Impact of Environmental Degradation on Life Expectancy: Evidence from Global and Regional Economies

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ABSTRACT

Background: Environmental degradation has significant implications for human health; however, empirical evidence on its global and regional impacts remains limited.

Objective: This study examines the effect of environmental degradation, proxied by CO_2 emissions, on health outcomes measured by life expectancy (LE).

Methods: The analysis employs panel data covering the period from 1990 to 2024 and incorporates control variables including GDP, education, access to healthcare, and urbanization. To establish robust causal relationships, the study employs pooled ordinary least squares (OLS), fixed-effects, random-effects, and system method of moments (GMM) estimators. In Addition, panel quantile regression is used to capture heterogeneous effects across different levels of LE.

Results: The findings show that CO_2 emissions have a significant negative impact on global health, reducing LE. Regional analysis further reveals substantial variations in the impact of CO_2 emissions on LE across different regions. Among all the regions, notably in Europe, the adverse effect of CO_2 emissions on LE is more pronounced at higher quantiles.

Conclusions: The results underscore the need for an equity-focused policy approach that strengthens resilience among vulnerable populations and mitigates the health impacts of environmental degradation.

Keywords: life expectancy, CO_2 emissions, panel data, system GMM, panel quantile regression

1. INTRODUCTION

The intensifying reality of climate change is defining the 21st century. The warming planet, primarily driven by greenhouse gas emissions such as carbon dioxide (CO_2), poses a systemic threat through environmental degradation and a challenge to human well-being. The dangers of climate change and environmental degradation are documented through record-breaking increases in temperature and the rising frequency and intensity of extreme weather events, which include heat waves, flooding, droughts and uncontrolled wildfires [18].

The damaging impacts of climate-induced disasters are evident across multiple dimensions of human well-being. Direct impacts include heat-related mortality and morbidity which disproportionately affect vulnerable populations, particularly the elderly whereas indirect consequences create ripple effects through environmental degradation. For instance, thermal shifts facilitate vector-borne diseases such as dengue and malaria [14,21].

Additionally, bad air quality cause respiratory diseases, skin diseases and allergies, premature deaths, and reduced life expectancy. In the long term, climate change has significant impacts on population dislocation and environmental justice as agricultural productivity is disrupted [7]. Life expectancy (LE), one of the aggregate metrics of population health, is therefore directly influenced by the risks of decreased environmental quality.

Huge scholarly efforts have been dedicated to quantifying the impact of environmental damage on human life longevity. While gross domestic product (GDP), healthcare expenditure, educational attainment and urbanization have a significant positive impact on LE, recent empirical evidence identifies negative impacts of CO_2 emissions [24]. The available literature has largely relied on theoretical analysis, whereas the empirical analysis employed robust econometric methodologies, including panel data analysis. This approach helps leverage multiyear and multi-country datasets to deploy the Fixed Effect Model to identify the causal relationship between CO_2 emissions and LE. Furthermore, this model allows for control of confounding factors such as GDP, education, urbanization and access to physicians. However, a fundamental methodological limitation exists across most of the literature. Those methodologies overlook the heterogeneous and disproportionate impact of climate change on health.

To fill the gap in existing literature, the study answers the following research questions:

- What is the relationship between CO2 emissions and LE across the panel?
- Does the relationship between CO2 emissions and LE vary across different quantiles?
- To what extent do control variables like GDP, education, availability of physicians, and urbanization mediate the impact of CO2 emissions on LE?
- How does the impact of CO2 emissions on LE differ across different geographic regions?

This study contributes to the literature in the following manner. First, it updates and extends the data set to 2024, capturing recent global developments, particularly the structural shifts associated with the COVID-19 pandemic. This updated dataset enables an assessment of the stability of the relationship between LE and CO2 emissions. Second, the study employs Panel Quantile Regression which allows for the estimation of covariate effects during various time periods. Finally, it introduces regional analysis based on major geographic regions defined by the World Bank. The impact of climate change is not uniform and by providing region-specific results, we aim for more targeted recommendations for environmental and public health policy makers.

