is heterogeneous. Since the null hypothesis of homogeneity is rejected at the 1% significance level, it can be concluded that the panel data exhibit heterogeneity.

Table 7: Findings from LM and delta tests

	Cross-section independence in models (LM test)			Testing for slope heterogeneity in models (delta test)	
	LM	**LM adj.***	**LM CD***	**Delta**	**Delta adj.**
Model 1	1,818***	13.76***	3.938***	12.809***	15.924***
Model 2	1,937***	18.05***	6.645***	16.345***	20.331***
Model 3	1,870***	15.72***	7.044***	18.480***	22.974***

Note: *** denotes statistical significance at 1% levels.
Source: Author's own calculations

Since the Jarque–Bera test results indicate no normal distribution in the dataset, it is not recommended to use the linear regression model. In this case, the coefficient values can result in misleading or meaningless results since the predictions may be incorrect. To overcome this problem, the PQR approach is applied, which can provide reliable predictions even in non-normally distributed datasets. PQR results are presented in table 8. The results are showed for the 10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th and 90th percentiles of the different poverty lines. Overall, the empirical findings show that the impacts of various factors on poverty are heterogeneous.

The results confirmed the existence of a positive relationship between *STC* and poverty in all the quantiles for all the models. However, an insignificant relationship between *STC* and poverty was observed in the first quantile for all the models. The results also confirmed a positive and significant relationship between *STC* and poverty in all the models' 60th, 70th, 80th and 90th quantiles. It is evident in table 8 that the coefficients of *STC* gradually increase throughout all the quantiles for all the models. As a result of these findings, it can be concluded that *STC* is a major positive contributor to poverty. In general, the results are in line with existing literature (Masron and Subramaniam, 2019; Baloch *et al.*, 2020; Koçak and Çelik, 2022; Bolarinwa and Simatele, 2024). Dang *et al.* (2024) stated that temperature change has greater impacts on poverty in the short term and the negative consequences of temperature variability are more pronounced for poorer countries. There are also studies that show that temperature has stronger effects on economic growth, which is an important determinant of human development and poverty (Kalkuhl and Wenz, 2020).

Table 8: Findings from PQR approach

	Models	*STC*	*HDI*	*INET*	*GINI*
10th	Model 1 Model 2 Model 3	0.1145 0.2973 2.2005	−39.6104 −82.6489*** −96.8279***	0.0055 −0.0055 −0.0748**	0.2115 0.5339*** 0.9677**
20th	Model 1 Model 2 Model 3	0.1654 0.4176* 0.3414	−43.6277 −90.2630*** −107.7558***	0.0084 −0.0023 −0.0745**	0.2356 0.5675*** 0.9685***
30th	Model 1 Model 2 Model 3	0.2043 0.5147** 0.4424	−46.7030 −96.4104*** −115.595***	0.0106 0.0002 −0.0743***	0.2540 0.5946*** 0.9691***
40th	Model 1 Model 2 Model 3	0.2608 0.6337*** 0.569*	−51.1641** −103.9385*** −125.4229***	0.0139 0.0034 −0.0741***	0.2808* 0.6277*** 0.9698***
50th	Model 1 Model 2 Model 3	0.3187 0.7568*** 0.7084**	−55.7295** −111.7257*** −136.2302***	0.0171 0.0067 −0.0739***	0.3082** 0.6620*** 0.9706***
60th	Model 1 Model 2 Model 3	0.3863** 0.88576*** 0.8538**	−61.0690*** −119.8875*** −147.5066***	0.0209 0.0100 −0.0736***	0.3402*** 0.6979*** 0.9714***
70th	Model 1 Model 2 Model 3	0.4659** 1.0341*** 0.9784**	−67.3532*** −129.273*** −157.1727***	0.0255 0.0140 −0.0733**	0.3778*** 0.7393*** 0.9721***
80th	Model 1 Model 2 Model 3	0.5372** 1.1570** 1.1119**	−72.9820*** −137.0514*** −167.5271***	0.0296 0.0172 −0.0731*	0.4115*** 0.7736*** 0.9728***
90th	Model 1 Model 2 Model 3	0.6399* 1.4104** 1.3164*	−81.0900** −153.0907*** −183.3898***	0.0354 0.0240 0.9739***	0.4601** 0.8442*** 0.9739***

