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How Do Green Technologies, Green Energy Consumption and Digitalization Influence Environmental Sustainability in E7 Economies? A Quantile-Based Analysis

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Abstract

Governments worldwide are grappling with the challenges of climate change. Following COP28 – the Dubai consensus – it has become even clearer that achieving CO_2 emission reduction targets is crucial to prevent the global temperature from rising above 1.5 °C. In this context, our study assesses these ambitious climate goals through the lens of green energy and technology adoption within the E7 countries. Using quantile regression and panel ordinary least squares (POLS) techniques on data spanning from 1991 to 2021, we provide insights into the vital role of digitalization and energy choices in reducing CO_2 emissions and advancing towards carbon neutrality. The Westerlund cointegration results indicate a long-run relationship among all the variables. Quantile regression findings reveal that economic growth, nonrenewable energy consumption and green technology adoption affect CO_2, while digitalization and green energy consumption help reduce CO_2. The POLS results confirm the quantile regression outcomes, enhancing the robustness of the analysis. Additionally, the Dumitrescu–Hurlin panel causality test shows that all the variables significantly predict CO_2 and vice versa. Based on these findings, we propose green growth policies supported by renewable energy and technological advancements to help E7 countries achieve their net-zero emission targets.

Keywords: CO_2 emissions, digitalization, economic growth, green energy consumption, green technologies

JEL Classification: Q53, Q54, Q33, Q56

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1. Introduction

For global stakeholders and economies alike, maintaining a high-quality environment while attaining economic growth is a crucial goal (Ozturk *et al.*, 2022; Ullah *et al.*, 2024). The increasing human-caused activities that stem from our socioeconomic positions in these changing societies have profound effects on the environment. In particular, it has been determined that frequent contributions to the rising number of anthropogenic events include actions that promote economic growth (Meo and Adebayo, 2024). Thus, an important aspect of economic progress that necessitates close consideration of sustainable environmental practices is a growth-determining factor, namely energy use (Alola and Adebayo, 2022; Samour and Pata, 2022).

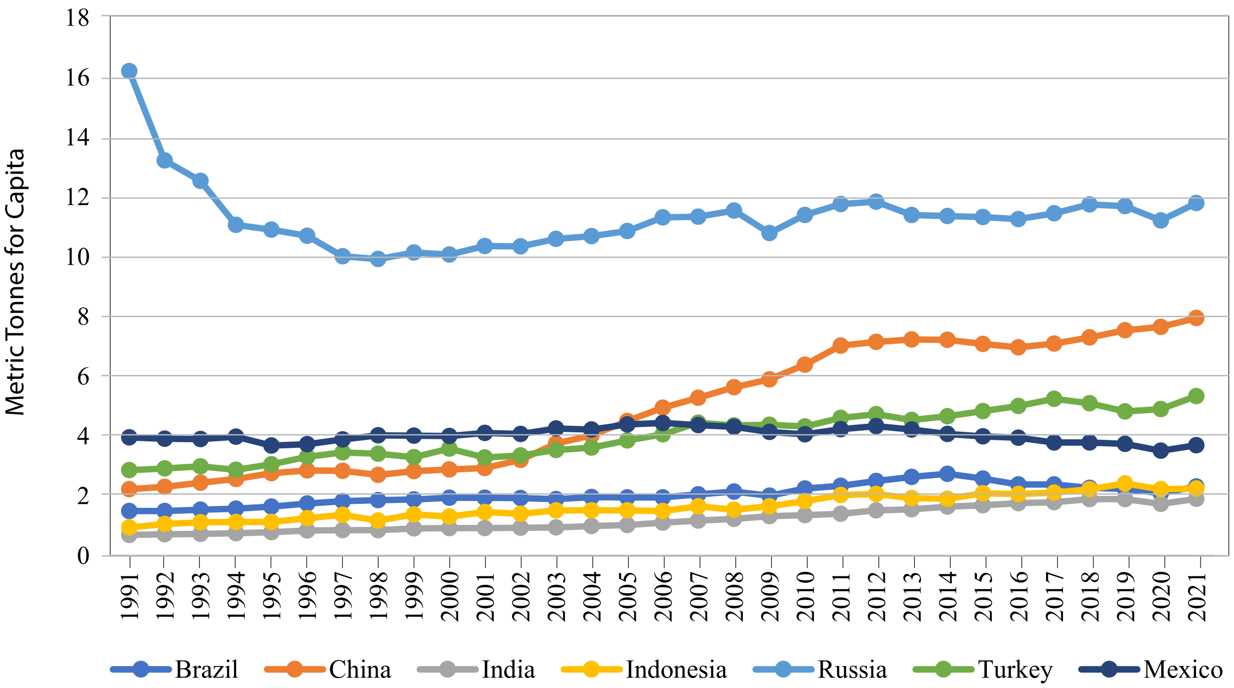
Within the global arena, the rapid economic growth coupled with the industrialization of the E7 countries[1] have made this group of countries a crucial player. Nevertheless, this growth is accompanied by a surge in ecological degradation, which is seen through a rise in CO_2 in these countries (see Figure 1). The use of green energy and the adoption of green technologies have emerged in these countries as a crucial tool for achieving both economic growth and ecological sustainability simultaneously (Usman *et al.*, 2024; Zambrano-Monserrate *et al.*, 2024). The capacity of these measures to alleviate ecological consequences while concurrently fostering green growth is an intriguing field of investigation, especially in the context of emerging economies that significantly contribute to a surge in CO_2 (Yan *et al.*, 2024; Zheng *et al.*, 2024).

