Natural Resources for Human Health

eISSN: 2583-1194

Original Research

Received 24 July 2026
Revised 19 Aug 2026
Accepted 03 Sep 2026

Natural Resources for Human Health 2026, Vol. 6 (21s): 450–468

KEYWORDS:
Digitalization, Green Energy Consumption, Environmental Degradation, CO2 emission, Methods of Moments Quantile Regression.

Heterogeneous Drivers of Environmental Degradation across Global Economies: A Quantile Analysis

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ABSTRACT: The rapid expansion of digital technologies and the transition towards cleaner energy system are reshaping the global environmental landscape. However, the environmental consequences of digitalization remain ambiguous as digital technologies can simultaneously improve resource efficiency and increase energy demand. The study examines the relationship between digitalization, green energy consumption and environmental degradation while accounting for economic growth, foreign direct investment (FDI), trade openness, and inflation. Further, the study employs Method of Moments Quantle Regression (MM-QR) to capture heterogeneous relationships across different levels of environmental degradation using a balanced panel of 105 countries over the period from 2005 to 2023. The findings reveal substantial distributional heterogeneity. Green energy consumption exhibits a negative and statistically significant association with CO2 emissions across all reported quantiles highlighting its consistent environmental benefits. In contrast, digitalization demonstrates a varying relationship which is positive at lower quantiles but becomes negative at higher quantiles suggesting that the environmental benefits of digital transformation become more pronounced among economies with higher levels of environmental degradations. Economic growth and trade openness remain positively associated with environmental degradation across the distribution while the influence of FDI weakens at higher quantiles. Moreover, the study demonstrates the environmental implications of digitalization are not uniform across the countries. Further it advocates quantile specific environmental strategies, greater renewable-energy deployment, and policies that align digital transformation with clean energy infrastructure to support global decarbonization.

1. INTRODUCTION

The Twenty-first century has witnessed an unprecedented convergence of two transformative megatrends across the globe. The first and foremost is the rapid expansion of digital technologies and the next accelerating transition towards sustainable energy system (Nepal et al., 2024). Together, these twin transformations are fundamentally reshaping the production structures, consumption patterns, financial systems and economic development throughout the world that reconcile growth with environmental sustainability (Aiello et al., 2025a; Al-Shetwi et al., 2025; Preziuso, 2026). According to the Intergovernmental Panel on Climate Change (IPCC, 2023), anthropogenic greenhouse gas (GHG) emissions remain the primary driver of global warming while the International Energy Agency (IEA, 2024) reports that the energy sector accounts for nearly three quarters of global carbon-dioxide (CO2) emissions. Despite decades of international climate agreements, unprecedented investments in green energy technologies and rapid technological progress global greenhouse gas emission continue to rise while environmental

degradation remains one of the principal threats to sustainable development. The precedented divergence between technological advancements and environmental improvements raises a fundamental question: can digitalization and green energy consumption jointly support economic development while reducing environmental degradation?

Digitalization has a dual environmental character. On the one hand, digital technologies can improve resource allocation, resource transactions and information costs, support smart grid management, enable real-time monitoring, facilitate teleworking and dematerialize some electronic activities (Al-Shetwi et al., 2025; Kharb et al., 2026). On the other hand, data centres, communication network, connected devices, and electronic equipment require energy and materials and can generate e-waste and rebound effects (Zheng et al., 2025). OECD evidence therefore characterizes digitalization as part of 'twin transition' in which environmental opportunities and environmental footprints must be managed simultaneously (OECD, 2024). The empirical literature consequently reports heterogeneous and sometimes non-linear relationships between ICT development and emissions. Whereas green energy consumption represents the second pillars of the transition. Renewable energy commonly known to be green energy can reduce the dependence on fossil fuels, diversify energy supply, improve energy security and lower carbon intensity (Zuo & Ren, 2025). IRENA (2023) emphasizes electrifications and energy efficiency as central components of a 1.5` C compatible transition. Yet the environmental effect of renewable energy need not be identical across countries. Moreover, economic growth remains a crucial conditioning factor. The Environmental Kuznets Curve (EKC) literature argues that environmental pressure may rise during early development and decline after economies achieve sufficient income, technological capability and regulatory capacity (Nibedita & Irfan, 2021). Grossman and Krugger (1995) provide early empirical evidence that the relationship between income and environmental indicators can shift from deterioration to improvement. However, turning point is not universal and growth driven by energy intensive industrialization may continue to increase emissions. Foreign direct investment and trade openness add further complexity because international integration can diffuse cleaner technologies while simultaneously expanding pollution-intensive production and energy demand (Y. Chen et al., 2023; Yu et al., 2025; Zuo & Ren, 2025).

An important conceptual and methodological gaps remain after having significant advancement in the literature also. Existing studies have extensively examined the relationships between the digitalization and environmental quality, renewable energy and carbon emissions, economic growth and environmental degradation, and globalization and sustainability, reflecting in fragmented evidence of the combined environmental implications of digital transformations and green energy transition. Moreover, empirical evidence remains inconsistent. Similar inconsistencies occur in renewable energy literature as well, where environmental benefits differ considerably across the nations. Such conflicting evidence suggests that the environmental consequences of digitalization and green energy consumptions are likely to be homogeneous across economies.

One important explanation for these inconsistencies lies in the methodological assumptions underpinning much of the existing empirical literature. Majorly, previous studies rely on conventional mean-based panel estimators, including pooled ordinary least squares, fixed effects, random effects, generalized method of moments, and panel autoregressive distributed lag models (Asif et al., 2025; Irfan & Ojha, 2023; Peng et al., 2021; Wang et al., 2021). Although these techniques provide valuable evidence about the average relationships which implicitly assume that the environmental effects of digitalization and green energy remain constant across the economies regardless their environmental situations (Aiello et al., 2025b; Lin & Xie, 2025). This assumption is particularly restrictive within a highly heterogeneous global economy where countries differ substantially in each and every manner. Consequently, the average-effects models may conceal important distributional heterogeneity and generate policy recommendations that are insufficiently, tailored to countries facing different environmental challenges (Nibedita & Irfan, 2024; Waaje et al., 2025).

