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Impact of population size on consumption-based carbon emissions in Sub-Saharan Africa: evidence from the method of moments quantile regression

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Abstract

Despite the plethora of studies on determinants of carbon dioxide emissions, studies that consider the role of population size in an environmental Kuznets curve (EKC) framework are scanty in the environmental literature. Relying on the stochastic impacts by regression on population, affluence, and technology (STIRPAT) model for analyzing environmental impacts, this study examined the impact of population size on consumption-based carbon dioxide emissions, controlling for per capita income, energy intensity, financial development, and natural resource rents in a panel of 19 Sub-Saharan African (SSA) countries over the period 1995-2017. The study adopted the method of moments quantile regression (MM-QR) and Fixed Effects Ordinary Least Squares (FEOLS) with Driscoll and Kraay standard error estimation techniques. Our findings are robust with alternative long-run panel specifications, including fully modified ordinary least squares, dynamic ordinary least squares, and canonical cointegration regressions, and show that population size, energy intensity, and financial development significantly promote consumption-based carbon dioxide emissions in SSA. The distributional effects of these factors, among other things, reveal that population size has a positive and significant effect on consumption-based CO2 emissions across the observed quantiles, with a more pronounced effect in lower consumption- based carbon dioxide emissions SSA economies. The model presented no evidence to validate the EKC hypothesis for Sub-Saharan Africa; policy implications of these findings were suggested.

Keywords: Sub-Saharan Africa, Population size, environmental Kuznets curve, consumption-based carbon emissions, method of moments quantile regression
JEL Classifications: Q32, Q044

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1. Introduction

Africa is at the lower end of developing economies' tables, but has a rapidly growing population, making it the second largest continent with a 17.21% growth rate, close to that of India. A growing population results in increased consumption of energy in aggregate (Yang et al., 2017), which enhances economic activity. It is also believed that population growth leads to urbanization, which significantly relates to energy consumption. A recent report showed an alarming increase in global CO2 emissions by 15.5% from 1975 to 32.53 giga tonnes in 2017 (IEA, 2019). Some studies have identified energy consumption, tourism, trade openness, economic growth, urbanization, financial development, and population size as determinants of carbon emissions (Nwani et al., 2021; Omoke et al., 2020; Zafar et al., 2019; Chebbi et al., 2011 & León et al., 2014). Much of Africa's CO2 emissions are embedded in imports rather than export. This is why studies in SSA are concentrating more on such factors as financial development-CO2 emissions link (Shahbaz et al., 2013; Tamazian et al., 2009; Jian & Ma, 2019) with little attention paid to population size as a determinant.

Today, the world's top three emitters of CO2 are China, the United States, and India, and they account for nearly 50% of the emissions worldwide. Sub-Saharan Africa (SSA) is not one of them, though natural resource dependent. But when it comes to population growth, Africa is a continent to watch in matters that concern energy consumption because population density could affect energy use and CO2 emissions (Liddle, 2015). The influence of large populations on energy consumption is derived from increased energy needs both in the industry and political and social life of a country. Population size (PS) increases economic activities, which in turn increases energy usage and carbon emissions (Birdsall, 1992). Therefore, the population density that could enhance energy inefficiency becomes an important determinant of CO2 emissions. Energy inefficiency leads to CO2 emissions (Babu & Kaechele 2015; Morrow et al., 2014).

Ordinarily, population growth should theoretically have a positive correlation with CO2 emissions because an increase in human activities leads to CO2 emissions. Nevertheless, only empirical evidence can firmly establish this link in SSA.

Literature on population size and carbon dioxide emissions in SSA is scanty and the few that exist do not take into consideration the implications of carbon emissions deeply rooted in the consumption pattern of the SSA economies. Since many of the countries in SSA are net importers, the need arises to explain the environmental implications of population size using a measure that will factor in CO2 emissions embedded in the consumption pattern. This study, therefore, uses consumption-based CO2 emissions as different from the territorial-based CO2 emissions that have been used by previous studies. To arrive at consumption-based CO2 emissions, the extra emissions from imports are added while subtracting CO2 associated with exports (Peters et al., 2011). We used a panel quantile regression method to estimate an extended STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model. In order to model environmental impacts, the STIRPAT framework has been variously adopted (see, for example, Anser et al., 2020; Wang et al., 2013). Individual and heterogeneous characteristics central to the SSA economies demand the use of the panel quantile regression method, which has an advantage over other methods in the population size/density-CO2 emissions literature in that it accounts for the distributional impact of explanatory variables on the explained variable in diverse quantiles, thus explaining the impact of population size on carbon emissions in the low, medium, as well as high-carbon emitting SSA countries.