Green technologies (*GTEC*) provide a means to decrease CO_2. This is effective in lessening the reliance on fossil fuel-based energy. In the same vein, the use of green energy directly acts as a substitute for orthodox energy sources. Previous investigations (Alola and Adebayo, 2022; Danish and Ulucak, 2020; Terzi and Pata, 2020) have shown that a decrease in CO_2 is attributed to a surge in green energy consumption (*GEC*). Therefore, increasing *GTEC* and *GEC* is seen as an effective way of curbing CO_2 (Acheampong, 2018; Yilanci and Pata, 2022). However, the effectiveness and degree of these connections vary significantly across the E7 countries. Although there are potential advantages, the implementation of green technologies and the transition to utilizing green energy sources has multiple issues. In order to tackle these difficulties, the E7 countries must implement both domestic policy readjustments and international investment and collaboration (Pata and Karlilar, 2024; Usman *et al.*, 2020). Therefore, it is important to investigate how various green technologies and green energy

1 Brazil, China, India, Indonesia, Mexico, Russia and Turkey.

sources influence CO_2. Understanding the specific scenarios in which green technology may contribute to the E7 countries' achievement of their zero-carbon objectives is made possible by previous research (Afshan and Yaqoob, 2022; Bello *et al.*, 2023).

Figure 1: Trends of CO_2 emissions in E7 countries



Source: Authors' own elaboration

Another determinant of CO_2 discussed in the literature is digitalization. Given that these developing countries are using digital technology to foster economic growth, it is crucial to comprehend its effect on the environment. Digitalization has the capacity to both lower and raise CO_2. A surge in digitalization may boost energy efficiency and usage. On the other hand, it can boost energy consumption, which can result in an increase in energy usage (Bansal *et al.*, 2022; Ha *et al.*, 2022). The nexus between CO_2 and digitalization is contingent upon several aspects, including the energy sources that fuel emerging technologies, the extent of their implementation and the efficacy of these technologies. Prior studies, including Hung (2023), Ren *et al.* (2023) and Saqib *et al.* (2023), have discovered that although digital technologies can initially contribute to higher emissions, they can also foster the mitigation of CO_2 in the long term.

The originality of this study lies in its focus on the E7 countries, which collectively represent a substantial share of the global population and economic output. The developmental paths that these countries choose will have profound implications for global sustainability and climate change mitigation efforts, making this analysis both timely and critical. As these economies advance, they face a unique opportunity to decouple economic growth from environmental degradation by integrating green energy, green technologies and digital solutions. This research provides new evidence on the role of green technologies and energy as effective tools for CO_2 reduction, highlighting their alignment with SDG 7 (Affordable and Clean Energy), SDG 8 (Decent Work and Economic Growth) and SDG 13 (Climate Action). Additionally, by examining the impact of digitalization on CO_2, this study equips policymakers in the E7 countries with insights into crafting policies that support energy efficiency and promote the adoption of green technologies. These strategies not only aim to lower CO_2 but also enhance ecological quality, thus contributing meaningfully to sustainable development goals and the global climate agenda.

The rest of the paper is organized as follows. The next section details information on previous studies, Section 3 presents data and methods, Section 4 discusses empirical findings and Section 5 presents policy recommendations.

2. Literature Review

The shift to carbon neutrality is important, and green energy consumption (*GEC*) is identified as a significant enabler of that shift (Ağa *et al.*, 2023; Pata and Tanriover, 2023; Q. Wang *et al.*, 2024). *GEC* is recognized as a low-emission, viable and clean energy source. It is also acknowledged as a means of achieving ecological viability and sustainable development. Studies on the role of *GEC* are numerous. There are many studies on the functioning of *GEC* in the literature. For example, Awosusi *et al.* (2023) looked at how carbon neutrality can be reached. They applied the ARDL to analyse data for Vietnam from 1990 to 2018, and their findings demonstrated that *GEC* is a useful technique for achieving zero emissions, despite its negative impact on CO_2. Additionally, using data from 1990 to 2018, the analysis by Ojekemi *et al.* (2022) for the BRICS revealed similar findings by confirming the impact of *GEC* in reducing CO_2. Though the majority of the studies report a negative effect of *GEC* on CO_2, some studies also documented a positive effect of *GEC* on CO_2. For instance, using the Chinese case, Alola's (2019) study using the quantile-based approach highlighted that a surge in *GEC* increases CO_2 using quarterly data from 1980 to 2021. The study of Ozturk *et al.* (2022) also affirmed the results of Alola *et al.* (2023) by registering that a surge in CO_2 is attributed to an increase in *GEC*.

The motive of all countries is to achieve constant growth; however, the way to achieve this growth in most cases is not sustainable as it is achieved via unstable energy sources. There is a large body of studies on the impact of nonrenewable energy (*NEC*) and *EG* on CO_2

in the empirical literature. The role of *NEC* and *EG* on CO_2 was examined by Zhao *et al.* (2021) for the BRICS-T countries from 1990 to 2018, considering EKC, with the results showing that a surge in *NEC* and *EG* intensifies CO_2 in the BRICS-T countries. In another study, *NEC* and *EG* effect on CO_2 in the BRICS countries was studied by Bekun *et al.* (2019) on panel data from 1990-2014 using the panel PMG-ARDL. They found that the increase in CO_2 is due to a surge in *NEC* and *EG*. This finding was also reported by Bekun *et al.* (2022) for the E7 countries, which reported that the decrease in the ecological quantile is caused by unsustainable growth and *NEC*. Moreover, using data spanning between 1980 and 2014, Shahbaz *et al.* (2016), in their study of the Malaysia case, suggested that *NEC*, in conjunction with *EG*, lessens ecological quality by increasing CO_2.

The effect of green technologies and digitalization on CO_2 is gaining momentum in the empirical literature. Zheng *et al.* (2023) inspected how digitalization drives carbon emissions in China using data for 281 cities. The findings indicate that the interrelationship between digitization and CO_2 in China follows an inverted U-curve, which is further backed by a set of rigorous tests to ensure the data accuracy and reliability. The impact of digitalization (*DIT*) on CO_2 is more pronounced in eastern regions, which are not resource-based, taking into account their geographical position and available resources. The influence of *DIT* in western and central areas of China follows an inverted U-shaped pattern with little statistical significance. Additionally, resource-based regions are still far from the point when CO_2 starts to accelerate. Wang *et al.* (2023), using BRICS from 1995 to 2019 to investigate the effect of *GTEC* and *DIT* on CO_2, reported that both *GTEC* and *DIT* lessen CO_2 in China. Besides, the Granger causality reveals the presence of unidirectional causality from *GTEC* and *DIT* to CO_2. Likewise, Yadav *et al.* (2023) reported that carbon neutrality can be achieved by investing in *GTEC* and *DIT* since they both lessen CO_2.