Against this backdrop, the present study investigates whether digitalization and green energy consumption mitigate environmental degradation across the global economy while accounting for the broader influences of economic growth, trade openness, and foreign portfolio investment. Rather than estimating a single average relationship, this study explicitly recognizes that countries occupy different positions within the global environmental degradation distribution and therefore may exhibits heterogeneous responses to technological and energy transitions. To capture this heterogeneity, the study employs a Method of Moment Quantile Regression framework which estimates the effects of explanatory variables across different conditional quantiles of environmental degradation (Koenker, 2019). By moving beyond conventional mean-based estimation, the analysis provides a more comprehensive understanding of whether the environmental benefits of digitalization and green energy strengthen, weaken, or even reverse as countries move from lower to higher levels of environmental degradation (Lin & Huang, 2023; Sadorsky, 2009; Waaje et al., 2025).

This study contributes to the literature in four distinguished ways. First, it develops an integrated empirical framework that jointly examines digitalization and green energy consumption while controlling for key macroeconomic and globalization drivers of environmental degradation, thereby providing a more comprehensive understanding of digital-green transition. Second, it advances the environmental economics literature by explicitly modelling cross-country heterogeneity through panel Method of Moment Quantile Regression rather than relying on conventional average-effect estimators. Third, it provides global evidence on how the environmental impacts of digitalization and green energy vary across different levels of emissions thereby, reflecting distribution specific dynamics that remain hidden in mean-based analyses. Finally, the findings offer differentiated policy implications by demonstrating that the environmental effectiveness of digital transformation and green energy depends upon countries' environmental conditions and stages of development, suggesting that uniform climate policies may be less effective than strategies tailored to heterogeneous national circumstances.

The remainder of this paper id organized as follows. Section 2 reviews the theoretical and empirical literature and develops the research Gap and research hypothesis. Section 3 describes the research methodology like data, variables, models, and the econometric estimation tools. Section 4 presents and discusses the empirical results. Section 5 provides the robustness analysis and policy implications. Section 6 concludes the paper and outlines directions for future research.

2.LITERATURE REVIEW

2.1. Digitalization and Environmental Degradation

Digitalization has become a fundamental driver of economic transformation, reshaping production systems, industrial organizations and environmental governance through widespread adoption of information and communication technologies, cloud computing, Artificial Intelligence and Internet of things (Y. Chen et al., 2023; Nepal et al., 2024). From the perspective of Ecological Modernization Theory, digital technologies enhance environmental sustainability by improving resource efficiency, facilitating cleaner production processes, optimizing energy management, and accelerating technological innovation (Imran et al., 2026). Digital Infrastructure also enables real-time environmental monitoring which supports the transition toward low-carbon development (OECD, 2024).

Empirical evidence generally supports the environmental benefits of digitalization. Several studies report that digital transformation reduces carbon emissions by improving energy efficiency, stimulating green innovation and promoting industrial upgrading (Alataş, 2021; Imran et al., 2026). Furthermore, digital technologies facilitate the integration of renewable energy systems, enhance environmental governance and reduces productions inefficiencies, contributing to sustainable development (Li et al., 2023; Xu & Ullah, 2023). However, an emerging body of literature presents contrasting evidence arguing that the rapid expansion of digital infrastructure increases electricity consumption, electronic waste, and resource extraction which intensify environmental degradation through rebound effects (Al-Shetwi et al., 2025). These conflicting findings suggest that the environmental consequences of digitalization are neither linear nor universal but depend on countries technological maturity, energy structure, and institutional quality.

On the other hand, despite having considerable academic attention, existing studies predominantly employ conventional mean-based econometric approaches that assumes homogeneous environmental responses across economies (Pesaran, 2007). Such method overlooks the possibility that digitalization may exert different environmental effects across economies with varying levels of environmental degradations. This limitation highlights the need for a distributional analysis capable of capturing heterogeneous impacts, thereby, providing a more comprehensive understanding of the digitalization-environment nexus.

Consequently, we proposed the Hypothesis

H1: Digitalization significantly impacts the environmental degradation.

2.2. Economic Growth and Environmental Degradation

Economic growth has long been recognized as key determinants of environmental degradation through its influence on industrialization, energy consumptions urbanizations and resource utilization (Nibedita & Irfan, 2024). The Environmental Kuznets Curve (EKC) hypothesis suggests that environmental degradation initially intensifies with economic growth but gradually declines beyond a certain income threshold as economies adopts cleaner technologies, strengthen environmental regulations, and shift towards service-oriented industries (Kharb et al., 2026; Meng et al., 2018; Ridwan et al., 2024). However, Empirical evidence remains inconclusive with studies reporting positive, negative and nonlinear relationships between

economic growth and environmental quality (Sethi et al., 2024). These mixed findings imply that the environmental consequences of economic growth vary across countries with different development stages.

Consequently, we proposed the Hypothesis:

H2: Economic growth significantly influences environmental degradation.

2.3. Green energy Consumption and Environmental Degradation

Green energy consumption has become a pillar of global decarbonization strategies owing to its potential to reduce dependence on fossil fuels, improve energy security, and mitigate environmental degradation (Nibedita & Irfan, 2021). Green energy sources generate substantially lower greenhouse gas emissions than conventional fossil fuels and are therefore widely recognized as essential for achieving carbon neutrality and sustainable development (Irfan & Shahbaz, 2022; Singh et al., 2022; Yueming & Shiyou, 2025; K. Q. Zhang et al., 2022)

. Theoretically, the environmental benefits of green energy are supported by Ecological Modernization Theory which argues that technological innovation and cleaner energy systems can simultaneously promote economic development and environmental protection by enhancing energy efficiency and reducing carbon intensity (Tiwari et al., 2026). A growing body of literature supports the environmental advantages of renewable energy consumptions. Cross country and regional studies consistently report that greater reliance on renewable energy significantly reduces environmental degradation. However, its consistencies indicate that conventional mean-based indicators may obscure important cross-country heterogeneity, highlighting the need for distributional approaches that capture how the environmental effects of green energy differ across varying level of environmental degradation.