2. LITERATURE REVIEW

To understand the determinants of health outcomes, a multidimensional perspective is required. Determinants of health outcomes can be socioeconomic, demographic and environmental in nature. Variables such as income, education, access to healthcare, environmental quality and urbanization are among the most widely recognized factors that interact to LE. For instance, an increase in GDP improves health by providing easier access to better healthcare facilities and adequate nutrition [8], higher education enables individuals to be more mindful of their nutrient intake, maintain a healthy weight and refrain from food that puts their health at risk like alcohol consumption [22].

Urbanization raises living standard of people, enabling them to avail better health care [40, 23]. Likewise, globalization has a positive impact on health because of affordable treatments, spread in medical knowledge and increasing access to nutritious food Ali & Majeed [9]. Moreover, renewable energy leads to high LE as clean energy helps in controlling chronic diseases Majeed et al., [25].

There is a growing body of studies, mapping the diverse health impacts of environment and climate change. Among them, the most studied impacts are increased incidences of infectious diseases such as dengue and malaria. The association is considered proportional as increased rainfall and higher temperatures are linked with vector-borne diseases [11, 28]. However, there are studies that suggest an inverse association, while others suggest no association at all. Extreme weather conditions are also related to vector-borne diseases, floods increase the risk of transmitting these diseases [13, 35]. Whereas some studies found no association between flood and dengue transmission.

The literature comprising respiratory illnesses diseases found their association with air pollution [23,4] while cardiovascular diseases are linked to heat exposure and extreme weather events. [15, 6]. Additionally, food and water-borne diseases, associated with meteorological factors, are considered significant outcomes stemming from environmental changes. Diseases like cholera, salmonella, and E-coli gastroenteritis are known to be caused by humidity and high temperature [3, 17]. Severe climatic events such as heavy rainfall are also associated with diseases like food contamination and diarrhea [1,5]. Drought can also cause food-borne diseases, but this relationship lacks empirical consensus [20].

Furthermore, mental health conditions such as anxiety and depression are widely recognized as significant outcomes of sudden natural disasters. Studies suggest that an increase in temperature and heat waves can have negative mental health impacts and increased hospital admissions for the said reason [19]. Additionally, droughts and flooding are associated with diverse mental health issues like psychological distress, anxiety, depression and substance abuse [2]. However, no link was found between droughts and suicide [32].

Climate change can also result in unnatural birth outcomes, and the impact is higher among the people who are exposed to heat, high temperatures, intense cold or humidity. These adverse outcomes include eclampsia in mothers, preterm birth, and low birth weight of children [19, 29]. Bad air quality caused by wildfire smoke exposure also causes lower birth weight [30, 38].

Moreover, environmental degradation causes nutritional changes, skin diseases and allergies. An et al. found a link between climate change and obesity [10]. Changes in temperature and precipitation, extreme weather conditions such as flooding and drought also cause undernutrition, malnutrition and child stunting [31, 27, 16]. A potential association also exists between climate change and skin diseases. High temperature, humidity and ultraviolet exposure cause skin allergies, eczema, sun burn and skin cancer [33, 37, 16]. Occupational health injuries are also associated with adverse climate conditions. Injuries due to slips and falls, dehydration, heat strains and kidney diseases are found in many occupational settings such as construction, agriculture and workers working in fisheries [36, 12]. A study by Zhang et al. [39] found a link between climate change and disability and changes in climate also increase the cost of disability adjusted life years.

Molina and Saldarriaga conducted a study on global temperatures and health conditions at birth and found that temperature increase has a significant negative impact on birth weight [26]. According to the authors, this is because of food insecurity during pregnancy and limited access to health care facilities. Road distortions caused by extreme weather conditions can also isolate people from health care facilities. Similarly, Majeed & Ozturk investigated the relationship between environmental degradation and population health across 180 countries using a fixed effects approach [24]. The study utilized Grossman's model of health and concluded that CO2 emissions negatively influence population health by decreasing LE and increasing the infant mortality rate.

Agache et al. highlight the urgent need to expand the research on the health impact of climate change, emphasizing the diversity of health impacts [7]. The study expanded the review by adding another category of long-term impacts of climate change on global health, apart from direct and indirect impacts. Longer-term impacts include population dislocation, famine, environmental justice and education. The study explains that health impacts vary depending on socioeconomic status, preexisting health conditions, and political and economic context. Similarly, Tatli empirically investigated the impact of surface temperature change on LE in the United Kingdom from 1990-2021 [34].

