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A Threshold Analysis of Internet Users and the CO2 Emissions Nexus

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Abstract
The study adopted threshold regression techniques to estimate the cross-section data spanning 2017 to 2021. It hypothesized that internet users affect CO2 emission between countries and this would vary depending on the level of population. Countries that have smaller populations may not have the same effect on CO2 emissions as compared to countries with larger populations. The empirical results show that internet users exert a significant influence on CO2 emissions, especially under high threshold regimes. Thus, the larger the population, the higher and more significant will be the impact on CO2 by internet users.

Keywords: CO2 emissions; population; threshold regression; Internet users

1.0 Introduction

Global CO2 emissions from energy combustion and industrial processes have recently increased to their highest annual level. Emissions rose by 6% from 2020 to 36.3 gigatonnes (Gt) (Global Energy Review 2021). In 2021, almost all global regions saw an increase in CO2 emissions, with annual incremental changes ranging from more than 10% in Brazil and India to less than 1% in Japan. China's emissions increased by 5%, while the United States and the European Union both saw increases of around 7% (IEA 2021). According to the United Nations' most recent projections, the global population could reach 8.5 billion in 2030, 9.7 billion in 2050, and 10.4 billion in 2100 (World Population Prospects 2022). Human resources are essential to growth since populations are factored in as inputs in production. A large population size provides a larger market for goods and services, but an excessive population means excessive human activity and excessive energy use, both of which result in CO2 emissions (Rahman, Saidi & Mbarek 2020).

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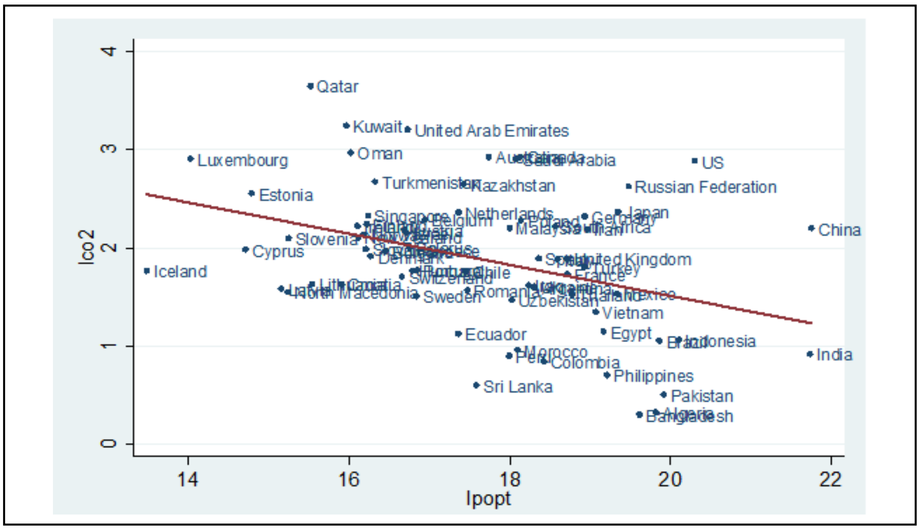

Fig. 1: The relationship between CO2 emissions and the population size of 72 countries (average from 2017 to 2021)
(Source: Primary data, authors' estimation)

Figure 1 depicts the average total population and average CO2 emissions in 72 countries from 2017 to 2021. It shows a negative linear relationship between the total population and CO2 emissions. According to the most recent ITU data, Internet adoption has increased to 4.1 billion people in 2019 (or 54% of global the population) during the pandemic. The number further increased by 782 million to 4.9 billion in 2021, or 63% of world the population. In the first year of the pandemic in 2020, internet users increased by 10.2% to 13.3%, the largest increase in a decade, driven by developing countries (ITU 2021).