Consequently, we proposed the hypothesis:

H3: Green energy consumptions significantly mitigate the environmental degradations but its environmental effects vary across different quantiles of environmental degradation

2.4. FDI and Environmental Degradation

Foreign direct investment (FDI) plays a significant role in shaping environmental outcomes through technology transfer, industrial expansion, and capital accumulation (Irfan & Shahbaz, 2022; Lin & Xie, 2025; M. Zhang et al., 2025). The relationship between FDI and environmental degradation is primarily explained by two competing theories: Pollution Heaven Hypothesis and Pollution Halo Hypothesis (Y. Chen et al., 2023; Nassar, 2025). It argues that multinational firms relocate pollution intensive industries to countries with less stringent environmental regulations which further leads to increasing environmental degradation (F. Chen et al., 2021). Conversely, pollution halo hypothesis suggests that facilitates the diffusion of cleaner technologies, superior management policies and environmentally efficient production processes, contributing to improved environmental quality (F. Chen et al., 2021). Overall, empirical studies report mixed evidence indicating the environmental impact of FDI depends on host country's environmental regulations and capabilities.

Consequently, we proposed the Hypothesis:

H4: Foreign Direct investment significantly influences environmental degradation across different quantiles.

2.5. Trade openness and Environmental Degradation

Trade openness has profound implications for environmental quality by influencing production patterns, technology diffusion, and international specialization (F. Chen et al., 2021; Irfan, n.d.; Irfan et al., 2024; Peng et al., 2021). Theoretically, the relationships are explained by the pollution heaven hypothesis and the technique effects of international trade (Peng et al., 2021). While greater trade integration may increase environmental degradation by encouraging pollution intensive production in countries with weaker environmental regulations (Irfan et al., 2021). It can also improve environmental quality through the transfer of cleaner technologies, enhanced production efficiency and stricter environmental standards associated with global markets (Jha & Singh, 2019). Conclusively, empirically studies provide mixed evidence, suggesting that the environmental effects of trade openness depend on countries income levels, industrial structures, and energy consumptions.

Consequently, we proposed the Hypothesis:

H5: Trade openness significantly influences environmental degradation vary at different quantiles.

2.6. Literature Summary and Research Gap

The literature demonstrates that the digitalization-environment and green energy – environment relationships are not settled. Three limitations are especially relevant. First, digitalization and green energy are frequently examined separately, despite their interaction within the broader twin transition. Second, many studies use mean-based estimators that conceal distributional heterogeneity. Third, globalization and macroeconomic conditions can modify the environmental effects of technology and energy transition but are not always incorporated jointly. The present study responds to these gaps by estimating a unified global model for 105 global economies over the period from 2005-2023 using MM-QR while considering the base year 2005 because of global acceptance year of Kyoto protocol which settled the cause of environmental degradation.

Table 1. selected literature and positioning of this study

Authors	Sample	period	Methods	Outcomes
Alatas, (2021)	93 countries	1995-2016	STIRPAT and mean group estimators	ICT is an important determinant of CO2 as well its effects differ across emission groups.
Chen, Pinar & Stengos (2023)	97 countries	1995-2015	Dynamic panel threshold	Renewable energy reduces CO2 emissions after a renewable-threshold is reached.
Chen, Zhang & Li (2023)	G7	1990-2020	MM-QR	Digitalization reduces GHG emissions whereas GDP increases the emissions.
Li, Zhang & Zhu (2023)	91 countries	2007-2015	PCA and nonlinear panel analysis	ICT- CO2 relationship is non-linear and heterogeneous across the country groups.
Trade-openness	64 BRI countries	2001-2019	Panel quantile regression	Trade openness increases CO2 with effects of varying across quantiles
Imran et al. (2026)	South Asia	1998-2023	MM-QR	Digitalization can raise CO2 while renewable electricity and government effectiveness mitigate degradation.
Present study	105 countries	2005-2023	MM-QR + Robustness checks	Joint distributional evidence on digitalization, green energy, FDI, GDP, Inflation and trade openness.

Source: Authors creation

2.7. Conceptual Framework

The framework links digitalization and green energy consumption to environmental degradation through competing channels. Digitalization may increase emissions through electricity demand, smart systems, network tower installation, cleaner production and environmental monitoring. Green energy consumption is expected to reduce emissions through substitution away from fossil energy. GDP, FDI, trade openness and inflation are included as macroeconomic conditioning variables. The empirical contribution is to allow these relationships to differ across the conditional distribution of CO2 emissions rather imposing a single average effect.

3.RESEARCH METHODOLOGY

3.1. Study Design and Data

The study follows a quantitative and explanatory research design. A balanced panel comprising 105 countries over the period from 2005 to 2023 is used comprising 1995 country-year observations. The study relies on secondary data from the World Development Indicators (WDI) which provides internationally comparable macroeconomic, energy, ICT and environmental indicators. The dependent variable is CO2 emissions used as the principal indicator of environmental degradation. Green energy consumption and a composite index of digitalization are the main explanatory variables while FDI, GDP, Inflation, and trade openness are included as control variables. Further, the analytical sequence consists of four stages. Stage 1 evaluates descriptive properties, rank correlations, stationarity and multicollinearity. Stage 2 evaluates cross-sectional dependency, heteroskedasticity, and serial autocorrelation and model specifications. Stage 3 estimates the distributional effects using MM-QR. Stage 4 evaluates

robustness through Driscoll-Kraay standard errors and pooled median quantile regression. This methodological approach provides more robust and policy relevant insights than the conventional mean-based panel estimators by capturing heterogeneous environmental responses across the countries with varying levels of environmental degradations illustrates in fig. 1.