Utilizing the ARDL model, the study reveals a long-term relationship between surface temperature change and LE. The author suggests that there is no short-term relationship between the two variables; however, in the long run, surface temperature significantly reduces LE.

A review of the above-mentioned studies reveals a clear link between environmental degradation and adverse health outcomes that range from infectious diseases, cardiovascular diseases, mental health problems and reduced LE. While earlier studies have focused on specific diseases and country case studies, recent studies confirm that environmental degradation negatively correlates with LE. Moreover, the existence of heterogeneity across regions underscores the need to examine the relationship between environmental degradation and health in detail. The present study is an attempt to address the existing gaps in the literature through a panel data analysis globally and across different regions.

3. DATA AND METHODOLOGY

The empirical model employed in this study follows the methodological framework developed by Majeed & Ozturk, who investigated the impact of CO2 emissions on LE and infant mortality rate, utilizing OLS, fixed effect approach and system GMM [24]. The following regression model is developed for the empirical analysis of this study:

$$H_{it} = \beta_0 + \beta_1 CO2E_{it} + \beta_2 X_{it} + v_i + \mu_t + \varepsilon_{it} \dots\dots (1)$$

In the above equation, t denotes the time period from 1990 to 2024 while β_0 denotes the intercept term. H Denotes the log of LE at birth, total (years). $CO2E$ Denotes Carbon dioxide (CO2) emissions (metric tons per capita). β_1 Are the slope coefficients, measuring the impact of climate change on health. The term X_{it} donates the row matrix, including all other variables other than the focused variables that can cause a change in health. The term v_i is a country-specific unobservable effect, and μ_t is a time-specific factor. The term ε_{it} is the error term that captures the effect of all omitted variables. The subscripts i and t denote country and time period, respectively.

To examine the empirical relationship between climate change on health GDP, education (EDU), urbanization (URB) and Physicians (PHY) is added in equation 1. All variables are naturally transformed in logarithmic form to improve estimation efficiency and interpretation in elasticity.

$$lnH_{it} = \beta_0 + \beta_1 lnCO2E_{it} + \beta_2 XlnGDP_{it} + \beta_3 lnEDU_{it} + \beta_4 lnPHY_{it} + \beta_5 lnURB_{it} + v_i + \mu_t + \varepsilon_{it} \ldots\ldots (2)$$

3.1. Econometric Methodology

This study covers the sample of 176 countries in global analysis, 46 in Asian economies, 47 in African economies, and 38 in European economies over the period 1990-2024 using the data of the World Bank (2025). The sample size is limited to 176 global, 46 Asian, 47 African, and 38 European countries because of data limitations. We have used OLS, fixed effects and random effects for assessing the relationship between climate changes on health. Additionally, GMM is used to address the endogeneity problem and Quantile regression analyzes the relationships of all the distributions of a dependent variable, giving a more complete picture compared to traditional regression. Table 1 delivers the description of the data applied for empirical analysis.

Table 1: Variable Description, Transformation and Data Sources

Var.	Description	Definition of Variables	Source
Dependent Variable			
LE	LE at birth, total (years)	"LE at birth indicates the number of years a newborn infant."	WDI (2025)
Focus Variable			
CO2 emissions	Carbon dioxide (CO2) emissions	"Total annual emissions of carbon dioxide (CO2), one of the six greenhouse gases (GHG), from the agriculture, energy, waste, and industrial sectors, excluding LULUCF, standardized to carbon dioxide equivalent values divided by the economy's population."	WDI (2025)
Independent Variables (Control Variables)			
GDP per capita	GDP per capita (constant 2015 US$)	"Gross domestic product is the total income earned through the production of goods and services in an economic territory during an accounting period. It is expressed in constant prices and the	WDI (2025)

		reference year is 2015."	
Education	School enrollment, secondary (% gross)	"Gross enrollment ratio is the ratio of total enrollment, regardless of age, to the population of the age group that officially corresponds to the level of education shown."	WDI (2025)
Physicians	Physicians (per 1,000 people)	"Physicians include generalist and specialist medical practitioners."	WDI (2025)
Urbanization	Urban population (% of total population)	"Urban population refers to people living in urban areas as defined by national statistical offices."	WDI (2025)

Source: Author's own.