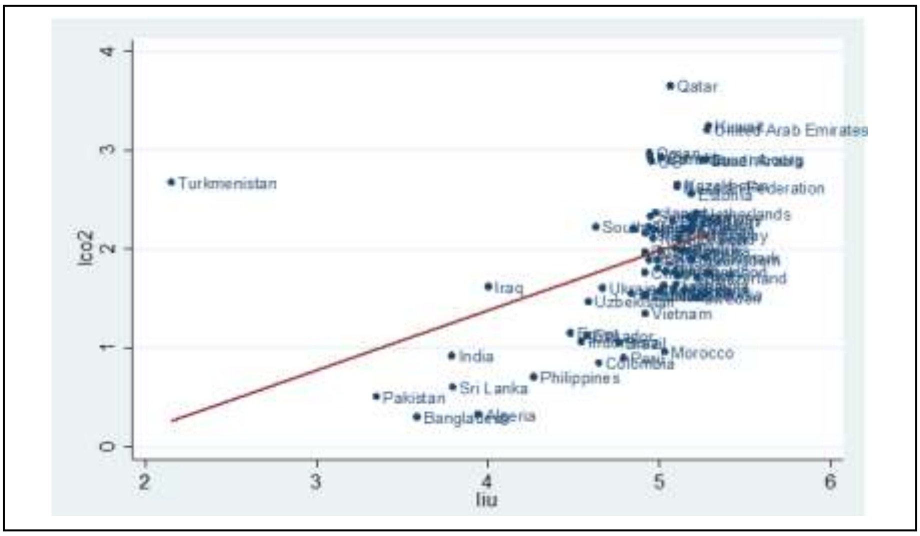

Fig. 2: The relationship between CO2 emissions and Internet users of 72 countries (average from 2017 to 2021)
(Source: Primary data, authors' estimation)

Figure 2 depicts the average CO2 emissions and average internet users in 72 countries from 2017 to 2021. It shows a positive linear relationship between internet users and CO2 emissions. By identifying the role of total populations as determinants of CO2 emissions, this study seeks to add to the body of literature on the global environment and ICT development. Thus, the objective of this study is to examine the nexus among internet users, the population size as the threshold variable and CO2 emissions. The threshold regression technique was adopted on data of annual averages from 72 countries, spanning 2017 to 2021. In this paper, the literature review is discussed in Section 2. The methodology is presented in Section 3 and the results in Section 4. Finally, the conclusion and recommendations are presented in Section 5.

2.0 Literature Review

2.1 Population and CO2 Emission

Most empirical research discovers that population growth is positively associated with an increase in CO2 emissions since it exerts an obvious impact on environmental quality (Weber & Sciubba, 2019). Every individual uses energy for necessities such as food, water, clothing, and shelter. In general, the greater the number of people there are, the more energy is required (Shi, 2003). Furthermore, rapid population growth causes an increase in CO2 emissions (Anon., 2014; Xu & Lin, 2015). This can happen in two ways: First, an increase in population may lead to an increase in energy demand. The energy consumption in OECD countries for example is primarily based on fossil energy. As such, population growth will lead to an increase in fossil energy consumption resulting in a consequent rise in CO2 emissions. Second, population growth will destroy forests and changes in land use, both of which are likely to increase CO2 emissions (Birdsall 1992). According to Anon, (2018), economic and population growth triggers an increase in CO2 emissions at both global and regional levels. Asongu, El Montasser and Toumi (2016) showed that economic and population growth, accompanied by energy consumption led to increased CO2 emissions in 24 African countries. Moreover, the relationship between population growth and carbon dioxide emissions is nuanced, and other factors besides per capita GDP also have an impact (Wang, & Li, 2021). Other indicators related to population, such as population density, life expectancy, and unemployment rate, have an impact on CO2 emissions (Liu et al., 2017; Rjoub et al., 2019; Adesina & Mwamba, 2019). Many different population-related issues are being faced by nations all over the world. Therefore, additional research is required to determine the precise effect of these issues on carbon dioxide emissions. In addition, many previous studies have only examined the effect of threshold values of population growth on carbon emissions (Wang, & Wang, 2021; Fan et al., 2021).