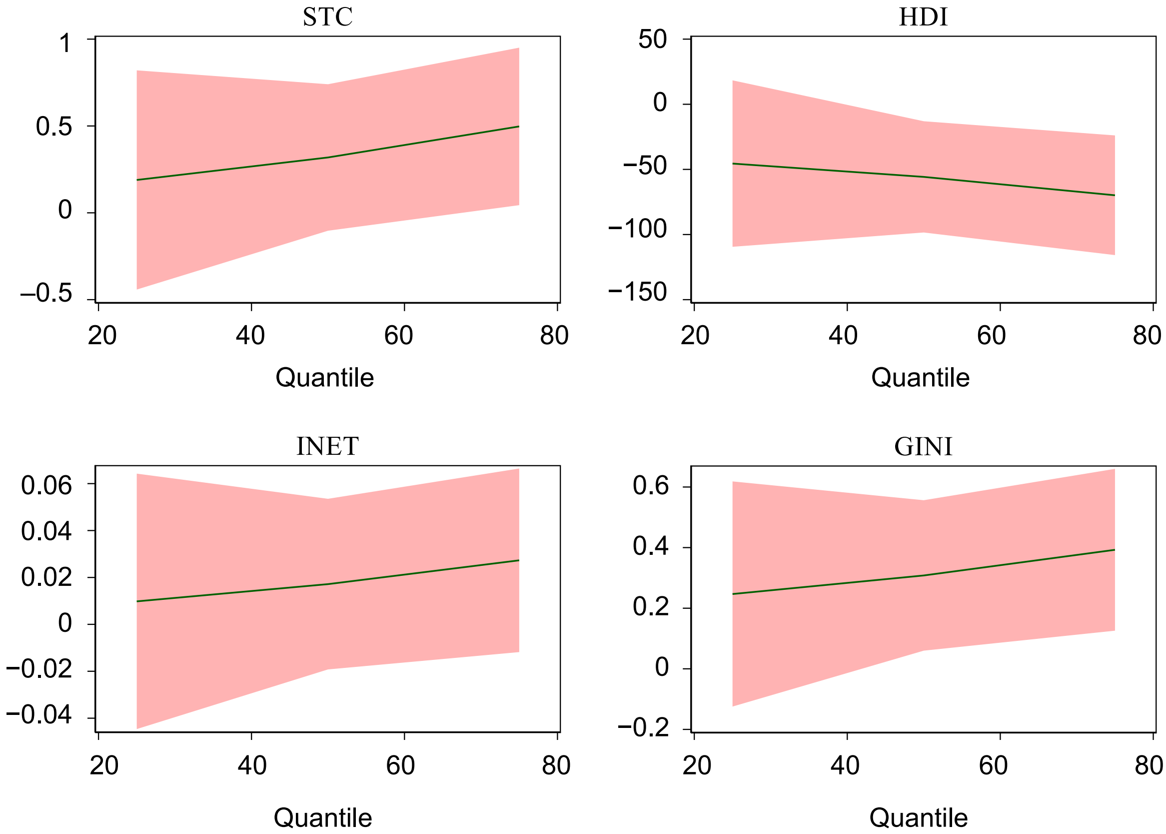
Note: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.
Source: Author's own calculations

Except in Model 1 at the 10th, 20th and 30th quantiles, *HDI* significantly decreases all types of poverty in all the quantiles. Additionally, *HDI* coefficients for all the poverty types increase across quartiles. Similar results have been reported by Sofilda *et al.* (2013), Singh (2012) and El Hasanah *et al.* (2022) among others. Also, Pardita *et al.* (2018) highlighted empirically that *HDI* has a significant impact on reducing poverty levels. Studies examining the relationship between *HDI* and poverty are limited in number, and their findings are often contradictory and do not always indicate a linear relationship (Mukhtar *et al.*, 2019). Except in Models 1 and 2, *INET* has a negative and significant effect on *POV*3 in all the quantiles as expected. This finding is in agreement with Zhu *et al.* (2022) and Yang *et al.* (2021). Also, Kaila and Tarp (2019) empirically demonstrated that internet use increases productivity and facilitates livelihoods. This finding shows that using the internet can be an important tool in reducing poverty.