4. RESULTS

4.1. Descriptive Statistics

Table 2 represents descriptive statistics of all variables. The results indicate that LE is relatively high and stable across observations (mean = 4.22, SD = 0.15) while CO2 emissions, GDP per capita, education, physician availability, and urbanization show substantial variation, reflecting differences in environmental, economic, and social conditions across countries and over time.

Table 2: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
LE	7,412	4.229374	.1515128	2.497987	4.458663
CO2 emissions	6,774	.4571424	1.861601	-6.718325	5.312541
GDP per capita	7,089	8.574815	1.497217	5.116258	12.322
Education	4,252	4.224299	.5922156	1.208318	5.100353
Physicians	3,660	.0814296	1.394291	-4.961845	2.24379
Urbanization	7,560	3.937541	.5180781	1.689358	4.60517

Source: Author's own.

4.2. Correlation Analysis

Table 3 demonstrates the variables used for empirical analysis. The correlation matrix shows strong positive relationships among all variables. LE is highly correlated with education (0.822), GDP per capita (0.805), and physicians (0.801), while CO2 emissions are also strongly associated with GDP per capita (0.844) and physicians (0.813).

These results are consistent with the mechanisms where economic growth enables better health care access and promotes better health infrastructures. Moreover, education promotes healthier behaviors and physicians' density enables access to better care. There is also a strong correlation between GDP per capita and CO2 emissions which highlights the role of industrialization and economic growth. These results suggest potential multicollinearity and the importance of controlling these factors in regression analysis.

Table 3: Correlation Matrix

Variables	LE	CO2 emissions	GDP per capita	Education	Physicians	Urbanization
LE	1.0000					
CO2 emissions	0.7694	1.0000				
GDP per capita	0.8046	0.8444	1.0000			
Education	0.8224	0.7864	0.7358	1.0000		
Physicians	0.8014	0.8129	0.7354	0.8255	1.0000	
Urbanization	0.7015	0.8020	0.7650	0.6962	0.7448	1.0000

Source: Author's own.

4.3. Pooled OLS

Table 4 reports empirical results using OLS. The result shows a subtle negative and significant effect on life expectancy for Global, Asia, Africa and Europe. A 1% change in CO2 emissions decreases LE globally by 0.006%, in Asia by 0.018%, in Africa by 0.029% and in Europe by 0.028%. The results are significant for Global, Asia and Europe at 1% level of significance. Negative coefficients indicate that LE declines, likely due to pollution and associated health risks such as cardiovascular and respiratory diseases and the results are consistent with prior studies [15, 23, 4, 6].

The results of control variables like GDP per capita, education, physicians, and urbanization are also statistically significant. Positive effects of GDP globally and across most of the regions suggest that greater access to resources improves nutrition, healthcare access and living conditions which cause an increase in LE. Similarly, higher education level increases awareness and the ability to make informed choices which in turn are associated with long LE.

In addition, higher physicians' density enables early diagnosis and access to medical care increasing LE. However, the impact of urbanization varies, in some regions the LE improves due to better infrastructure whereas in some it decreases, likely because of high pollution.

The last rows of Table 1 show post-estimation tests for multicollinearity and heteroskedasticity are mentioned. VIF indicates no multicollinearity, whereas Breusch-Pagan shows that heteroskedasticity is present ($p<0.05$) in the analysis. Therefore, results become inefficient.

Table 4: Results of Pooled OLS (LE)

Variables	Global	Asia	Africa	Europe
CO2 emissions	-0.00632***	-0.0184***	-0.0209*	-0.0278***
	(0.00204)	(0.00294)	(0.0110)	(0.00245)
GDP per capita	0.0364***	0.0538***	-0.0586***	0.0519***
	(0.00176)	(0.00269)	(0.0165)	(0.00137)
Education	0.0907***	0.0612***	0.110***	0.0259***
	(0.00468)	(0.00697)	(0.0122)	(0.00951)
Physicians	0.0242***	0.00881***	0.0478***	-0.0115***
	(0.00190)	(0.00248)	(0.00875)	(0.00361)
Urbanization	0.000823	0.0210***	-0.00127	-0.0173**
	(0.00484)	(0.00756)	(0.0166)	(0.00774)
Constant	3.555***	3.489***	4.220***	3.857***
	(0.0266)	(0.0402)	(0.150)	(0.0362)
VIF Breusch-Pagan	4.10 1643.88 0.0000	4.37 132.62 0.0000	5.60 125.68 0.0000	1.75 40.34 0.0000
Observations	2,253	657	397	785
R-squared	0.780	0.784	0.496	0.747

Source: Author's own.