The rest of the paper is organized as follows: Section 2 contains theoretical and empirical literature, while Section 3 discusses the data and methodology. Section 4 contains empirical results and discussion, while Section 5 concludes the study and suggests some policy implications.

2. Theoretical and empirical literature

Population growth is a major contributor to CO2 emissions in both developed and developing countries. A rise in human activities would unavoidably put more strain on the environment, which would cause it to deteriorate. Deforestation, increased water and air pollution, soil erosion, and damage to marine and coastal ecosystems are all direct consequences of rapid population growth. As the world's population grows, so does the demand for transportation, electricity, and industrial energy, all of which could lead to an increase in global emissions from fossil fuels.

As earlier stated, the literature that considers population size as a determinant of CO2 emissions in SSA is small and previous studies have also shown that results can vary depending on the variables used. According to some of these studies, population growth is a major factor in CO2 emissions regardless of the development level of the country (see O'Neill et al., 2014; Ohlan 2015; Mamun et al., 2014; Sehrawat et al., 2015).

Shi (2001) discovered that population growth accounts for 1.28 percent of CO2 emissions and that the impact of population growth on CO2 emissions is stronger in developing nations than in industrialized countries. Pastpipatkul and Panthamit (2011) using a panel Tobit model, examined population size and CO2 emissions in 76 provinces in Thailand from 2001 to 2008. Their findings indicate that while population size has a statistically significant effect on carbon emissions, it has a very low elasticity to carbon emissions, implying that it contributes little to changes in carbon emissions. In addition, they found that per capita GDP and energy consumption also have a statistically significant relationship with carbon emissions in Thailand's provinces.

Mamun et al. (2014) examined the relationship between population growth and CO2 emissions in 136 countries and discovered that, in the long run, population size increased CO2 emissions, even after controlling for other variables. Later, Ohlan (2015) demonstrated that India's population density has a significant positive influence on CO2 emissions in the short run and in the long run. Hanif and Gago-de-Santos (2017) used instrumental variable (IV) regression to study the effect of population size and macroeconomic stability on CO2 emissions in 86 selected developing nations spanning 1972 to 2011. From their findings, demographic and economic instability had a considerable impact on CO2 emissions in the selected economies. Other studies that have discovered a positive influence of population size on carbon dioxide emissions include: (Cheng et al 2020; Rahman, et al., 2020). In addition, Rahman et al. (2020) discovered a one-way causality? between population density and CO2 emissions in South Asia.