2.1 Internet users and Co2 Emission

It is well established that information and communication technologies (ICTs) have profound impacts on essential global systems. On the positive side, ICT is accelerating the process of industrialization, which drives economic growth. However, on the converse and negative side, this development has resulted in increased environmental pollution due to increased energy consumption (Anon, 2021). Ulucak and Khan (2020) investigated the role of ICT in CO2 emissions for the BRICS economies between 1990 and 2015. Their empirical findings revealed that ICT reduces CO2 emissions. Further, Asongu (2018) used the GMM approach to investigate the relationship between openness, CO2 emissions, and ICT in Africa. The author established that ICT can help mitigate potential negative impacts of globalization on environmental pollution. Anon (2020) who evaluated the impact of ICT on environmental pollution in Sub-Saharan African economies established that the technologies promote CO2. Faisal, Tursoy and Pervaiz (2020) observed that ICT increased CO2 emissions in China, India, Brazil, and South Africa in the early stage of economic development but then reduced the pollution beyond an inflection point of economic growth. Numerous studies have discovered the relationship between information and communication technology (ICT), the consumption of electricity, GDP, and CO2 emissions. Still, these studies with different approach failed to reach a consensus, resulting in two contradictory conclusions about the ICT and CO2 emissions nexus.

3.0 Methodology

3.1 Data Description

The empirical investigation was based on cross-section macro data from 72 countries. The study spans the average years spanning 2017 to 2021. Data were collated from the World Development Indicators and the descriptions presented in Table 1. The values of all variables were converted into logarithmic form.

3.2 Model Specification and Empirical Strategy

The threshold model for the linkages between internet users and the CO2-population nexus was based on Zmami and Ben-Salha (2020). We used Equation (1) in the following form:

$$lco2_{it} = \alpha_0 + \beta_1 lpopt_{it} + \beta_2 liu_{it} + \beta_3 X_i + \varepsilon_i \quad (1)$$

where,
$lCO2$ = CO2 Emission
$lpopt_{it}$ = the total population
X_i = vector of control variables that affect the CO2 emission
i = country, i = *1, 2, 3, ...n*
t = time, i = *1, 2, 3, ...T*
ε = error term

Equation (2) is the threshold effect hypothesis in this study:

$$H_0 : \beta^1 = \beta^2$$
$$H_1 : \beta^1 \neq \beta^2 \quad (2)$$

β_s are the vectors of the parameters. The null hypothesis is presented by linear regression. The alternative hypothesis is a nonlinear regression while the threshold regression is nonlinear (Equation 2). We will have a two-regime condition if the null hypothesis is rejected. Equation (3) is suitable for testing the hypothesis and securing the presence of contingency effects between the population and CO2 emissions.

The threshold regression model is as follows:

$$lCo2_{it} = \begin{cases} \beta_0^1 + \beta_1^1 lpopt_{it} + \beta_2^1 liu_{it} + \beta_3^1 X_{it} + e_{it}, & lpopt_{it} \leq \gamma \\ \beta_0^2 + \beta_1^2 lpop_{it} + \beta_2^2 liu_{it} + \beta_3^2 X_{it} + e_{it}, & lpopt_{it} > \gamma \end{cases} \quad (3)$$

where γ is the unknown threshold parameter. The threshold variable is $lpopt_i$ adopted in dividing the sample into groups or regimes. This particular form of modeling strategy allows the total population to employ a different role which is dependent on population size relative to that of the threshold level, γ. The total population acts as a sample-splitting or threshold variable in this equation. The β_1^1 and β_1^2 parameters represent countries with a low or high total population regime on CO2 emissions.

Accordingly, the model becomes linear and reduced to Equation (1) if the hypothesis $\beta^1 = \beta^2$.

4.0 Findings and Discussions

Table 1 shows the descriptive statistics of all the variables used in the estimations for 72 countries. The mean CO2 emission is 1.90 % and the mean total population and number of individual internet users are 17.57 % and 4.86 %, respectively. Table 2 presents the correlation matrix of the variables employed in the analysis. All the variables show a positive sign on CO2 emissions except for the total population.