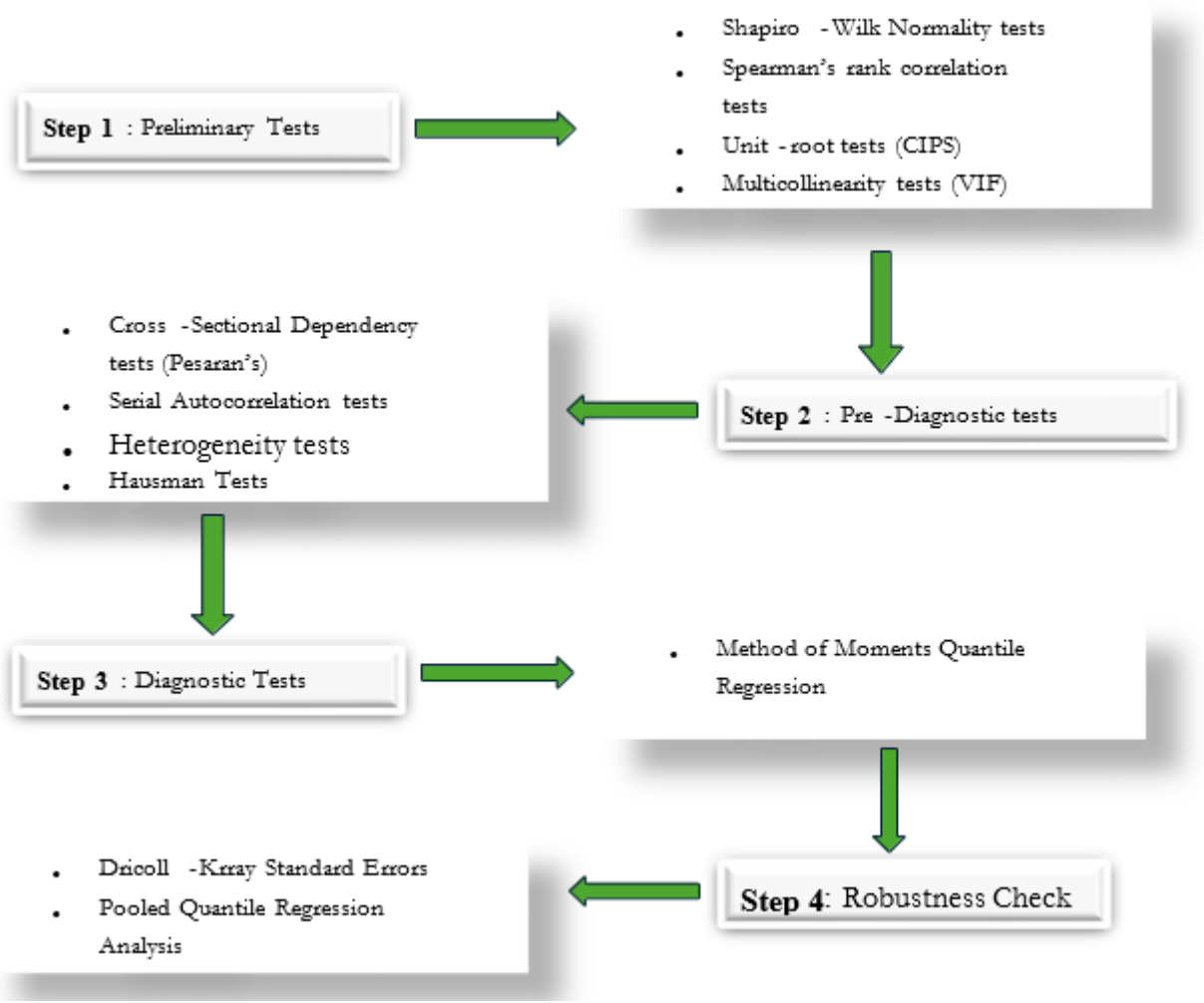


Fig. 1: Visual representation of empirical Analysis

Sources: Authors creation

3.2. Variables and Measurement

Table 2. Variable and data sources

Variables	Log form of Variables	Descriptions	Data Sources
Carbon Dioxide emission (CO2)	lco2	Carbon emission measured in metric tons per capita are used as an indicator of environmental degradation.	World Development Indicators (WDI)
Green energy Consumption (REC)	lrec	Renewable energy consumption measured in percentage of renewable energy out of total energy consumption are used as an indicator of green energy consumption.	World Development Indicators (WDI)
Digitalization Index (DIGI)	ldigi	Index prepared using averages of the Fixed telephone subscriber, mobile cellular subscriber, fixed broadband	World Development Indicators (WDI)

		subscriber, and Internet users (as a percentage of total population)	
Foreign Direct Investment (FDI)	lfdi	Foreign direct Investment measured in Current US$	World Development Indicators (WDI)
Economic Growth (GDP)	lgdp	Gross Domestic products measured in Current US$ used as a proxy of Economic growth.	World Development Indicators (WDI)
Trade Openness (TO)	lto	Trade openness is measured in percentage annually to the GDP [{(Export +Import)/GDP} *100]	World Development Indicators (WDI)
Inflation (CPI)	lcpi	Consumer Price Index is measured in percentage annually.	World Development Indicators (WDI)

Source: Authors own Creation

3.3. Empirical Model

The baseline empirical relationship can be expressed as:

$$ED_{it} = \beta_0 + \beta_1 GEC_{it} + \beta_2 DIGI_{it} + \beta_3 FDI_{it} + \beta_4 GDP_{it} + \beta_5 CPI_{it} + \beta_6 TO_{it} + \mu_i + \varepsilon_{it}$$

Where ED denotes environmental degradation measured through CO2 emissions, μi captures country-specific effects, and εit is the idiosyncratic error term. All these variables' data converted into a log form which is already reflected in the section 3.2. variables and measurement to make all into a standardized format in their measurement unit.

3.4. Econometric Estimation Strategy

3.4.1. Preliminary Diagnostics

Descriptive statistics summarize the distribution of each variable. Spearman rank correlations are used because Shapiro-Wilk tests reject normality for all variables. Multicollinearity is assessed using variance inflation factor (VIF). The CIPS unit root test of Pesaran (2007) is employed because it allows for cross-sectional dependence and cross-sectional dependency are examine through Pesaran's CD test (Pesaran, 2007). Heteroskedasticity and serial autocorrelation are tested using the Breusch-Pegan/Cook-Weisberg and Wooldridge procedures respectively (Driscoll & Kraay, 1998).