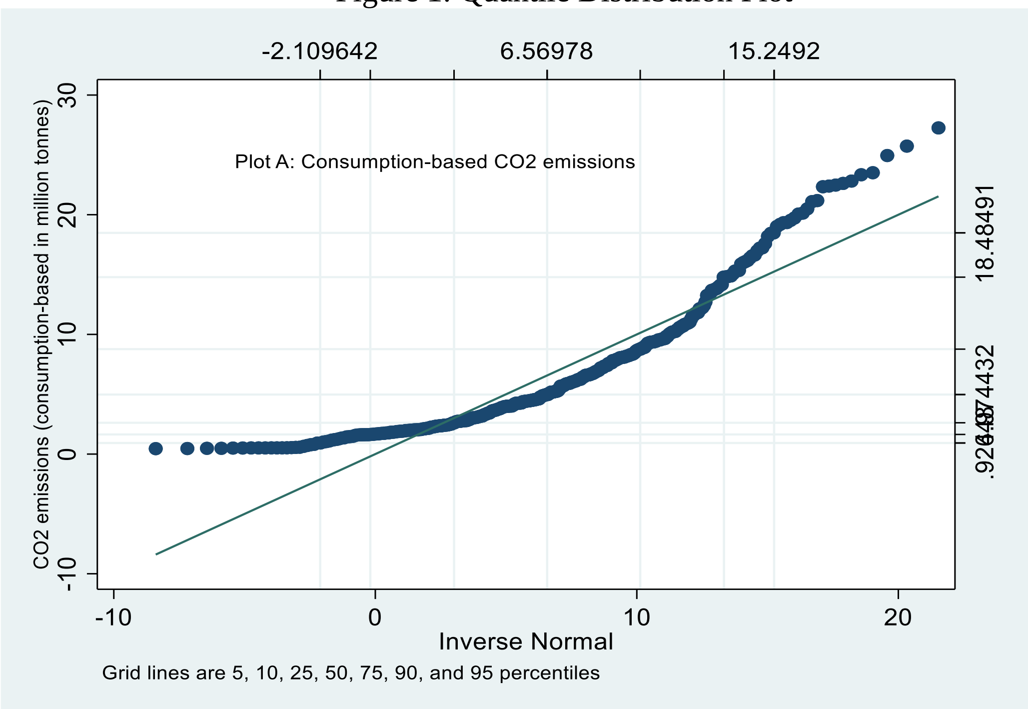
3. Data and Methodology

3.1 Data sources and description

This study used a balanced panel dataset comprising nineteen (19) selected Sub-Saharan Africa's net carbon importers over the period 1995 – 2017. A list of the selected countries, the data sources and a description of the variables are contained in Table 1, while the descriptive statistics of the variables used are shown in Table 2. The 19 SSA economies have 0.454, 27.257, and 6.570; million tonnes as minimum, maximum, and mean values of consumption-based CO2 emissions, respectively. For population size, the minimum, maximum and mean values are 1469174, 106000000, and 19814489, respectively.

In order to determine whether the distribution of the variables is normal or not, the Jarque-Bera (JB) test for normality was used. From the p-values of the Jarque-Bera statistic in Table 2, it can be observed that all the variables are not-normally distributed. Further support of the non-normality condition is presented in Figure 1 via the Quantile–Quantile (Q–Q) normality test, which contrasts the actual distribution of the variables with the expected normal distribution (green line). The quantile distribution plot demonstrates how the probability distribution of consumption-based CO2 emissions in SSA economies departs from the expected normal distribution. The non-normality condition implies that the traditional panel regression approaches, which assume normal distribution of the series, may perhaps provide insufficient information for policy (for related concern, see Gyamfi et al., 2021).

Figure 1: Quantile Distribution Plot



Source: authors graph

Table 1: Definition of Variables and Source of Data

Variable	Symbol	Definition and measurement	Data Source
Consumption-based carbon Emissions	ConCO2	Consumption-based carbon Emissions (million tonnes)	Global Carbon Budget (Friedlingstein, et al., 2019)
Population size	PS	Population (Total, number)	WDI, World Bank
Economic growth	PCI	GDP per capita (constant 2010 US$)	WDI, World Bank
Energy Intensity	EI	Energy intensity level of primary energy (mega joules per constant 2011 purchasing power parity GDP	WDI, World Bank
Financial Development	FD	Financial Development Index	IMF's Financial Development Index computed by Sahay et al. (2015) and Svirydzenka (2016)
Natural resources Rents	Nrr	Total Natural resources Rents (% of GDP)	WDI, World Bank
Selected Sub-Saharan African countries: Benin, Botswana, Burkina Faso, Cameroon, Côte d'Ivoire, Ethiopia, Ghana, Guinea, Kenya, Madagascar, Malawi, Mozambique, Namibia, Rwanda, Senegal, Tanzania, Togo, Uganda, Zambia			

Source: Global Carbon Budget (Friedlingstein, et al., 2019) is available at https://doi.org/10.5194/essd-11-1783-2019; WDI available at https://databank.worldbank.org/source/world-development-indicators#advancedDownloadOptions; Financial Development Index is available at: http://data.imf.org/fdindex.