The Gini coefficient has a positive and significant effect on *POV*1 (40th–90th), *POV*2 (all quantiles) and *POV*3 (all quantiles). Inequality of income leads to poverty, as these findings confirm once again. This finding was also reported by Ravallion (2005), who showed a positive relationship between the rate of change in income inequality and the rate of change in poverty rates. In addition, the results echo those of Besley and Burgess (2003) and Honohan (2004), who found a positive association between inequality and poverty.

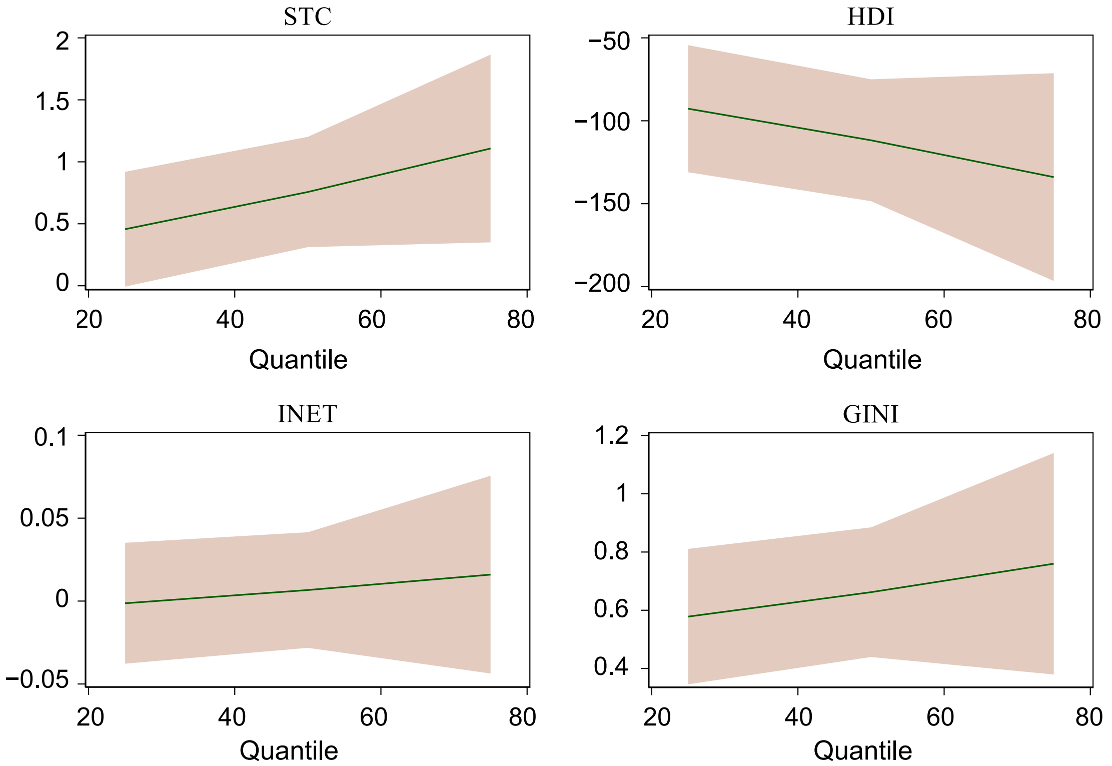
Specific variations of coefficients across quantiles obtained from PQR models are depicted in Figures 2, 3 and 4 respectively.