3.4.2. Random Effects vs Fixed Effects

The Hausman specification test compares fixed -effects and random – effects estimates. The reported χ^2 statistic is 91.11 with $p < 0.001$ leading to rejection of the null hypothesis underlying the random – effects specification. The fixed effects specifications are therefore preferred for the conventional benchmark model (Hausman, 1976).

3.4.3. Method of Moments Quantile Regression

Quantile regression introduced by Koenkar & Basset, 1978, allows effect of covariates to vary over the conditional distribution of the dependent variable. The MM-QR framework of Machado and Santos Silva (2019) extends this logic to setting with individual effects and potential endogeneity concerns. Instead of estimating only the conditional mean, MM-QR estimates coefficients at selected quantiles of environmental degradation. The present study reports the 0.05, 0.25, 0.50, 0.75, and 0.95 quantiles. This is especially useful when countries with low emissions respond differently from countries located in the upper tail of the emissions distribution.

3.4.4. Robustness Checks

Two robustness procedures are followed. First, Driscoll-Kraay standard errors are used to address heteroskedasticity, serial correlation and cross-sectional dependence in the covariance structure (Driscoll & Kraay, 1998). Second, pooled median quantile regression is used as a distributional benchmark (Koenker, 2019). Agreement across the main and robustness estimates increases confidence in relationships that retain their sign and significance across specifications.

4. EMPIRICAL RESULTS

4.1. Descriptive Statistics

Table 3. Descriptive statistics

Variable	Observations	Mean	Std. Dev.	Min.	Max.
CO2	1995	308.4911	1150.893	.0569	12717.66
FDI	1995	1.76e+10	5.46e+10	-3.09e+11	7.34e+11
GDP	1995	6.93e+11	2.23e+12	1.12e+08	2.77e+13
REC	1995	27.48145	25.96994	0	94.5
CPI	1995	5.186113	9.417972	-16.85969	221.3416
TO	1995	92.8455	61.34179	22.10598	442.62
DGI	1995	47.59951	21.73429	.720192	125.6331

Source: Author's calculation

The descriptive statistics reveal substantial cross-country dispersion. CO2 emissions show a particularly a wide range, indicating that the sample combines countries with very different environmental and production structures. FDI and GDP also exhibit large dispersion, consistent with the inclusion of economies at markedly different development stages. Green energy (REC) ranges from Zero to 94.5% while digitalization ranges from 0.72 to 125.63 under the composite construction used in the study. The latter is possible because some underlying ICT penetration measures, particularly mobile subscriptions can exceed 100% of population. This table also provides an important data-validation signal like FDI and CPI contain negative observations and REC contains zero observations.

4.2. Spearman Rank Correlations

Table 4. Spearman rank correlation coefficients

	CO_2	FDI	GDP	REC	CPI	TO	DGI
CO2	1.0000						
FDI	0.6563*** (0.0000)	1.0000					
GDP	0.9284*** (0.0000)	0.7159*** (0.0000)	1.0000				
REC	-0.4989*** (0.0000)	-0.3112*** (0.0000)	-0.3815*** (0.0000)	1.0000			
CPI	-0.0512** (0.0223)	-0.1201*** (0.0000)	-0.1527*** (0.0000)	0.1717*** (0.0000)	1.0000		

TO	-0.1975*** (0.0000)	-0.0164 (0.4645)	-0.1771*** (0.0000)	-0.2851*** (0.0000)	-0.1783*** (0.0000)	1.0000	
DGI	0.3987*** (0.0000)	0.4205*** (0.0000)	0.5482*** (0.0000)	-0.4352*** (0.0000)	-0.3524*** (0.0000)	0.3267*** (0.0000)	1.0000

Note: Level of significance *(10%), **(5%), ***(1%)

Source: Author's Calculation

CO2 is strongly positively correlated with GDP (0.9284) and FDI (0.6563) while renewable energy is negatively correlated with CO2 (-0.4989). Digitalization has a positive bivariate association with CO2 (0.3987) but this does not imply that digitalization raises emissions after conditioning on the other variables.

4.3. Multicollinearity

Table 5. Multicollinearity test

Variables	VIF	1/VIF
lgdp	4.97	0.201338
lfdi	4.16	0.240302
ldgi	1.84	0.543384
lto	1.68	0.593565
lrec	1.28	0.780249
lcpi	1.09	0.913402
Mean VIF	2.50	

Source: Author's Creation

The mean VIF is 2.50. The highest VIF is 4.97 for GDP followed by 4.16 for FDI. These values do not indicate severe multicollinearity under common diagnostic rules of thumb. The variables can therefore be retained jointly in the baseline model.

4.4. Unit root tests

Table 6 Unit root tests

		CIPS	
Variables		**Intercept (at level)**	**Intercept (at first difference)**
lco2		-1.962	-3.648***
lfdi		-2.513***	
lgdp		-1.775	-3.608***
lrec		-1.539	-3.303***
lcpi		-2.733***	

lto		-1.550	-3.659***
ldgi		-2.502***	
Critical values at	1%	-2.14	-2.14
	5%	-2.04	-2.04
	10%	-1.99	-1.99

Note: Level of significance *(10%), **(5%), ***(1%)

Source: Authors own calculations

The CIPS results indicate that some variables are stationary in levels while lco2, lgdp, lrec, and lto become stationary after first differencing. This mixed-order integration pattern reinforces the need to avoid relying on a single conventional mean-based estimator and supports the study's distributional modelling strategy subject to the precise transformation and stationarity definitions used in the estimation datasets.