Table 2: Descriptive Statistics

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability	Observations
ConCO2	6.570	4.974	27.257	0.454	5.277	1.419	4.785	204.699	0.000	437
PS	19814489	14962112	106000000	1469174	18222205	2.252	8.977	1020	0.000	437
PCI	1289.818	815.874	7864.253	183.548	1532.259	2.623	9.051	1167.866	0.000	437
EI	9.465	7.765	44.709	3.041	6.389	2.237	8.872	992.293	0.000	437
FD	0.126	0.108	0.503	0.046	0.065	2.535	9.996	1359.419	0.000	437
Nrr	8.505	7.162	36.141	0.540	5.622	1.185	5.210	191.219	0.000	437

Source: Authors computation

3.2 The Model

Following York et al. (2003) and Dietz & Rosa (1994), this study adopts the stochastic impacts by regression on population, affluence, and technology (STIRPAT) framework for analyzing environmental impacts and thus specifies the following log-linear equation for investigation:

$$lnConCO2_{i,t} = \mho_0 + \mho_1 lnPS_{i,t} + \mho_2 lnPCI_{i,t} + \mho_3 lnPCIsq_{i,t} + \mho_4 lnEI_{i,t} + \mho_5 lnFD_{i,t} + \mho_6 lnNrr_{i,t} + \varepsilon_{i,t} \tag{1}$$

where, Con*CO2* denotes consumption-based CO_2 emissions, *PS* is population size, *PCI* is GDP per capita and stands for economic growth, PCIsq is the square of GDP per capita, which is here incorporated to test the validity of the Environmental Kuznets Curve (EKC) hypothesis in SSA. The EKC hypothesis envisages an inverted U-shaped curve with positive and negative values for $\mho_2$ and $\mho_3$ respectively. *EI* is energy intensity. Financial development is represented as FD, while natural resources rent is denoted as Nrr. Nrr is incorporated in the model to factor in the economic dependence of Sub-Saharan Africa on natural resources. $\mho_0$ is the constant of the equation,and $\mho_1 ... \mho_6$ are coefficients to be estimated, and ε is the error term.

3.2 Estimation Techniques

The estimation procedure commenced with Pesaran (2004, 2015) test for cross-section dependence (CD) in the variables. To examine the stationarity properties of the variables, the study uses the Im et al (2003) unit root test and Pesaran (2007) Cross-Sectional Augmented Dickey-Fuller (CADF) unit root test. Pesaran (2007) CADF unit root test gives efficient results in the presence of serial correlation and cross-sectional dependence in the variables. Thereafter, Westerlund (2007) panel cointegration technique was used to check whether a long-run relationship exists between ConCO2 and population size and the other explanatory variables. Westerlund (2007) panel cointegration technique gives efficient and reliable results in the presence of serial correlation and deals with issues of cross-sectional dependence using bootstrap tests.

The study uses the Fixed Effects Ordinary Least Squares (FEOLS) estimator with Driscoll and Kraay standard errors (FE-DK) to estimate the parameters in Equation (1). We also employed three other traditional panel data estimation methods (Fully Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS) and Canonical Cointegrating Regression (CCR)) for robustness checks on the results of the FEOLS estimation under the assumption of cross-sectional independence. The FEOLS estimator is efficient in the presence of cross-sectional dependence in the variables. In addition, we extend our analysis by using the Method of Moments Quantile Regression (MM-QR) method developed by Machado & Silva (2019) since the quantile on the quantile plot in Figure 1 and the p-values of the Jarque-Bera test statistic in Table 2 reveal that ConCO2 considerably violates the condition of normal distribution, which implies that modelling the mean values of the distribution may not offer very efficient estimates for policy. The major advantage of the MM-QR method is its capability to account for the distributional impacts of the explanatory variables on ConCO2 in diverse quantiles.

The conditional quantile, $Q_Y(\tau|X)$ estimates of the location-scale variant model is defined by the MM-QR as follows:

$$Q_Y(\tau|X_{it}) = (\alpha_i + \delta_i qi) + X'_{it}\beta + Z'_{it}\gamma q(\tau) \tag{2}$$

In Equation (2) $X_{it}^{'}$ is a vector of explanatory variables.$Q_Y(\tau|X_{it})$ denotes the quantile distribution of ConCO2, conditional on the location of the explanatory variable (X_{it}). $\alpha_i(\tau) = \alpha_i + \delta_i q(\tau)$ stands for the scalar coefficient of the quantile-τ fixed effect for individual i, or the distributional effect at τ. $q(\tau)$ represents the τ-th quantile determined from the following optimization function:

$$\min_q \sum_i \sum_t \rho_\tau \left(\hat{R}_{it} - \left(\hat{\delta}_i + Z_{it}^{'}\hat{\gamma}\right) q\right) \tag{3}$$