4.4. Fixed Effect Results

Table 5 shows fixed-effect model results. CO2 emissions have a significant negative effect on LE for Global, Asia, Africa, and Europe. Except for Africa, the results are significant at 1% level of significance. The control variables show the expected signs as GDP per capita, education, physicians, and urbanization have a positive impact on LE. The effect of control variables on African LE is insignificant except for CO2 emissions and education. The results for control variables are significant for the rest of the regions.

Table 5: Results of Fixed Effect (LE)

Variables	Global	Asia	Africa	Europe
CO2 emissions	-0.0201***	-0.0122***	-0.0298**	-0.0404***
	(0.00314)	(0.00373)	(0.0146)	(0.00291)
GDP per capita	0.0460***	0.0582***	0.0275	0.0520***
	(0.00398)	(0.00443)	(0.0272)	(0.00306)
Education	0.104***	0.0382***	0.135***	0.0259***
	(0.00474)	(0.00924)	(0.0154)	(0.00824)
Physicians	0.00723***	0.00885***	0.0155	0.0187***
	(0.00247)	(0.00285)	(0.00982)	(0.00436)
Urbanization	0.0812***	0.105***	0.0579	0.0802***
	(0.0121)	(0.0157)	(0.0446)	(0.0193)
Constant	3.110***	3.215***	3.192***	3.432***
	(0.0468)	(0.0556)	(0.242)	(0.0765)
Observations	2,253	657	397	785
Number of id	176	46	47	38
R-squared	0.502	0.656	0.474	0.639

Source: Author's own.

4.5 Random Effect Results

Table 6 shows Random effect model results. The results are insignificant for CO2 emissions, GDP per capita and urbanization in Africa and significant for the rest of variables. CO2 emissions, as expected, have negative impact on LE globally, in Asia and in Europe. For Africa the impact is negative but insignificant. Similarly, control variables have significant positive impacts in most of the regions. Hausman test indicates that fixed effects would be preferred for most regions except Africa.

Table 6: Results of Random Effect (LE)

Variables	Global	Asia	Africa	Europe
CO2 emissions	-0.0154***	-0.0139***	-0.0199	-0.0415***
	(0.00284)	(0.00362)	(0.0135)	(0.00281)
GDP per capita	0.0438***	0.0511***	0.0133	0.0515***
	(0.00352)	(0.00391)	(0.0229)	(0.00270)
Education	0.109***	0.0660***	0.141***	0.0291***
	(0.00435)	(0.00787)	(0.0122)	(0.00813)
Physicians	0.0103***	0.0116***	0.0198**	0.0203***
	(0.00237)	(0.00277)	(0.00936)	(0.00406)
Urbanization	0.0465***	0.0516***	0.0240	0.0421***
	(0.00992)	(0.0127)	(0.0327)	(0.0158)
Constant	3.228***	3.369***	3.390***	3.585***
	(0.0400)	(0.0497)	(0.200)	(0.0617)
Hausman Test	46.74 0.0000	20.75 0.0009	6.97 0.2226	23.12 0.0003

Observations	2,253	657	397	785
Number of id	176	46	47	38

Source: Author's own.

4.6 System GMM Results

Table 7 reports the results of system GMM, which addresses heteroskedasticity and endogeneity. The value of Hansen's test ensures the validity of instruments. Except for Africa, the results of all variables are significant at 1% level of significance.