Figure 2: Findings of first PQR model



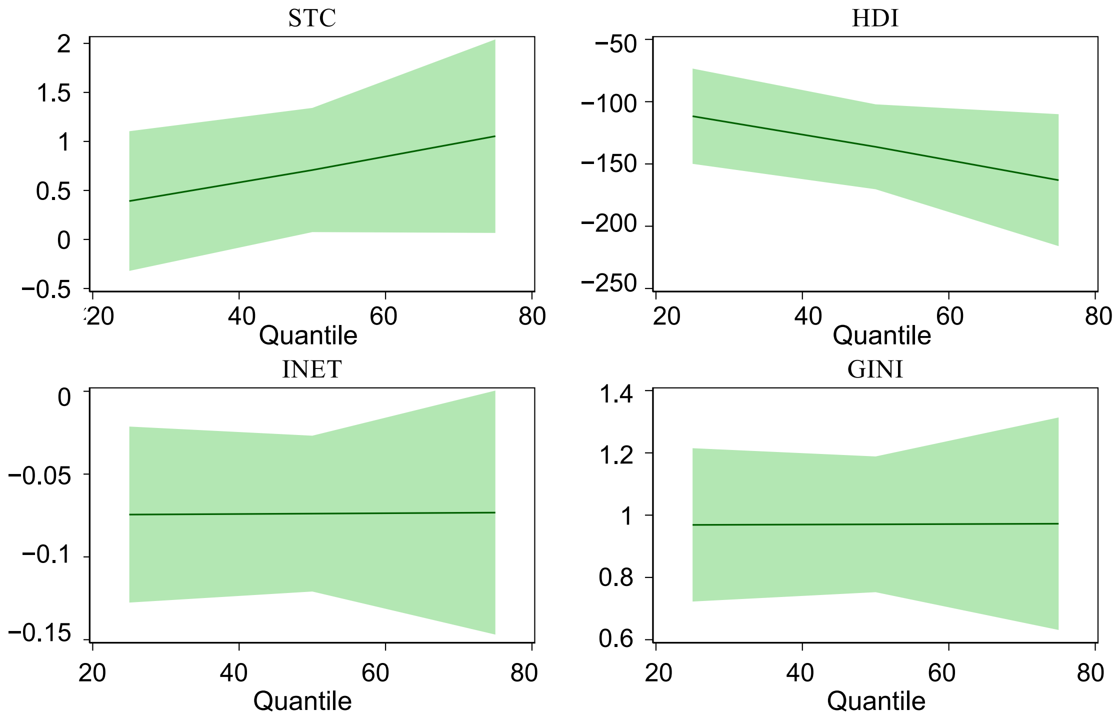
Source: Author's own elaboration

Figure 3: Findings of second PQR model



Source: Author's own elaboration

Figure 4: Findings of third PQR model



Source: Author's own elaboration

Table 9: Findings from OLS regression

Models		FE	RE	Robust FE	Robust RE
Model 1	***STC***	0.3312***	0.2480**	0.3312**	0.2480***
	HDI	−56.7166***	−31.0626***	−56.7166***	−31.0627*
	INET	0.0179**	−0.0109*	0.0179	−0.0109
	GINI	0.3140***	0.2414***	0.3141***	0.2414*
	C	36.1866***	19.4614***	36.1866***	19.4614
Model 2	***STC***	0.7667***	0.6941***	0.7667**	0.6941***
	HDI	−112.3545***	−84.3361***	−112.3545***	−84.3361**
	INET	0.0069	−0.0280**	0.0069	−0.0280
	GINI	0.6648***	0.5344***	0.6648***	0.5344**
	C	73.5029***	57.2435***	0.6647959***	57.2435*
Model 3	***STC***	0.7076**	0.7743***	0.7076**	0.7743
	HDI	−136.1626***	−139.9229***	−136.1626***	−139.9229***
	INET	−0.0739***	−0.0791***	−0.0738**	−0.0791*
	GINI	0.9705***	0.8392***	0.9706***	0.8392***
	C	97.4728***	105.4826***	97.47281***	105.4826***
Model 1		$F(4, 796) =$ 125.86***	Wald $\chi^2(4) =$ 494.17***	$F(4, 49) =$ 306.70***	Wald $\chi^2(4) =$ 77.61***
Model 2		$F(4, 796) =$ 195.57***	Wald $\chi^2(4) =$ 788.89***	$F(4, 49) =$ 451.11***	Wald $\chi^2(4) =$ 114.16***
Model 3		$F(4, 796) =$ 318.81***	Wald $\chi^2(4) =$ 1,362.32***	$F(4, 49) =$ 1,075.44***	Wald $\chi^2(4) =$ 147.71***

Note: ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively.