In which, $\rho_\tau(A) = (\tau - 1)AI\{A \leq 0\} + \tau AI\{A > 0\}$ provides the check-function. For panel quantile estimation, we reformulate the extended STIRPAT specification in Equation (1) as follows:

$$Q_{lnConCO2_{i,t}}[\tau|\alpha_i, \varepsilon_{it}, X_{i,t}] = \mho_{0\tau} + \mho_{1\tau} lnPS + \mho_{2\tau} lnPCI_{i,t} + \mho_{3\tau} lnPCIsq_{i,t} + \mho_{4\tau} lnEI_{i,t} + \mho_{5\tau} lnFD + \mho_{6\tau} lnNrr_{i,t} + \varepsilon_{i,t} \tag{4}$$

4. Empirical results and discussion

The results of Pesaran (2004, 2015) cross-section dependence (CD) test are presented in Table 3. Based on the results, we reject the null hypothesis of cross-sectional independence in the variables due to the statistical significance of the test statistics. This implies that the variables are related across the selected 19 SSA economies. The presence of cross-sectional dependence suggests that the selected SSA economies are linked through some means, for instance, cross-border trade and so on, and thus share a similar structure. The importance of testing for cross-sectional dependence stems from the need to determine the generation of the econometric techniques to be adopted in subsequent analyses. Table 4 summarizes the results of the panel unit root tests. Results from Im et al. (2003) panel unit root test are reported first, followed by results from Pesaran (2007) Cross-sectional Augmented Dickey- Fuller (CADF) panel unit root test. In this study, it became expedient to extend Im et al. (2003) unit root test by implementing Pesaran (2007) CADF unit root test due to the reported presence of cross-section dependence in the variables, given that Pesaran (2007) CADF accounts for the presence of cross-section dependence in the variables. From the panel unit root test results, it was revealed that the variables are integrated of order one, I (1). The results, overall, point to the potential of a long-term link among the variables. The cointegration test was performed using Westerlund (2007) with 100 bootstrapping, which accounts for the presence of cross-sectional dependence in the variables. The results presented in Table 5, Panel A disclose that the p-values for group test statistics and panel test statistics are smaller than 0.05, implying that the null hypothesis of no cointegration is discarded for the cross-sectional units as well as for the entire panel at 5% level of significance. Furthermore, as a preliminary test, the Hausman test was carried out to determine the suitability of the panel fixed effects method for estimating the model. The outcome reported in Table 5, Panel B revealed statistical significance of the test statistics, indicating the aptness of the fixed effects method for the investigation of the models in the present study.

Table 3: Pesaran (2004, 2015) Cross-Section Dependence Test

Variable	**CD-test**	**p-value**	**average joint**	**mean ρ**	**mean abs(ρ)**
lnConCO2	53.09 ***	0.000	23.00	0.85	0.85
lnPS	62.507 ***	0.000	23.00	1.00	1.00
lnPCI	44.550 ***	0.000	23.00	0.71	0.72
lnPCIsq	44.708 ***	0.000	23.00	0.71	0.72
lnEI	19.426 ***	0.000	23.00	0.31	0.58
lnFD	21.124 ***	0.000	23.00	0.34	0.39
lnNrr	13.358 ***	0.000	23.00	0.21	0.36

*Note: A*** $p<0.01$, ** $p<0.05$, * $p<0.1$;*

Source: Authors computation

Table 4: First and Second Generational Panel Unit Root Tests

	First generation: Im, Pesaran and Shin (IPS) unit root test				Second generation: CADF (Pesaran, 2007) unit root test				
	Level I(0)		1st Difference I(1)		Level I(0)		1st Difference I(1)		
Variables	**Without Trend**	**With Trend**	**Without Trend**	**With Trend**	**Without Trend**	**With Trend**	**Without Trend**	**With Trend**	**Decision**
lnConCO2	4.4338	-0.4239	-6.8291 ***	4.9186 ***	-1.854	-1.850	-3.690***	-3.810***	I(1)
lnPS	3.9491	0.1909	-5.6853***	-4.6153***	-1.436	-1.498	-2.648***	-3.108***	I(1)
lnPCI	4.6742	0.7375	-5.7320***	-4.3875***	-1.549	-1.531	-2.579***	-3.112***	I(1)
lnPCIsq	7.2564	4.8288	-16.0436***	-23.6268***	-0.946	-1.103	-2.926***	-3.933***	I(1)
lnEI	1.2685	-1.1299	-15.877***	-14.6443***	-1.826	-1.698	-2.797***	-3.151***	I(1)
lnFD	1.3466	-1.1539	-12.8152***	-10.3627***	-1.998	-2.043	-3.604***	-3.674***	I(1)
lnNrr	-0.7317	-1.2724	-8.9996***	-6.5619***	-1.528	-2.024	-3.049***	-3.198***	I(1)