4.5. Shapiro-wilk normality test

Table 7. Shapiro-wilk normality test

Variable	Observations	W	V	Z	Prob > Z
lco2	1995	0.98696	15.433	6.960	0.0000
lfdi	1995	0.97443	30.257	8.673	0.0000
lgdp	1995	0.98793	14.282	6.763	0.0000
lrec	1995	0.86616	158.345	12.883	0.0000
lcpi	1995	0.97413	30.606	8.702	0.0000
lto	1995	0.98341	19.627	7.572	0.0000
ldgi	1995	0.82454	207.617	13.572	0.0000

Note: Level of significance *(10%), **(5%), ***(1%)

Source: Authors own calculations

The probability values are 0.0000 for all variables which results in rejection of normality. This result further justifies the use of rank correlations for descriptive association and quantile-based estimation for the main empirical analysis.

4.6. Cross-sectional dependence, Heteroskedasticity and Autocorrelation test

Table 8. Cross-sectional dependence test

Variables	CD-test	p-value	corr	Abs(corr)
lco2	39.76***	0.000	0.123	0.654
lfdi	21.00***	0.000	0.065	0.268
lgdp	238.58***	0.000	0.741	0.755
lrec	-	-	-	-

lcpi	98.59***	0.000	0.306	0.365
lto	44.11***	0.000	0.137	0.396
ldgi	272.82***	0.000	0.847	0.858
	Tests			**p-value**
Breusch-Pagan/ Cook-Weisberg test for heteroskedasticity			17.50***	0.0000
Wooldridge tests for autocorrelation			178.254***	0.0000

Note: Level of significance *(10%), **(5%), ***(1%)

Source: Authors own calculations

There is strong evidence of cross-sectional dependence is reported for CO2, FDI, GDP, CPI, Trade openness and digitalization. This is economically plausible for a global panel because countries share global shocks, technology diffusion, commodity-price movements and international financial diffusion, commodity-price movements and international financial conditions. The supplied table does not report a CD statistic for REC because several countries have zero (0%) consumptions of renewable energy and further it conveys the limitations of the statistical analyzing software (STATA MP 14.2). Further, both diagnostics rejects the null hypothesis of homoskedasticity and no serial autocorrelation. Consequently, conventional standard errors may be unreliable, supporting the use of robust covariance estimation and a distributional estimator that is less dependent on a homoskedasticity mean structure.

4.7. Hausman Specification test

Table 9. Hausman test: Fixed effects versus random effects

Variables	**Fixed Effects**			**Random Effects**		
	Coef.	**Std. Errors**	**p-value**	**Coef.**	**Std. Errors**	**p-value**
lfdi	0.0053206***	0.0018278	0.004	-0.0009661	0.0008431	0.252
lgdp	0.1310943***	0.0152081	0.000	0.1431132***	0.0150259	0.000
lrec	-0.1570962***	0.014248	0.000	-0.1681622***	0.0135971	0.000
lcpi	-0.0034245*	0.0020826	0.100	-0.0013021	.0017459	0.456
lto	0.1363562***	0.0161558	0.000	0.134184***	0.0160284	0.000
ldgi	-0.0059158	0.0039624	0.136	-0.0152241***	0.0031223	0.000
_cons	-0.0753957*	0.0387699	0.052	0.091809***	0.0165415	0.000

Hausman test for panel datasets	Chi2(X^2)	Prob>Chi2
	91.11***	0.0000

Note: Level of significance *(10%), **(5%), ***(1%)

Source: Authors own calculations

Hausman X2 = 91.11, p < 0.001. the null hypothesis is rejected, indicating that the fixed-effects estimator is preferred to random effects for the conventional benchmark.

4.8. Methods of Moments Quantile Regression Results

Table 10. Methods of Moments Quantile Regression Results

Variable	Q = 0.05	Q = 0.25	Q = 0.50	Q = 0.75	Q = 0.95
lfdi	0.0092*	0.00681**	0.00531**	0.0039	-0.00156
lgdp	0.16348***	0.14353***	0.13101***	0.11925***	0.9968***
lrec	-0.1925***	-0.17069***	-0.157***	-0.14415***	-0.12275***
lcpi	-0.00163	-0.00273	-0.00343	-0.00408	-0.00517
lto	0.16749***	0.14831***	0.13627***	0.12497***	0.10615**
ldgi	0.03593	0.01015	-0.00603	-0.02122***	-0.04651***

Source: Author's own calculation

Note: Level of significance *(10%), **(5%), ***(1%)

The MM-QR results provide the central evidence of the study. The coefficients vary meaningfully across the conditional distribution, confirming that the environmental effects of the explanatory variables cannot be summarized by a single average coefficient.

4.8.1 Green Energy Consumption

REC is negative and statistically significant at every quantile. The coefficient as -0.19250 at Q = 0.05, -0.17069 at Q = 0.25, -0.15700 at the median, -0. 14415 at Q = 0.75 and – 0.12275 at Q = 0.95. Thus, green energy consumption consistently mitigates CO2 emissions, but the absolute magnitude of the coefficient becomes smaller as countries move towards the upper tail of environmental degradation. This is an important result where renewable energy is broadly beneficial, yet its marginal mitigation effect is weaker among the most environmentally degraded observations. The finding is consistent with the broader literature showing that renewable energy can reduce emissions, while also supporting the argument that scale, infrastructure and development conditions matter.

4.8.2 Digitalization

It displays the strongest distributional heterogeneity. At Q = 0.05 its coefficient is positive and significant (0.03593) suggesting that digital expansion is associated with higher environmental degradation among countries located at the low-emissions end of the conditional distribution. At Q = 0.25 the coefficient becomes statistically insignificant (0.01015) and at the median it is slightly negative but insignificant (-0.00603) at Q = 0.95 (-0.04651). this sign reversal provides the study's most novel distributional results. It indicates that digitalization is not automatically green. Its environmental payoff emerges more clearly in economics facing higher levels of environmental degradation, where digital technologies may support efficiency, monitoring, optimization and cleaner production.

4.8.3 Economic Growth

GDP is positive and highly significant across all five quantiles. The coefficient declines from 0.16348 at Q = 0.05 to 0.09968 at Q = 0.95. Economic expansion is therefore associated with higher environmental improvements. The result does not by itself reject the EKC because the present model does not include a squared income term and therefore does not directly estimate a turning point.