Source: Author’s own calculations

The FE model is also conducted for robustness to check the results of PQR (table 9). Which of the classical panel methods to use can be determined by conducting certain tests. According to the Hausman test, all of the FE models are more efficient than the random effects (RE) models; therefore, FE is chosen[2]. Furthermore, the Breusch and Pagan Lagrangian multiplier test was conducted to compare the RE model with pooled OLS. The result rejects the pooled OLS model[3]. Hence, FE is the most efficient model for this study. The estimators supply the correct standard error and thereby the significant level of correct coefficient. All the results are found to be similar to PQR across all the estimators except *STC* in Model 3, which is insignificant only in RE. The sign and significance of coefficients are similar to PQR.

The functional relationships *GINI* = f(*POV*1, *STC*, *HDI*, *INET*) and *HDI* = f(*POV*1, *STC*, *GINI*, *INET*) are also analysed using the PQR method. These results are not included in the study because the study would be too long. Except the first quartile, the results reveal that poverty has a positive and significant effect on income inequality in all the quantiles. Compared to lower quantiles, the effect is more intense in higher quantiles. Also, the results show that internet use has a negative and significant effect on income inequality in all the quartiles. The intensity of this effect increases with higher quantiles. It establishes that internet use has a positive and essential role in reducing income inequality. The results also show that poverty has a diverse negative influence on *HDI* in all the quantiles. The results indicate that internet use is statistically significant and contains a positive sign across all the quantiles. This implies that internet use increases *HDI* in the countries in the panel.

5. Conclusion

The present study analysed the effect of climate change, human development, internet use and income inequality on poverty in selected countries. A PQR model was espoused to estimate the empirical relationship between poverty, human development and climate variables. Among the various quantile levels associated with the dependent variable, the PQR model provided a good explanation of the heterogeneous impacts of these factors. The panel regression included 50 high-, middle and low-income countries as the cross-sectional units and the study used the time span from 2004 to 2020. Firstly, empirical results of the PQR revealed that climate change and income inequality increase poverty, while internet use and the *HDI* decrease it. The results of this study indicate that poverty is highly vulnerable to climate change, and special attention needs to be paid by policymakers to reducing the neg-

2 The results are available upon request.

3 The results are available upon request.

ative effects. This suggests that the adverse effects of climate change exacerbate the existing challenges of poverty, potentially leading to further economic and social vulnerabilities. Secondly, the analysis revealed that factors associated with human development and internet use exhibit significant negative effects on poverty. This implies that investments and advancements in human development initiatives, as well as access to the internet and related technologies, may serve as effective strategies for alleviating poverty levels within these countries. However, it is noteworthy that the study also identified income inequality as a contributing factor to poverty, with a positive effect observed. This underscores the importance of addressing income disparities and implementing equitable economic policies to mitigate poverty effectively. The robustness of the findings was further confirmed through the application of various models, including one-way and two-way models, as well as fixed-effect models, enhancing the reliability and validity of the results obtained.

Based on the empirical findings, several policy implications are proposed. Firstly, it is necessary for policymakers to ensure global cooperation that will promote green growth, green production and green consumption. Secondly, policymakers should adopt an integrated approach, integrate climate action with poverty reduction efforts, invest in human development, promote digital inclusion and regularly assess policy effectiveness to reduce poverty in the face of climate change and other challenges. Thirdly, policymakers should ensure that climate policies are closely linked with SDGs and poverty reduction strategies. This alignment can enhance the impact of both climate and poverty-related interventions.

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