*Note: A*** p<0.01, ** p<0.05, * p<0.1;*
Source: Authors computation

Table 5: Cointegration and Hausman Tests

Model Specifications	**Statistic**	**Value**	**P-value**	**Robust P-value**
Panel A: Cointegration test (Westerlund, 2007)				
lnConCO2, lnPS, lnPCI, lnPCIsq, lnEI, lnFD, lnNrr	Gt	-3.4731***	0.000	0.010
	Ga	-1.563	1.000	0.990
	Pt	-15.550 **	0.000	0.030
	Pa	-6.189 *	1.000	0.090
Panel B: Estimates from Hausman test				
		chi2(6)		**Prob>chi2**
lnConCO2, lnPS, lnPCI, lnPCIsq, lnEI, lnFD, lnNrr		25.31 ***		0.000

*Note: *** p<0.01, ** p<0.05, * p<0.1; Robust P-Value are from 100 Bootstrap replications of the critical values*
Source: authors computation

The results of estimation based on the FE-DK are reported in column 4 of Table 6. The estimates afford support for appreciating the conditional mean effects of the independent variables (PS, PCI, PCIsq, EI, FD, and Nrr) on ConCO2 in SSA.

Starting with the main explanatory variable of this study, the effect of population size on consumption-based carbon dioxide emissions is statistically significant and positive at the 1% significance level. Specifically, a 1% rise in Population Size (PS) other things being equal, raises consumption-based carbon emissions (ConCO2) in the selected SSA economies by about 1.74%. The outcome of a significant positive effect of PS on ConCO2 is in agreement with Sarkodie et al. 2020 and Anochiwa et al. (2022) who found that PS promotes ConCO2. The likely rationale for this outcome may be that the population size of SSA has been growing tremendously needing corresponding increases in the availability and consumption of goods and services, for instance; residential buildings, household appliances, transportation, energy, etc. that positively drive consumption-based carbon emissions. A report by the United Nations (UN, 2019) has it that the size of SSA's population has been increasing and is predicted to continue, with the population of youths rising faster than the other groups. This may be due to the crisis of unplanned population growth due mainly to illiteracy, cultural and religious beliefs that support polygamy, relentless breeding of children and early child marriage.

Furthermore, the results of the FE-DK evaluation in column 4 of Table 6 reveal a statistically insignificant negative coefficient for lnPCI and a positive coefficient for lnPCIsq that is significant at a 10% level. Relying on these coefficient estimates, we can confirm that the EKC hypothesis is not valid for the selected SSA economies because, unlike the EKC hypothesis's theoretical expectation of an inverted U-shaped association between economic growth and consumption-based carbon dioxide emissions, increased income does not lead to a reduction in consumption-based carbon emissions in the selected SSA economies in the long run. This finding agrees with Anochiwa et al. (2022), who found an insignificant negative effect of economic growth on consumption-based carbon emissions in some selected SSA economies but disagrees with Yang et al. (2018) for China and Kizilkaya (2017) for Turkey, who found that increase in per capita income (PCI) significantly deteriorates the environment by increasing carbon emissions. In addition, energy intensity has a positive and statistically significant effect on consumption-based carbon emissions at the 1% level of significance. Specifically, a 1% increase in energy intensity (EI), other things being equal, raises consumption-based carbon emissions (ConCO2) in the selected SSA economies by about 0.398%. The outcome of a significant positive impact of energy intensity (EI) on ConCO2 is in agreement with Anochiwa et al. (2022) for SSA, Nwani (2021) for Venezuela, Sarkodie et al. (2020) for 206 countries and territories, and Ulucak and Khan (2020) for the USA, who found that energy intensity promotes carbon emissions. This finding may be because of the technological under-development of the SSA region, which makes it difficult for many of the countries to engage modern and efficient machinery in economic endeavours. In many SSA economies, old and inefficient equipment that consumes more energy is common, and since these economies depend more on fossil fuel energy consumption, there is a higher tendency for increased carbon dioxide emissions in the SSA region.