4.8.4 Foreign direct investment

FDI is positive and significant at the 5th, 25th, and 50th quantiles with coefficients of 0.00920, 0.00681 and 0.00531, respectively. It becomes statistically insignificant at the 75th and 95th quantiles. The results suggest that FDI is associated with higher environmental degradation mainly in the lower and middle portions of the conditional distribution, while the relationships weaken at higher degradation levels. This pattern is compatible with the co-existence of pollution-heaven and pollution-halo mechanisms.

4.8.5 Trade openness

Trade openness is positive and significant across the distribution. Its coefficient declines from 0.16749 at Q = 0.05 to 0.10615 at Q = 0.95. The result suggests that the scale and production effects of international integration dominate the potential technology-transfer in the sample. The declining coefficient nevertheless indicates that the marginal association of trade with emissions is weaker in the upper tail. This pattern is consistent with prior quantile evidence showing positive and heterogeneous Trade-CO2 relationships.

4.8.6 Inflation

Inflation is negative but statistically insignificant at all reported quantiles. The coefficients range from -0.00163 to -0.00517. thus, the study does not find robust evidence that inflation systematically influences environmental degradation after controlling for the other variables. Inflation should therefore be treated primarily as a macroeconomic control rather than a central explanatory mechanism in the present framework.

4.9 Robustness Analysis

Table 11. Driscoll-Kraay robust standard errors

D-K standard errors (robust)

No. of Obs.: 1995

Variables	Coef.	Robust std. errors	p-value
lfdi	0.0053206***	0.0009779	0.000
lgdp	0.1310943***	0.0277898	0.000
lrec	-0.1570962***	0.0294059	0.000
lcpi	-0.0034245	0.0020467	0.112
lto	0.1363562***	0.0359383	0.001
ldgi	-0.0059158	0.0053322	0.282
_cons	-0.0753957**	0.0326213	0.033

Note: Level of significance *(10%), **(5%), ***(1%)

Source: Authors own calculations

The Driscoll-Kraay estimates confirm the positive association of FDI, GDP and trade openness with CO2 and the negative association of renewable energy CO2. Inflation remains insignificant. Digitalization is negative but statistically insignificant in this mean-oriented robustness specification. This is not a contradiction of the MM-QR result, rather it demonstrates precisely why a mean estimator can hide distribution-specific effects.

Table 12. Pooled median quantile regression

Pooled-Quantile Regression (Median Regression)

No. of Obs. : 1995

Variables	Coef.	std. errors	p-value
lfdi	-0.0016521**	0.0006471	0.011
lgdp	0.1143917***	0.0122587	0.000
lrec	-0.2116023	0.110245	0.000
lcpi	-0.0005131	0.0013888	0.712
lto	0.1071392***	0.0130928	0.000
ldgi	-0.0161735***	0.0024664	0.000
_cons	0.1107178***	0.0024664	0.000

Note: Level of significance *(10%), **(5%), ***(1%)

Source: Authors own calculations

The pooled median model confirms the positive effect of GDP and trade openness and the negative effect of renewable energy consumption. Digitalization is negative and significant in the pooled median model, supporting the environmental-benefit interpretation at the centre of the distribution. FDI however, changes sign and becomes negative, demonstrating that its effect is specification-sensitive. The overall robustness pattern therefore provides strongest support for the stable roles of GDP, REC, and trade openness, while the distributional MM-QR estimates remain essential for understanding digitalization and FDI.

5. DISCUSSION

The empirical evidence supports the central argument that the digital-green transition is distributional dependent. The strongest and most stable result is the negative effect of green energy consumption. Across all quantiles, renewable energy is associated with lower CO2 emissions. This finding is consistent with the logic of energy substitution: as renewable sources occupy a larger share of the energy mix, the need for fossil-fuel combustion can decline. However, the declining magnitude from -0.19250 to -0.12275 indicates that simply increasing renewable energy is not sufficient to guarantee proportionately larger environmental gains in highly degraded economics. Complementary investment in grids, storage, transmission, energy efficiency and demand management is likely to be necessary.

The digitalization results is more nuanced and arguably more important for policy. Digitalization is associated with higher environmental degradation at the lowest quantiles but with lower degradation at the upper quantiles. This pattern is consistent with the idea of a digital environmental transition: early digital expansion can increase electricity demand, device ownership, infrastructure construction and data traffic, whereas more mature digital ecosystems can generate efficiency, optimization and dematerialization gains. The findings also align with OECD's emphasis on the environmental footprints of digital technologies alongside their decarbonization potential (OECD, 2024). The implication is not that countries should slow digitalization; rather, they should make digitalization energy efficient and powered by clean electricity from the outset.

The positive GDP coefficients across all quantiles indicate that economic expansion remains emissions intensive in the sample. The decline in the coefficients across quantiles suggests some attenuation at higher environmental degradation levels, but the results do not establish an EKC turning point because a nonlinear income specification was not estimated. Policymakers should therefore avoid interpreting economic growth as automatically compatible with environmental improvement. Green industrial policy, energy-efficiency standards and clean technology investment are required to change the composition and techniques effects of growth.

The positive trade coefficients indicate that international integration, in the observed sample and specification, is associated with higher CO2 emissions. The result is compatible with scale effects and pollution-intensive specialization. Yet trade can also be an instrument for the diffusion of clean technologies. The policy challenge is therefore to green trade rather than reduce trade: environmental standards, carbon-accounting requirements, clean-technology imports and supply-chain disclosures can strengthen the technique effect.

Foreign Direct Investment is positive in the lower and middle quantiles but insignificant in the upper tail under MM-QR. This suggest that FDI-related environmental pressure is strongest where economies are undergoing expansion but nay weaken environmental constraints become more binding. The results is consistent with a conditional pollution-heaven/pollution-halo interpretation, although the study does not identify causal mechanisms directly. Future work should distinguish green FDI from conventional FDI and test interaction with environmental regulation and institutional quality.