Table 1. Descriptive statistics

Variable	Unit of Measurement	Mean	Std. Dev	Min	Max
$lco2$	CO2 emissions (metric tons per capita)	1.90	0.71	0.31	3.65
leg	Electricity Generation	5.24	1.52	1.52	9.62
lec	Primary Energy Consumption	1.71	1.19	0.10	5.67
$leximp$	The sum of exports and imports (% of GDP)	5.01	0.61	3.57	6.61
$lfdi$	Foreign direct investment, net inflows (% of GDP)	1.32	1.31	-2.98	3.98
$lgdperc$	GDP per capita (constant 2015 US$)	10.29	1.11	7.96	12.27
liu	Individuals using the Internet (% of the population)	4.86	0.52	2.15	5.29
$lpopt$	Population, total	17.57	1.69	13.48	21.76

Table 2. Correlations

	$lco2$	leg	lec	$leximp$	$lfdi$	$lgdperc$	liu	$lpopt$
$lco2$	1.00							
leg	0.06	1.00						
lec	0.15	0.95	1.00					
$leximp$	0.30	-0.52	-0.46	1.00				
$lfdi$	0.00	-0.16	-0.08	0.18	1.00			
$lgdperc$	0.66	-0.07	-0.05	0.43	-0.09	1.00		
liu	0.45	-0.04	-0.04	0.57	0.01	0.65	1.00	
$lpopt$	-0.38	0.84	0.81	-0.63	-0.05	-0.50	-0.36	1.00

4.1 Hansen (2000) Threshold Regression

Equation (3) was used to examine the impact of internet use on CO2 emissions and condition on the population level for the years 2017–2021. Table 3 shows the threshold estimates for the total population. The hypothesis of no threshold effects was rejected at a 5% significance level. These findings demonstrate that the relationship between total population and CO2 emission effects was non-linear, where internet users could significantly contribute to CO2 emissions at a certain level of the total population.

Conversely, the low total population impact group was investigated on the possibility of it dividing into sub-regimes. The bootstrap p-values for the second sample split were found significant at the 10% level. This indicates that two threshold values are sufficient for both models. After identifying the non-linear relationship between the total population and CO2 emissions, we can conclude that the sample can be divided into two regimes based on whether the country's total population is above or below the threshold point, conditional on the number of internet users in the country. The first and second sample splits were accordingly used in this study in order to identify the turning point.

Table 3. Threshold estimates of the total population for average 2017 – 2021

	First sample split	**Second sample split**
LM test for no threshold	18.79	14.14
Bootstrap p-value	0.011**	0.098*
Threshold estimate	16.75	18.14
95% Confidence interval	[16.33, 18.30]	[18.13,18.60]

Notes: ***, ** and * denote significant at 1%, 5% and 10% levels respectively.

Source: Primary data, authors' estimation.

The threshold model specifications in Table 4, for the average year 2017–2021, show that the coefficient estimate for liu is not significant and positive when the total population is below the threshold value ($lpopt$ <16.75). There were 26 countries categorized as having a low total population during this period. In comparison, above the threshold level of the total population ($lpopt$ > 16.75), the liu variable shows a positive coefficient at a 5 % significance, in 46 countries. This thus suggests that liu significantly contributes to CO2 emissions, where a 1 % increase in liu will increase CO2 emissions by 0.46 %. The results also show that all selected variables were significant except for the $lfdi$ variable. Three variables, namely electricity consumption, openness, and economic growth, have a positive and significant impact on CO2 emissions.

Table 4: Regression results using the total population as a threshold variable

Dependent variable: CO2 emissions			
Variable	**First sample split** 2017 - 2021		
	Global OLS	$lpopt \leq 16.75$	$lpopt > 16.75$
$Intercept$	-1.780*	2.756**	-2.463***
	(1.154)	(1.157)	(0.991)
leg	-0.330***	-0.400**	-0.550**
	(0.129)	(0.192)	(0.248)
lec	0.526***	1.099***	0.804***
	(0.143)	(0.344)	(0.265)
$leximp$	0.058	-0.334*	0.171*
	(0.130)	(0.228)	(0.116)
$lfdi$	0.004	0.017	-0.024
	(0.044)	(0.057)	(0.049)
$lgdperc$	0.397***	0.121	0.268***
	(0.084)	(0.095)	(0.086)
liu	0.026	0.131	0.459**
	(0.300)	(0.201)	(0.193)
R-squared	0.53	0.47	0.74
Heteroskedasticity Test (P-Value)	0.94	-	-
Observations	72	26	46
Degrees of Freedom	65	19	39