The influence of FD on consumption-based carbon dioxide emissions is statistically significant and positive at the 1% significance level. The results imply that a 1% increase in the financial development index, ceteris paribus, results in about a 0.3% rise in consumption-based CO2 emissions in the selected SSA economies. The outcome is in agreement with Qayyum et al. (2021) who studied India, Shen et al. (2021) in a study of Chinese provinces and Anochiwa et al. for SSA but disagrees with the statistically significant and negative influence revealed by He et al. (2021) in a study of Mexico. Lastly, natural resource rents exert (Nrr) a statistically insignificant positive effect on consumption-based carbon CO2. This result implies that there seems to be no statistical justification for connecting the economic utilization of natural resources to consumption-based CO2 emissions in the selected SSA economies. This finding conflicts with Shen et al. (2021), who studied Chinese provinces and found a statistically significant and positive connection between Nrr and CO2 emissions but aligns with Anochiwa et al. (2022) for some selected SSA economies that found an insignificant effect of natural resource rent on consumption-based carbon emissions. The FMOLS, DOLS, and CCR estimations validate the results from the FE-DK estimation.

Table 6: Parameter Estimates Based on the Conditional Mean Effects Analysis

Variables	**(1) FMOLS**	**(2) DOLS**	**(3) CCR**	**(4) FE-DK**
lnPS	0.8854***	0.8520***	0.8854***	1.7352***
	(0.0512)	(0.1101)	(0.0524)	(0.1336)
	[17.281]	[7.735]	[16.885]	[12.984]
lnPCI	1.4998**	1.8132	1.4961**	-0.7076
	(0.6743)	(1.4571)	(0.6918)	(0.5754)
	[2.224]	[1.244]	[2.163]	[-1.230]
lnPCIsq	-0.0329	-0.0621	-0.0326	0.1127*
	(0.0491)	(0.1072)	(0.0506)	(0.0542)
	[-0.671]	[-0.579]	[-0.646]	[2.080]
lnEI	0.3800***	0.3960*	0.3781***	0.3980***
	(0.0976)	(0.2089)	(0.1002)	(0.0992)
	[3.894]	[1.895]	[3.773]	[4.011]
lnFD	0.6040***	0.7180**	0.6047***	0.2957***
	(0.1538)	(0.3617)	(0.1649)	(0.0649)
	[3.926]	[1.985]	[3.667]	[4.559]
lnNrr	0.0113	-0.0131	0.0127	0.0189
	(0.0631)	(0.1421)	(0.0659)	(0.0362)
	[0.178]	[-0.092]	[0.193]	[0.522]
Constant	-21.1243***	-21.0933***	-21.1090***	-27.6310***
	(2.2387)	(4.7085)	(2.2776)	(3.3669)
	[-9.436]	[-4.480]	[-9.268]	[-8.207]
Observations	436	434	436	437
R-squared	0.308	0.751	0.265	
Number of groups				19

*Note: fully modified ordinary least squares (FMOLS); dynamic ordinary least squares (DOLS); canonical cointegration regression (CCR); FE-DK is for Fixed-effects regression with Driscoll-Kraay standard errors; Standard errors in ( ); t-statistics in [ ]; *** p<0.01, ** p<0.05, * p<0.1*

Source: Authors computation

Table 7 reports estimates of the consumption-based CO_2 emissions (ConCO2) model obtained from the method of moments quantile regression (MM-QR). The estimates offer grounds for appreciating the distributional effects of each independent variable on the consumption-based CO_2 emissions in the selected SSA economies. From table 7, the distributional effects of PS on ConCO2 reveal that the positive effect of PS on ConCO2 is statistically significant across all the observed quantiles. The results show that the positive impact of PS on ConCO2 is stronger at the lower quantiles than at the higher quantiles of the ConCO2 distribution.