3. Data and Methodology

3.1 Data

Table 1 outlines the variables used in the analysis, their measurement units and the data sources. The variables include CO_2, which represents carbon emissions per capita, and economic growth (*EG*), which is measured by GDP per capita in constant US dollars (2015). Furthermore, the variable *GTEC* refers to patents in environment-related technologies, expressed as a percentage, green energy consumption (*GEC*) is measured per capita in kilowatt-hours and nonrenewable energy consumption (*NEC*) is calculated as per capita. Finally, digitalization (*DIT*) is measured by the percentage of individuals using the internet. Variables such as *DIT* and *EG* are sourced from WDI (2024), *GTEC* is gathered from OECD (2024) and CO_2, *NEC* and *GEC* are obtained from OWD (2024). The data used span the period from 1991 to 2021 for a group of E7 countries. Furthermore, we took logarithms of the variables to ensure that data align with normality.

Table 1: Sources, units and variables

Sign	Variable	Unit	Source
CO_2	Carbon emissions	Per capita	OWD (2024)
EG	Economic growth	GDP per capita constant US$2015	WDI (2024)
GTEC	Green technologies	Patents in environment-related technologies %	OECD (2023)
GEC	Green energy consumption	Per capita (kWh)	OWD (2024)
NEC	Nonrenewable energy consumption	Per capita	OWD (2024)
DIT	Digitalization	Individuals using internet (% of population)	WDI (2024)

Source: Authors' own elaboration

Table 2 provides a comprehensive set of descriptive statistics for various economic and environmental variables, giving insights into their distribution across and within different groups. The table is divided into three types of statistical measures: overall, between and within. The overall statistics present a general view of the data. For example, CO_2 has an average (mean) of 1.1429 with a standard deviation of 0.7562, indicating variability around the mean. The range from the minimum (−0.3678) to the maximum (2.785) highlights the spread of carbon emission data among all the observations (N = 217). Between-group statistics reflect variations between different groups (in this case, potentially countries or regions) within the dataset (n = 7 for each variable). This shows how the mean values differ from one group to another. For instance, *EG* shows a relatively high between-group variation with a mean of 0.8160, indicating significant differences in economic growth rates across groups. Within-group statistics describe the variability of observations within each group over time (T = 31 for each variable), capturing the temporal fluctuations within each group. For *GTEC*, the within-group standard deviation of 1.0286 suggests notable year-to-year variability in green technology patents within the same group.