Table 7: Results of System GMM

	Global	**Asia**	**Africa**	**Europe**
Variables	LE	LE	LE	LE
CO2 emissions	-0.00893***	-0.0175***	0.0127	-0.0232***
	(0.00208)	(0.00372)	(0.0105)	(0.00298)
GDP per capita	0.0395***	0.0552***	-0.0530***	0.0514***
	(0.00159)	(0.00352)	(0.0133)	(0.00115)
Education	0.0760***	0.0505***	0.1000***	0.0285***
	(0.00733)	(0.00826)	(0.0110)	(0.00834)
Physicians	0.0218***	0.00823***	0.0497***	-0.00745
	(0.00243)	(0.00249)	(0.00803)	(0.00465)
Urbanization	0.00710	0.0164	0.0103	-0.0205***
	(0.00538)	(0.0110)	(0.0172)	(0.00720)
Constant	3.574***	3.542***	4.178***	3.851***
	(0.0345)	(0.0533)	(0.130)	(0.0313)
Hansen's Test	6.67713 (0.0829)	8.74777 (0.0328)	.487565 (0.7837)	.881776 (0.6435)
Observations	1,657	498	333	729
R-squared	0.810s	0.792	0.555	0.751

Source: Author's own.

4.7 Quantile Regression Analyses

Table 8 provides results for quantile regression globally. The results show that at lower quantiles (q25), CO2 emissions have stronger negative impact on LE whereas at higher quantiles (q75), the impact is insignificant. This indicates that CO2 emissions can be particularly detrimental for countries with lower life expectancies. Similarly, at higher quantiles, better health infrastructure mitigates the adverse effects of CO2 emissions and therefore LE increases, as shown in the graph too. Positive impact of GDP per capita, education, number of physicians and urbanization are stronger for lower quantiles, suggesting that these factors have stronger impact for countries where LE is low because of additional resources that can be transformative.

Table 8: Results of Quantile Regression (Global)

	(1)	(2)	(3)
Variables	**q25**	**q50**	**q75**
CO2 emissions	-0.00885***	-0.00568***	-0.00288
	(0.00272)	(0.00150)	(0.00223)
GDP per capita	0.0409***	0.0385***	0.0308***
	(0.00175)	(0.00107)	(0.00143)
Education	0.0902***	0.0724***	0.0736***
	(0.00812)	(0.00438)	(0.00537)
Physicians	0.0258***	0.0204***	0.0124***
	(0.00271)	(0.00200)	(0.00246)
Urbanization	0.00175	0.00645	0.0212***
	(0.00755)	(0.00523)	(0.00804)
Constant	3.492***	3.598***	3.631***
	(0.0347)	(0.0319)	(0.0428)
Observations	2,253	2,253	2,253

Source: Author's own.

Table 9 reports results of quantile regression for Asia. The negative impact of CO2 on LE is significantly stronger for countries in lower quantiles (q25), that is, with already lower life expectancies. For higher quantiles, the result is insignificant. GDP per capita and education also have a stronger positive impact in the lower quantile than higher. For physicians' density, the impact on LE is slightly stronger in higher quantiles whereas for urbanization, the impact is positive for lower quantile (q25) and negative in higher quantiles (q50, q75). The impacts can also be seen visually on graphs for different variables.

Table 9: Results of Quantile Regression (Asia)

	(1)	(2)	(3)
Variables	**q25**	**q50**	**q75**
CO2 emissions	-0.0295***	-0.0148***	0.000930
	(0.00592)	(0.00353)	(0.00409)
GDP per capita	0.0529***	0.0551***	0.0505***
	(0.00579)	(0.00386)	(0.00239)
Education	0.0712***	0.0589***	0.0454***
	(0.0146)	(0.00558)	(0.0171)
Physicians	0.0117***	0.0122***	0.0142***
	(0.00289)	(0.00336)	(0.00313)
Urbanization	0.0598***	-0.00130	-0.0288***
	(0.0225)	(0.0143)	(0.00798)
Constant	3.286***	3.575***	3.784***
	(0.0809)	(0.0386)	(0.0827)
Observations	657	657	657

Source: Author's own.

Table 10 provides results of quantile regression for Africa. The results are insignificant for a lower quantile (q25), whereas for higher quantiles, surprisingly, the impact is significantly positive and stronger. This suggest that for African countries with longer LE, the impact of CO_2 coincides with higher GDP per capita and better health that comes with economic growth. This sign reversal aligns with the study of Majeed & Ozturk [24].