Notes: Number in parentheses are standard errors.
***, ** and * denote significant at 1%, 5% and 10% levels respectively.
leg = electricity generation, lec = electricity consumption, $leximp$= the sum of exports and imports (% of GDP), $lfdi$ = foreign direct investment net inflows (% of GDP), $lgdperc$ = GDP per capita (constant 2015 US$), liu= Individuals using the Internet (% of the population)

The threshold model specifications for the second sample split are given in Table 5. The results show that above the threshold level ($lpopt$ > 18.14), the coefficient of liu is positive and highly significant at a 1% level in influencing $lco2$ (CO2 emissions). This indicates that a 1 % increase in liu will influence positively $lco2$ by 0.79 %. A similar result was obtained when the total populations were below the threshold value ($lpopt \leq 18.14$) with the coefficient of liu statistically significant at 5 % and positive in generating CO2 emissions ($lco2$). It shows that a 1 % increase in liu will raise the $lco2$ by 0.84 %. The results support the hypothesis that the larger the total population of the country, the greater the expansion of internet users (and consequently the higher the electricity consumption), thus producing a harmful impact on the country's environment. As a result of modernization, a higher population will lead to an upsurge in global demand for electricity and mobile phones. Thus, the demand for electricity rises in tandem with the demand for mobile phones (Manchester, & Swan, 2013).

Table 5. Regression results using the total population as a threshold variable

Dependent variable: CO2 emissions			
Variable	**Second sample split** 2017 - 2021		
	Global OLS	$lpopt \leq 18.14$	$lpopt >$ 18.14
$Intercept$	-2.463***	-0.921	-4.367***
	(0.991)	(1.085)	(1.199)
leg	-0.550**	-1.193***	0.080
	(0.248)	(0.436)	(0.295)
lec	0.804***	1.653***	0.186
	(0.265)	(0.438)	(0.303)
$leximp$	0.171*	-0.310*	0.199**
	(0.116)	(0.201)	(0.108)
$lfdi$	-0.024	0.062**	-0.315***
	(0.049)	(0.030)	(0.060)
$lgdperc$	0.268***	0.366***	0.072
	(0.086)	(0.087)	(0.077)
liu	0.459**	0.839**	0.790***
	(0.193)	(0.320)	(0.174)
R-squared	0.741	0.891	0.823
Heteroscedasticity Test (P-Value)	0.88	-	-
Observations	46	19	27
Degrees of Freedom	39	12	20

Notes: Number in parentheses are standard errors.
***, ** and * denote significant at 1%, 5% and 10% levels respectively.
leg = electricity generation, lec = electricity consumption, $leximp$= the sum of exports and imports (% of GDP), $lfdi$ = foreign direct investment net inflows (% of GDP), $lgdperc$ = GDP per capita (constant 2015 US$), liu= Individuals using the Internet (% of the population)

5.0 Conclusion and Recommendations

This study examines the internet users-CO2 emissions nexus, as conditional on the sizes of total population using data from 72 countries for the average years from 2017 to 2021. The cross-section model was used to capture the effect of internet users on CO2 emissions across countries and total populations. The study recorded two major findings. First, a threshold effect is evident in the relationship between size of total population and CO2 emissions. Second, the impact of internet users on CO2 emissions is positive and highly significant, particularly at high regime threshold levels in the population ($lpopt$). The effect of internet users is much greater for countries with larger populations rather than those with smaller ones. Finally, these findings are of particular importance for policymakers focusing on the tipping point and characteristics of ICT development to ensure a greater reduction of CO2 emissions, particularly in countries with higher population growth. Future studies may use other ICT indicators and urban populations as threshold variables in the context of ASEAN, high-income and middle-income countries.

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Paper Contribution to Related Field of Study

This study contributes to the body of knowledge in three important aspects: Firstly, there is a threshold effect on the relationship between CO2 emissions and population levels, FDI inflows, GDP per capita, openness, electricity generation, electricity consumption, and number of internet users. Secondly, the nonlinear approach enabled us to endogenously identify the nonlinearity of the CO2 relationship. Thirdly, this idea provides new evidence on the effect of different population levels on internet users and the CO2 emissions nexus.

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