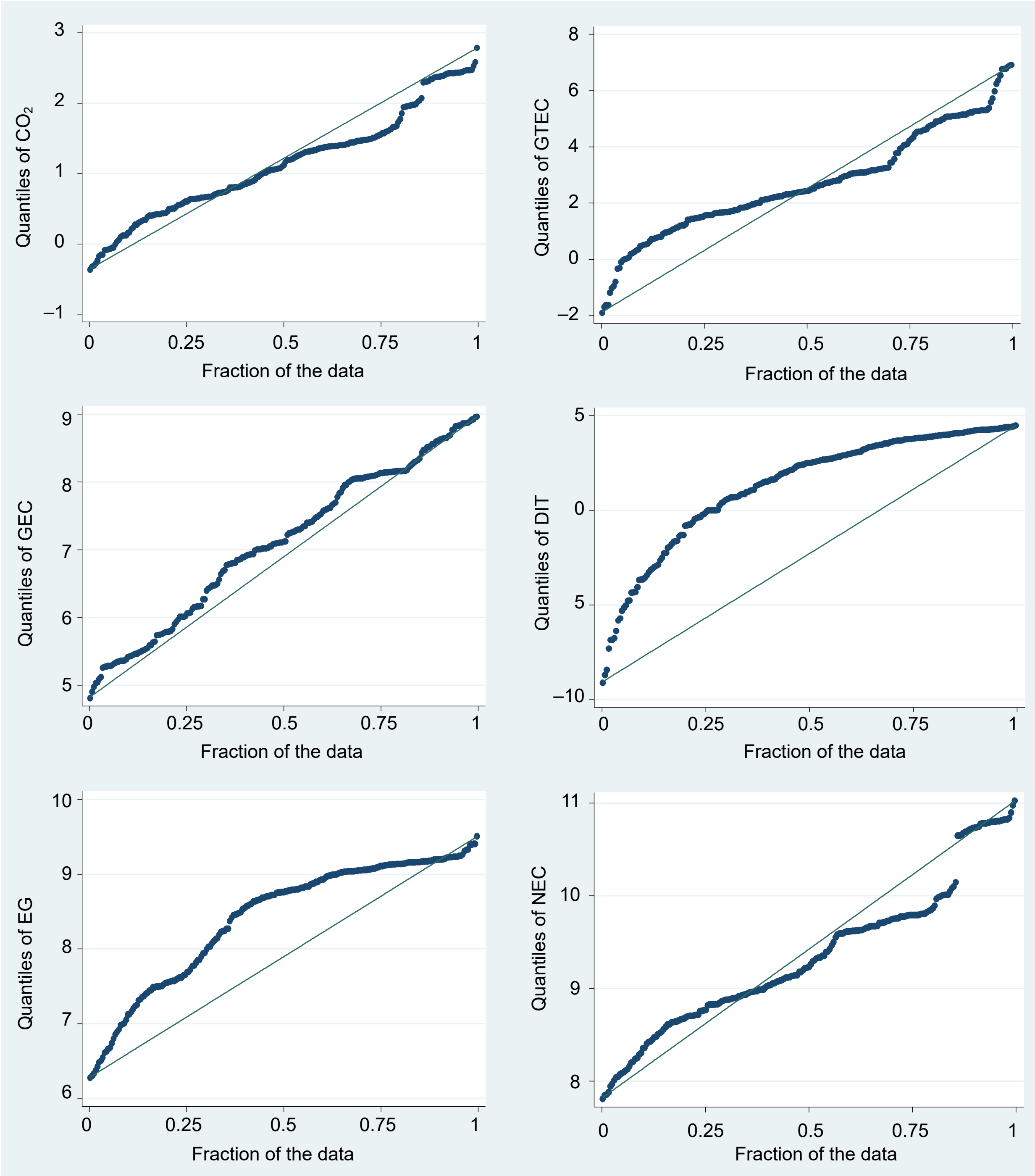
Table 2: Descriptive statistics

Variable	Scope	Mean	Std. dev.	Min.	Max.	Obs.
CO_2	Overall	1.1429	0.7562	−0.3678	2.785	N = 217
	Between	0.7676	0.1448	2.4222		n = 7
	Within	0.2539	0.4397	1.7126		T = 31
EG	Overall	8.4120	0.8459	6.2708	9.5067	N = 217
	Between	0.8160	6.9245	9.1491		n = 7
	Within	0.3771	7.0782	9.5210		T = 31
GTEC	Overall	2.7134	1.8743	−1.9053	6.9082	N = 217
	Between	1.6885	0.2416	5.1021		n = 7
	Within	1.0286	0.0924	5.1605		T = 31
GEC	Overall	7.1022	1.1646	4.8089	8.9629	N = 217
	Between	1.1687	5.5414	8.7224		n = 7
	Within	0.4245	5.8571	8.5337		T = 31
NEC	Overall	9.3504	0.7984	7.8108	11.023	N = 217
	Between	0.8160	8.2813	10.7789		n = 7
	Within	0.2534	8.6289	9.9477		T = 31
DIT	Overall	1.3076	3.1364	−9.1032	4.4797	N = 217
	Between	0.7121	0.1355	2.0351		n = 7
	Within	3.0660	−8.5825	5.0074		T = 31

Source: Authors' own calculations

Figure 2 displays a series of quantile-quantile (Q-Q) plots for various variables, typically used to assess the normality of data distributions. Each plot corresponds to a different variable (CO_2, $GTEC$, GEC, DIT, EG, NEC) and illustrates how closely data points adhere to a theoretical normal distribution. The diagonal line in each plot represents where the data points would lie if they were perfectly normally distributed. Observing the plots, deviations from the diagonal line indicate departures from normality. For example, most variables show data points deviating from the line at both tails (lower and upper), suggesting that these variables may have heavy tails compared to the normal distribution – indicating skewness or the presence of outliers. The deviation patterns vary, with some variables showing more pronounced skewness or heavier tails than others. Since there is evidence of nonlinearity and nonnormal distribution, we use a nonlinear technique, specifically panel quantile regression, to explore this connection.

Figure 2: Quantile plot



Source: Authors' own elaboration

3.2 Empirical methodology

3.2.1 Stationarity test results

Two common methods are the cross-sectional Im–Pesaran–Shin (CIPS) test and the cross-sectional augmented Dickey–Fuller (CADF) test, which are used to conduct tests for unit roots in panel data. The CIPS test is an extension of the standard unit root test to a panel data context, incorporating cross-sectional dependence among the units. The test statistic is computed from the average of individual CADF statistics. The model equation for the CADF, which is used to compute the CIPS, is given by:

$$\Delta y_{it} = \alpha_i + \beta y_{it-1} + \sum_{j=1}^{p} \gamma_j \Delta y_{it-j} + \epsilon_{it} \tag{1}$$

where $\Delta\gamma_{it}$ is the first difference of the variable of interest for the individual i at the time t. Moreover, α_i, β, y and ε_{it} denote individual-specific intercept, coefficient of the lagged level of the variable, coefficients of the lagged first differences of the variable and an error term.

$$\text{CIPS} = \frac{1}{N}\sum_{i=1}^{N} t_{i,\text{CADF}} \tag{2}$$

where $t_{i,\text{CADF}}$ is the t-statistic from the CADF test for each cross-section i. The CADF test, developed by Pesaran (2007), specifically accounts for cross-sectional dependence by augmenting the Dickey–Fuller regression with cross-sectional averages of lag levels and first differences. The equation is:

$$\Delta y_{it} = \alpha_i + \beta y_{it-1} + \bar{y}_{t-1} + \sum_{j=1}^{p} \gamma_j \Delta y_{it-j} + \sum_{j=1}^{p} \delta_j \Delta \bar{y}_{t-j} + \epsilon_{it} \tag{3}$$

Furthermore, $\bar{y}_{t-1}$ and $\Delta\bar{y}_{t-j}$ represent a cross-sectional average of the lagged levels of the variable and the cross-sectional averages of the lagged first differences of the variable.

3.2.2 Westerlund cointegration

The Westerlund (2007) cointegration test is a widely used statistical method developed to test for cointegration in panel data sets. It is particularly valuable because it accounts for cross-sectional dependence and heterogeneity across panels, which are common in economic data. The test proposes four different test statistics that can be used to detect the presence of cointegration. The equation for the cointegration is depicted as follows:

$$\Delta y_{it} = \alpha_i + \beta_i y_{it-1} + \sum_{j=1}^{p} \gamma_{ij} \Delta y_{it-j} + \delta_i' x_{it} + \lambda_i z_{it-1} + \epsilon_{it} \tag{4}$$

3.2.3 Panel quantile regressions

A panel quantile regression can be effectively utilized to model the heterogeneity in relationships across different quantiles of the dependent variable. A basic panel quantile regression equation for a balanced panel data model could be specified as follows:

$$Q_{y_{it}}(\tau) = \beta_0(\tau) + \beta_1(\tau) x_{it1} + \beta_2(\tau) x_{it2} + \cdots + \beta_k(\tau) x_{itk} + \alpha_i(\tau) + \epsilon_{it}(\tau) \tag{5}$$

where $Q_{yit}(\tau)$ represents the τ quantile of the dependent variable y for the individual I at the time t. $\beta_0(\tau)$, $\beta_1(\tau)$, ... $\beta_k(\tau)$, are the quantile-specific coefficients for the explanatory variables x_{it1}, x_{it2}, ..., x_{itk}. $\alpha_i(\tau)$ is the individual-specific effect, capturing unobserved heterogeneity that can vary across quantiles but is constant over time for each individual. $\varepsilon_{it}(\tau)$ is the error term.