GDP per capita has a significant negative impact in all quantiles; the impact is particularly stronger for lower quantiles (q25). Similarly, education has a strong significant positive impact in all quantiles, especially in the lower quantile (q25) which suggests that countries with lower LE can benefit the most from education.

Physicians' density has significant positive impact on all quantiles, strongest at median quantile (q50). Finally, urbanization has positive but insignificant impact at lower quantile (q25) whereas at median (q50) and higher quantile (q75) the impact is significantly negative, indicating the health risks that come with urbanization.

Table 10: Results of Quantile Regression (Africa)

	(1)	**(2)**	**(3)**
Variables	**q25**	**q50**	**q75**
CO2 emissions	-0.00212	0.0248**	0.0406***
	(0.0119)	(0.0104)	(0.0104)
GDP per capita	-0.0590***	-0.0354***	-0.0469***
	(0.0145)	(0.0102)	(0.0114)
Education	0.126***	0.108***	0.0820***
	(0.0158)	(0.00843)	(0.00974)
Physicians	0.0392***	0.0446***	0.0412***
	(0.0106)	(0.00817)	(0.00486)
Urbanization	0.0294	-0.0186	-0.0221*
	(0.0179)	(0.0142)	(0.0121)
Constant	3.973***	4.138***	4.373***
	(0.117)	(0.104)	(0.0905)
Observations	397	397	397

Source: Author's own.

Table 11 suggests results of quantile regression for Europe. For all the quantiles, the impact of CO_2 emissions is significantly negative, and the impact is strong for the higher quantile (q75). This suggests that even countries with longer life expectancies have health risks from pollution. GDP per capita is significantly positive for all the quantiles and shows consistent benefits.

Education is significantly positive and stronger for lower quantile (q25), whereas for median (q50) and higher quantile (q75) the impact is insignificant. The number suggests that education has diminishing returns for countries with higher life expectancies. The results for physicians' density and urbanization are insignificant for all the quantiles.

Table 11: Results of Quantile Regression (Europe)

	(1)	**(2)**	**(3)**
Variables	**q25**	**q50**	**q75**
CO2 emissions	-0.0231***	-0.0167***	-0.0334***
	(0.00326)	(0.00529)	(0.00433)
GDP per capita	0.0522***	0.0480***	0.0506***
	(0.00183)	(0.00182)	(0.00189)
Education	0.0205**	0.0169	0.00824
	(0.00986)	(0.0131)	(0.0102)
Physicians	0.00415	0.00343	-0.0130
	(0.00798)	(0.00710)	(0.00796)
Urbanization	-0.00726	-0.000334	-0.00932
	(0.00815)	(0.00922)	(0.00928)
Constant	3.793***	3.828***	3.950***
	(0.0270)	(0.0423)	(0.0304)
Observations	785	785	785

Source: Author's own.

5. CONCLUSION

This research aims to investigate the impact of key socio-economic indicators of health, evaluated through LE, with a particular focus on CO_2 emissions. A global and regional analysis of Asia, Africa, and Europe is conducted utilizing traditional econometric techniques, along with dynamic system GMM and panel quantile regression. This detailed analysis provides deeper insight into drivers of CO_2-related health outcomes not only on average but also across different emissions levels.

The empirical findings reveal that the increasing level of CO_2 emissions in the atmosphere is detrimental to human health (LE) by increasing the number of pollutants in the air and spreading air-borne and water-borne diseases. In contrast, education, the number of physicians, and GDP per capita play a positive contributive role by increasing LE. This signifies investment in human capital, better access to health care facilities, and economic growth aid in improving the health of the residents. However, urbanization has a positive but insignificant impact on LE, suggesting its influence may be country specific.

The global estimates, in accordance with the regional evaluations, suggest that health-environmental relationships are not uniform. The differences in structure, institutions, and economic well-being are instrumental in quantifying LE. This underscores the need for region-specific health and environmental policies rather than setting up a cumulative global strategy.

In sum, the study emphasizes the crucial role of mitigating CO2 emissions while enhancing education, health infrastructure, and economic growth. In the future, studies can extend it further by using other health and environmental indicators, technological factors, and institutional quality to get a deeper understanding and formulate better policies.

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