5.1 Hypothesis assessment

The Hypothesis are assessed using MM-QR coefficients. Because the study is observational and no separate identification strategy is reported, the assessments below refer to table 13 for empirical support for the proposed relationships rather than causal confirmation.

Table 13. Hypothesis evidence

Hypothesis	Evidence	Assessment	Meaning
H_1	DIGI is (+ve) and significant at Q = 0.05; insignificant at Q = 0.25/0.50; and (ve) and significant at Q = 0.75/0.95.	Supported with heterogeneity	Digitalization changes from an environmental pressure at the lower tail to an environmental improvements' association at the upper tail.
H_2	GDP is positive and significant at all five quantiles.	Supported	Growth remains associated with higher CO_2 across the distribution
H_3	REC is negative and significant at all five quantiles.	Strongly supported	Renewable-energy use is the most stable mitigation factor.
H_4	FDI is positive and significant at Q = 0.05, 0.25 and 0.50, but insignificant at Q = 0.75 and 0.95.	Supported with heterogeneity	FDI related pressure is concentrated in lower and middle quantiles.
H_5	Trade openness is positive and significant across all quantiles.	Supported	Scale/production effects dominate the observed trade CO_2 relationships.

Source: Authors own creation

6. POLICY IMPLICATIONS

• Build a clean-energy foundation for digitalization. Because digitalization becomes environmentally beneficial mainly in the upper quantiles, governments should prevent the early-stage energy footprint of digital infrastructure from locking economies

into fossil-fuel dependence. Data centres, telecom networks and digital public infrastructure should increasingly be powered by renewable electricity and subject to energy efficiency standards.

• Move from renewable energy quantity to system integration. The negative REC coefficient across all quantiles is encouraging, but its declining magnitude indicates that renewable generation alone is insufficient, grid modernization, storage, transmission capacity, demand response and regional electricity interconnection should accompany renewable-energy deployment.

• Use differentiated digital-climate policies. Low degradation economies should prioritize energy efficient digital infrastructure and lifecycle standards because digitalization is initially associated with higher emissions. Highly degraded economies can place greater emphasis on digital optimization of industrial processes, smart energy systems, environmental monitoring and digital logistics because the estimated digitalization effect is negative in the upper quantiles.

• Green the growth model. The positive GDP coefficients at every quantile shows that economic expansion remains environmentally costly in the sample. Industrial policy should therefore shift toward renewable powered manufacturing, electrification, circular production, energy efficiency and green innovation rather than relying on growth to deliver environmental improvement automatically.

• Make trade policy climate compatible. The positive trade coefficients suggest that trade related scale effects dominate. Governments should integrate environmental standards into trade agreements, strengthen carbon-accounting and supply-chain disclosure, and facilitate imports of clean technologies so that trade produces stronger techniques effects.

• Screen FDI for environmental quality. FDI should be evaluated not only by its volume but also by its technology, energy intensity and environmental performance. Incentives can be tied to clean production, technology transfer, renewable energy use and variable environmental standards.

• Coordinate digital and energy policy institutions. The results indicate that digital policy and energy policy should not be designed separately. Ministries and regulators responsible for digital infrastructure, electricity, industry and climate should coordinate standards for data center energy efficiency, renewable procurements, electronic waste, network efficiency and digital measurement of emissions.

The policy implications is therefore conditional rather than uniform: renewable energy expansion has a consistently favorable association with CO2 emission, whereas digitalization appears to become environmentally beneficial mainly towards the upper part of the emissions distributions. This pattern supports coordinated digital, energy and industrial policies rather than treating digitalization as automatically green.

CONCLUSION

This study examined whether digitalization and green energy consumption mitigate environmental degradation across points of the global CO2 distribution. Using balanced panel of 105 countries over period from 2005 to 2023, the analysis combined conventional panel diagnostics with MM-QR and two robustness approaches. The central finding is that the environmental transition is heterogeneous rather than uniform. Green energy consumption emerges as the most stable environmental improvements factor. Its coefficients are negative and significant across all five quantiles, confirming that greater renewable energy use is associated with lower environmental degradation. Nevertheless, the magnitude declines towards the upper tail indicating that highly degraded economies may require complementary investments in grids, storage, efficiency and institutional capacity to convert renewable deployment into larger emissions reductions. Digitalization produces the most distinctive distributional pattern. It is positive and significant at the lowest quantiles, becomes insignificant around the lower-middle and median portions of the distribution, and becomes negative and significant at the 75th and 95th quantiles. This sign reversal suggests that digitalization has an environmental footprint during early expansion but can become a mechanism for environmental improvements when digital systems are sufficiently mature and integrated with efficiency and clean energy systems. Economics growth and trade openness are positively associated with environmental degradation across the distribution, while FDI is positive mainly in the lower and middle quantiles. Inflation does not display a statistically robust effect. The robustness analysis confirms the central roles of GDP, renewable energy, and trade openness while also demonstrating that digitalization and FDI are sensitive to the estimator used. This reinforces the values of MM-QR for the research question. Further, the study contributes to environmental economies by demonstrating that the question is not simply whether digitalization and renewable energy are 'green', but under what environmental conditions their effects become beneficial. Policy should therefore move from uniform targets towards distribution-sensitive strategies: clean electricity for

digital infrastructure, integrated renewable-energy systems, green industrial growth, climate-compatible trade environmentally screened FDI. Moreover, the study has several limitations. Firstly, the analysis uses CO2 as a single environmental degradation indicator and therefore does not capture broader ecological dimensions such as ecological footprint, methane, biodiversity or material consumption. Second, the digitalization index is constructed from a limited set of ICT penetration indicators. Third, the study is explanatory rather than a causal identification design; MM-QR should not be interpreted as proving causality in the absence of credible identification strategy. Finally, the supplied estimation tables require verifications of the exact transformations applied to variables with zero or negative raw observations. Future research should address these issues using richer digital economy indicators, green FDI measures, institutional quality, renewable-energy threshold, interaction terms and causal or dynamic distributional methods.

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