4. Results and Discussion

4.1 Cross-sectional dependence test results

Table 3 displays the results of the cross-sectional dependence (CD) test across various variables, such as CO_2, EG, $GTEC$, GEC, NEC and DIT. The CD-test statistic in each case is significantly high, with p-values at 0, strongly rejecting the null hypothesis of CD. This indicates a significant presence of CD in each variable across the observed units, suggesting that changes in one unit (*e.g.*, a country) could potentially affect others. The table also provides additional statistics such as the average joint T (all at 31), which relates to the average statistic across time or groups and measures of correlation: mean ρ (rho) and mean abs(ρ). These rho values, such as 0.43 for CO_2 and 0.91 for DIT, indicate the average degree of linear correlation across units, with higher values in EG and DIT suggesting particularly strong interdependencies. The absolute values (mean abs(ρ)) support this, indicating that, on average, the absolute strength of the correlation is similarly high, reflecting significant interconnectedness in data behaviour across sections.

Table 3: Cross-sectional dependence (CD) test results

Variable	CD-test	*p*-value	Average joint *T*	Mean ρ	Mean abs(ρ)
CO_2	11.000***	0.000	31	0.43	0.49
EG	22.551***	0.000	31	0.88	0.88
GTEC	18.387***	0.000	31	0.72	0.72
GEC	16.697***	0.000	31	0.65	0.65
NEC	15.108***	0.000	31	0.59	0.62
DIT	23.275***	0.000	31	0.91	0.91

Note: *** denotes statistical significance at the 1% level.
Source: Authors' own calculations

4.2 Slope heterogeneity

Next, the study will inspect the slope heterogeneity of the model. The null hypothesis being tested here is that the slope coefficients are homogenous across groups or over time. Homogeneity means that the same regression relationship (slope) holds across different segments or subsamples. The delta statistic (14.562) and the adjusted delta (16.550) are measures of heterogeneity. These values represent the degree to which the slope coefficients differ within the data. This suggests that the slope coefficients exhibit heterogeneity across different panels or groups in the model. Rejecting the null hypothesis indicates substantial disparities in the connections represented by the regression across various panels or groups.

Table 4: Slope heterogeneity

Statistic	Value	*p*-value
Delta	14.562	0.000
Adj. delta	16.55	0.000

Source: Authors' own calculations

4.3 Stationarity test results

Table 5 presents the results of the CADF and CIPS tests. These tests are crucial for determining whether the data series are stationary. The results disclose that the CO_2 variable in the first difference shows a CIPS value of −5.031 ($p < 0.01$), hence confirming stationarity at first difference. Similar patterns are observed for other variables; at first, differences are taken, as seen with values such as −5.797 ($p < 0.01$) for $GTEC$ and −5.971 ($p < 0.01$) for GEC. Only DIT −4.151 ($p < 0.01$) displays strong stationarity even at level as shown by CADF and CIPS values.

Table 5: CIPS and CADF test results

	CIPS		CADF	
Variable	**Level**	**First difference**	**Level**	**First difference**
CO₂	−2.778	−5.031***	−2.818	−3.035
EG	−1.899	−3.920***	−2.538	−2.808*
GTEC	−3.210***	−5.797***	−2.343	−4.116***
GEC	−2.951*	−5.971***	−2.438	−4.119***
NEC	−2.234	−4.514***	−2.585	−2.949**
DIT	−4.151***	−5.813***	−4.698***	−5.000***

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

4.4 Westerlund cointegration

The study also used the Westerlund cointegration with the results shown in table 6. Based on these results, we found support for long-run association between CO_2 and its determinants (EG, $GTEC$, GEC, NEC and DIT).

Table 6: Westerlund cointegration

Statistic	Value	*Z*-value	*p*-value	Robust *p*-value
Gt	−3.422	−2.155	0.016	0.000
Ga	−13.807	0.375	0.646	0.000
Pt	−8.348	−1.914	0.028	0.020
Pa	−13.631	−0.735	0.231	0.020

Source: Authors' own calculations

4.5 Quantile regression results

Table 7 and Figure 3 present the results of quantile regression analysis at three different quantiles (0.25, 0.50 and 0.75) for the variables *EG*, *GTEC*, *GEC*, *NEC* and *DIT*. Quantile regression is utilized here to explore how these variables affect CO_2 across different parts of its distribution, providing insights beyond traditional mean regression by capturing heterogeneous effects across quantiles. At the 25th quantile, the coefficients indicate the effect of each independent variable on CO_2 for the lower end of the distribution. *EG* shows a positive effect on CO_2 (t-stat = 5.7, $p < 0.01$). This demonstrates that higher *EG* is associated with a surge in CO_2 among countries or regions with relatively lower emission levels. In a similar way, *GTEC* and *NEC* affect CO_2 positively with coefficients of 0.0944 ($p < 0.01$) and 0.8123 ($p < 0.01$). This indicates that advancements in green technologies and higher nonrenewable energy usage contribute significantly to the growth in CO_2. In contrast, *GEC* and *DIT* affect CO_2 negatively, as shown by the coefficients of −0.1021 ($p < 0.01$) and −0.0047 ($p < 0.01$).

At the 50th quantile, we observed a similar effect of *EG*, *GTEC*, *GEC*, *NEC* and *DIT* on CO_2. The coefficients show identical trends at the 75th quantile, which corresponds to greater CO_2 levels, although there is some variance in magnitude. *EG* and *GTEC* continue to show positive effects on CO_2, albeit with slightly reduced coefficients compared to lower quantiles. *GEC* and *DIT* maintain their negative impacts on CO_2, indicating that the benefits of green energy adoption and digitalization in reducing emissions persist across different emission levels. *NEC*, while still positive, shows a reduced coefficient compared to lower quantiles, suggesting that the effect of *NEC* on CO_2 diminishes as emissions increase.

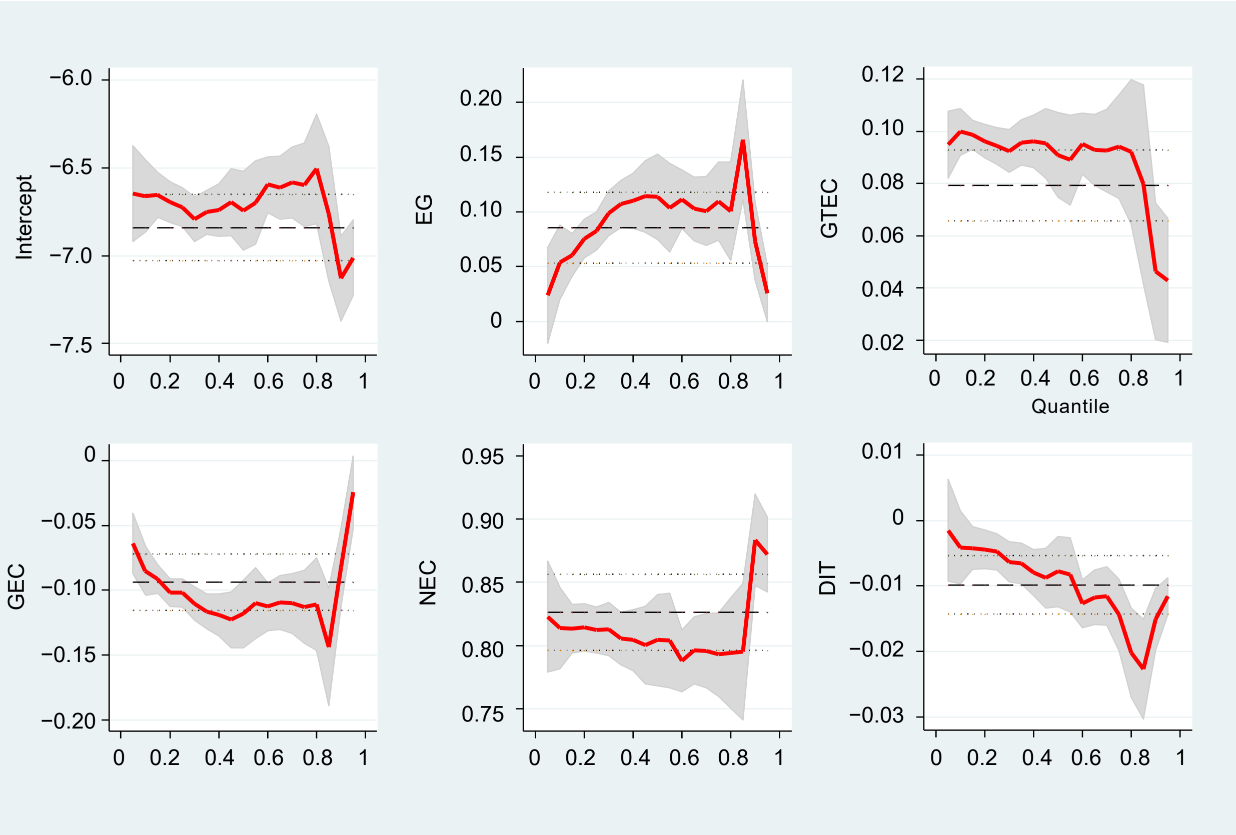
Table 7: Quantile regression (0.25, 0.50 and 0.90)

Variables	**Coefficient**	**Std. error**	***t*-score**	***p* > *t***
Quantile (0.25)				
EG	0.0825***	0.0145	5.7	0.000
GTEC	0.0944***	0.006	15.64	0.000
GEC	–0.1021***	0.0097	–10.56	0.000
NEC	0.8123***	0.0135	60.1	0.000
DIT	–0.0047**	0.002	–2.4	0.017
Cons	–6.7237	0.0837	–80.33	0.000
Quantile (0.50)				
EG	0.1139***	0.0176	6.46	0.000
GTEC	0.0909***	0.0073	12.37	0.000
GEC	–0.1183***	0.0118	–10.04	0.000
NEC	0.8042***	0.0165	48.86	0.000
DIT	–0.0078***	0.0024	–3.24	0.001
Cons	–6.7447	0.1019	–66.17	0.000
Quantile (0.75)				
EG	0.1098***	0.0368	2.98	0.003
GTEC	0.094***	0.0154	6.12	0.000
GEC	–0.1129***	0.0246	–4.59	0.000
NEC	0.7928***	0.0344	23.05	0.000
DIT	–0.0144***	0.005	–2.87	0.005
Cons	–6.5962	0.213	–30.97	0.000

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

Source: Authors' own calculations

Figure 3: Quantile regression plot



Source: Authors' own elaboration

4.5 Robustness check

For a robustness check, we used the panel OLS (see table 8). The *F*-statistic is highly significant (4009.66), indicating that the collective predictive power of the model is very strong, with virtually zero probability of the *F*-statistic being this large if the null hypothesis of no effect was true. The R^2 of 0.98 suggests that approximately 98.96% of the variability in CO_2 is explained by the model, which is extremely high, demonstrating excellent model fit. The root MSE, which is the standard deviation of the residuals, is 0.07808, indicating the average deviation of the observations from the fitted line. The results show that economic growth, nonrenewable energy consumption and green energy technologies affect CO_2, while digitalization and green energy consumption decrease CO_2.

Table 8: Panel OLS

Variable	Coefficient	Std. error	*t*-score	*p* > *t*	95% confidence interval
EG	0.0856***	0.0165	5.190	0.000	[0.0531, 0.1180]
GTEC	0.0794***	0.0069	11.55	0.000	[0.0658, 0.0929]
GEC	−0.0938***	0.0110	−8.510	0.000	[−0.1155, −0.0721]
NEC	0.8263***	0.0154	53.68	0.000	[0.7960, 0.8567]
DIT	−0.0098***	0.0022	−4.370	0.000	[−0.0142, −0.0054]
Cons	−6.8398***	0.0953	−71.75	0.000	[−7.0277, −6.6519]
R^2	0.989	F(5, 211)	4009.6	RMSE	0.078
Adj R^2	0.989	Prob > *F*	0.000	–	–

Note: *** denotes statistical significance at the 1% level, respectively.
Source: Authors' own calculations

4.6 Dumitrescu–Hurlin causality test results

Table 9 presents the results of the Dumitrescu–Hurlin panel causality test, which assesses the directional causality between pairs of variables related to environmental and economic factors. These tests provide critical insight into whether one variable can be said to forecast another statistically within the context of panel data. For instance, the test results between *EG* and CO_2 indicate significant causality from *EG* to CO_2, with the test statistics *Z*-bar and *Z*-bar tilde showing high levels of significance ($p < 0.01$). This suggests that economic growth in the sample does indeed predict changes in CO_2. Conversely, there is also significant causality from CO_2 to economic growth, with both directions strongly implying a feedback loop between economic activity and environmental impact. Furthermore, the test results for other variables such as *GTEC*, *GEC*, *DIT* and *NEC* relative to CO_2 reveal varying levels of causality. Notably, *GTEC* and CO_2 show significant mutual causality, indicating that the adoption of green technologies is both influenced by and influences CO_2. The results for *GEC*, however, demonstrate weaker causality, particularly from *GEC* to CO_2, suggesting that while there is some predictive power, it is less robust compared to other variables. In the case of digitalization and nonrenewable energy, significant causality exists predominantly from these variables to CO_2, highlighting their roles as potential drivers of CO_2.

Table 9: Dumitrescu–Hurlin causality test results

	W-bar	*Z*-bar	*Z*-bar tilde
***EG* ≠ CO_2**	5.5068	8.4315***	7.2124***
CO_2 ≠ *EG*	7.4377	12.0438***	10.3582***
***GTEC* ≠ CO_2**	5.6321	8.6659***	7.4166***
CO_2 ≠ *GTEC*	4.4471	6.4489***	5.4858***
***GEC* ≠ CO_2**	2.2239	2.2898**	1.8637*
CO_2 ≠ *GEC*	3.1375	3.9989***	3.3522***
***DIT* ≠ CO_2**	3.6772	5.0085***	4.2315***
CO_2 ≠ *DIT*	3.6995	5.0503***	4.2678***
***NEC* ≠ CO_2**	4.2815	6.1391***	5.2160***
CO_2 ≠ *NEC*	1.9261	1.7325*	1.3785

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

4.7 Discussion of findings

Our analysis reveals that economic growth (*EG*) intensifies CO_2 emissions, particularly aligning with SDG 8 and SDG 13. In the lower to middle quantiles (10^{th} to 75^{th}), the relationship of *EG* with CO_2 becomes more statistically significant, suggesting that as countries such as China and India experience industrial expansion, CO_2 rises correspondingly. This is largely due to urbanization, infrastructure development and industries that rely heavily on carbon-intensive energy sources such as coal. However, in the upper quantiles (80^{th} to 95^{th}), the impact of *EG* on CO_2 starts to diminish, potentially indicating a decoupling effect. At this stage, economic growth may no longer directly correspond to increased emissions as countries increasingly turn to renewable energy sources to support *EG*. This shift, observed in countries such as Brazil and China, demonstrates progress towards SDG 7 and SDG 12, as renewables contribute significantly to economic output, reducing the adverse environmental impact of growth. With sustainable practices, economic growth can be aligned with emission reduction goals. This result aligns with prior studies (Ahmad *et al.*, 2021; Arminen and Menegaki, 2019; Aye and Edoja, 2017; Zafar *et al.*, 2019).

The study finds that green technologies (*GTEC*) have a weakly positive impact on CO_2 emissions, suggesting limited effectiveness in the E7 countries, particularly in high-emission countries such as India and China. While *GTEC* adoption is growing, the scale of economic activity in these countries can dilute its impact. In higher emission quantiles (80^{th} to 95^{th}), the effect of *GTEC* on CO_2 further weakens, likely due to high baseline emissions and a saturation point where emissions from heavy industries such as manufacturing and fossil fuel energy overshadow *GTEC* benefits. This highlights the need for stronger investments in green technologies and renewable energy to meet SDG 9 and SDG 13. This result aligns with prior studies (Afshan *et al.*, 2022; Ali *et al.*, 2021; Chien *et al.*, 2022).

The study reveals that green energy consumption (*GEC*) has a consistently negative and significant impact on CO_2, supporting SDG 7 (Affordable and Clean Energy), SDG 13 (Climate Action) and SDG 12 (Responsible Consumption and Production). Although *GEC* reduces CO_2 across all quantiles, its relative impact decreases as emissions increase. It is likely due to rising industrialization and economic growth, which drive *GEC* up without fully offsetting greenhouse gas emissions from nonrenewable, energy-intensive industries. This underscores the need for continued expansion of renewable energy capacity to counterbalance emissions effectively. In the higher quantiles (80^{th} to 95^{th}), however, the negative effect of *GEC* on CO_2 intensifies, indicating that in extreme emission scenarios, green energy plays a stronger role in reducing CO_2. This surge in impact may result from increased efforts in E7 countries to adopt alternative energy sources as part of their commitments to global environmental goals and local pollution control. This trend highlights the critical role of renewable energy in achieving sustainable development targets, especially as emissions reach higher levels. This result aligns with prior studies (Abbasi *et al.*, 2021; Adedoyin *et al.*, 2021; Fakher *et al.*, 2023; Kirikkaleli and Adebayo, 2021).

The impact of nonrenewable energy consumption (*NEC*) on CO_2 is positive, aligning with SDG 7 (Affordable and Clean Energy) and SDG 13 (Climate Action). From the 10^{th} to the 75^{th} percentiles, this positive effect decreases slightly, possibly due to energy efficiency improvements or a shift towards cleaner energy. However, in higher quantiles (80^{th} to 95^{th}), the impact of *NEC* on CO_2 increases significantly, indicating that at very high emission levels, fossil fuel use remains a major contributor to CO_2. This underscores the need to accelerate renewable energy adoption to meet sustainability goals. This is particularly applicable in situations when there is a need for significant energy input due to fast economic expansion and the energy infrastructure relies primarily on fossil fuels. This trend highlights the difficulties that these countries face in achieving a balance between *EG* and protecting the environment, especially when dealing with high emission levels. In such cases, reducing reliance on unsustainable energy sources becomes vital but challenging. This result aligns with prior studies (Fakher *et al.*, 2023; Özkan *et al.*, 2023; Sharif *et al.*, 2019).

Digitalization has a negative impact on CO_2, aligning with SDG 9 (Industry, Innovation and Infrastructure) and SDG 13 (Climate Action). Initially, from lower to mid-quantiles (10th to 75th), digitalization helps reduce CO_2, likely by improving efficiencies and decreasing reliance on energy-intensive processes. However, this effect weakens as emissions increase, as rising energy demand for digital infrastructure, still largely fossil fuel-based, offsets early gains. Interestingly, at higher quantiles (80th to 95th), the negative impact strengthens slightly, indicating that at very high emission levels, digitalization might again help reduce emissions. This highlights the need to pair digital growth with renewable energy to maximize its benefits, supporting SDG 7 (Affordable and Clean Energy) and SDG 12 (Responsible Consumption and Production). In scenarios where emission levels are exceptionally high, the role of digitalization in reducing emissions could become more significant. This enhanced effectiveness might stem from the broader adoption of energy-efficient technologies and greater integration of renewable energy into digital systems. Digitalization can lead to better management of energy use through smart grid technologies and can optimize processes in manufacturing and logistics to reduce CO_2 footprints. This slight improvement in its impact illustrates that digitalization, when supported by comprehensive policies that promote sustainable energy and innovative technological solutions, can significantly contribute to environmental sustainability. This result aligns with prior studies (Bansal *et al.*, 2022; Hung, 2023; Mehmood *et al.*, 2023; Pata and Karlilar Pata, 2024; Zou *et al.*, 2024).

5. Conclusion and Policy Remarks

5.1 Conclusion

This research looked at how green energy usage and technologies affect CO_2 in the context of the E7 countries. The impact of digitization, nonrenewable energy usage and economic growth were all examined. The data included spanned from 1991 to 2021. Several panel estimators were used in the investigation, such as panel quantile regression, panel CIPS, panel QQ plot, Westerlund cointegration and CADF. The QQ plot outcome reveals the nonlinear characteristics of the series. Furthermore, the results of the panel CIPS and CADF show that the variables are stationary at level and first difference. The results of the Westerlund cointegration show that all the variables have a long-run association. Finally, the results of the quantile regression show that economic growth, nonrenewable energy consumption and green energy technologies affect CO_2, while digitalization and green energy consumption decrease CO_2. As a robustness check, the panel OLS affirmed the results obtained from the quantile regression. In addition, the Dumitrescu–Hurlin panel causality test showed that all the variables can significantly predict CO_2 and *vice versa*.

5.2 Policy remarks

The study proposes several measures for the E7 countries derived from the observed impacts of their current economic practices. Given the unsustainable trajectory of economic growth reliant on nonrenewable energy sources, these countries must dissociate economic expansion from CO_2 by integrating clean energy solutions. To achieve this, a fundamental transformation is needed: shifting from a growth paradigm rooted in ecological degradation to one aligned with sustainable development. To facilitate this transition, the study recommends the implementation of a differentiated financial framework. Specifically, we suggest lower interest rates for projects that are eco-friendly while imposing higher rates on those that contribute to environmental harm. This financial structuring would naturally discourage investments in harmful industries and foster capital flow into sustainable ventures. We further recommend strategic subsidies to drive investment in green projects, aligning with SDG 7, SDG 8 and SDG 13. By carefully implementing these subsidies, E7 countries could reduce their dependency on fossil fuels, transitioning towards renewable energy. This policy approach not only encourages green energy consumption but also fosters sustainable economic growth, building resilience within these economies.

The results of this study further show that both green energy consumption and digitalization foster a decrease in CO_2, which implies effective policies on the part of the E7 countries. Based on this, policymakers in E7 need to stimulate digital technologies that will effectively curb CO_2 via energy efficiency optimization. This can be done by implementing smart grids and IoT technologies that are capable of improving infrastructure monitoring in various industries. In addition, R&D in green energy technologies can be supported by providing grants and incentives which will boost green technologies. Besides, acceptance and use of green technologies rely on public consciousness and education. Thus, initiatives to boost green technology and practices should be encouraged.

5.3 Study limitations and future pathways

This research contributes to the ongoing discussions regarding the E7 roadmap for achieving environmental sustainability. It focuses on identifying strategies that could reduce the ecological footprints of countries while simultaneously promoting economic growth. However, there are noticeable limitations in several key areas. Although CO_2 emissions are a widely accepted indicator of ecological degradation, they do not account for the consumption of environmental resources. Therefore, future studies should include additional indicators of ecological quality, such as the load capacity factor. Future research could also explore the asymmetric impacts of exogenous factors on the carbon footprint.

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