In particular, the statistically significant and positive impact of PS on ConCO2 is strongest (about 2.087%) at the 10th quantile countries, where the existing level of ConCO2 is lowest, and progressively abates in the direction of the upper quantile countries to its weakest level (about 1.376%) at the 90th quantile countries, where the existing level of ConCO2 is highest. This finding aligns with Anochiwa et al. (2022), who found that the positive effect of population size on consumption-based carbon emissions is higher at the lower quantiles of economies than at the upper quantiles of economies. Therefore, SSA economies should not ignore the environmental consequences of population expansion. Population expansion translates to increased demand for consumer goods and services such as energy, transportation, residential housing, household appliances, increased economic activities, and unavoidably amplified reliance on trade to provide for the increasing population.

From the 10th to 70th quantiles, PCI has an insignificant negative influence on consumption-based CO_2 emissions, and an insignificant positive impact on consumption-based CO_2 emissions from the 80th and 90th quantiles, while per capita income square (PCIsq) exhibited a positive and significant impact on consumption-based CO_2 emissions (at 10% level) from the 10th to 40th quantiles, and a positive and insignificant impact on consumption-based CO_2 emissions from the 50th to 90th quantiles. The results contradicted the EKC hypothesis of an inverted U-shaped curve relationship between GDP and CO_2 emissions. The non-conformity of the PCI and PCIsq to the a priori expectations of the EKC hypothesis is not surprising in ConCO2 net-importing Sub-Saharan African nations, since many of the studies that validated the EKC hypothesis used production-based CO_2 in net-exporting economies. This non-validity of the EKC hypothesis on the link between economic growth and CO_2 emissions in SSA may not be unconnected to the region's abysmal level of domestic production activities and its over-dependence on import trade.

In addition, the MM-QR results show that the positive impact of EI on ConCO2 is stronger at the upper quantiles than at the lower quantiles of the ConCO2 distribution. In particular, the statistically significant and positive impact of EI on ConCO2 is strongest (about 0.3993%) at the 90th quantile economies where the existing level of ConCO2 is highest and progressively weakens in the direction of the lower quantile economies to its weakest level (about 0.3968%) at the 10th quantile economies where the existing level of ConCO2 is lowest. This finding aligns with Anochiwa et al. (2022), who found that the positive effect of energy intensity on consumption-based carbon emissions is higher at higher quantiles of economies than at the lower quantiles of economies.

Furthermore, estimates reported in Table7 reveal that the positive effect of FD on ConCO2 is insignificant amongst the lower quantiles (10th - 30th) of consumption-based CO_2 emitting economies but significant amongst the medium and upper quantiles (40th - 90th) of consumption-based CO_2 emitting countries. Specifically, the positive effect of financial development on consumption-based CO_2 emissions is strongest (about 0.495%) at the 90th quantile countries, where the existing intensity of consumption-based carbon dioxide emissions is highest, but gradually abates in the direction of the lower quantile economies, where the existing level of ConCO2 is lower. This finding aligns with that of Anochiwa et al. (2022), who found that FD exerts a heterogeneous positive impact on consumption-based carbon dioxide emissions in SSA.

Natural resources rent (Nrr) has a positive but insignificant impact on consumption-based CO_2 emissions in the 10th to 60th quantiles and a negative and insignificant impact in the 70th to 90th quantiles with diminishing coefficients. The insignificance of the impact of Nrr on consumption-based CO_2 emissions may not be unconnected with the reality that the selected net carbon-importing SSA economies are not amongst the oil-rich SSA economies that heavily rely on rents from natural resources and depend on fossil fuel as their principal source of energy, resulting in considerable CO_2 emissions.

Table 7: MM-Qreg Estimates with Distributional Effects

Variables	**(1) location**	**(2) Scale**	**(3) qtile_10**	**(4) qtile_20**	**(5) qtile_30**	**(6) qtile_40**	**(7) qtile_50**	**(8) qtile_60**	**(9) qtile_70**	**(10) qtile_80**	**(11) qtile_90**
lnPS	1.7352***	-0.2293***	2.0873***	1.9875***	1.9156***	1.8409***	1.7378***	1.6478***	1.5644***	1.4902***	1.3762***
	(0.1238)	(0.0822)	(0.2107)	(0.1752)	(0.1560)	(0.1408)	(0.1256)	(0.1198)	(0.1220)	(0.1319)	(0.1645)
	[14.020]	[-2.789]	[9.906]	[11.341]	[12.275]	[13.074]	[13.839]	[13.755]	[12.822]	[11.297]	[8.367]
lnPCI	-0.7076	0.8786	-2.0570	-1.6747	-1.3991	-1.1129	-0.7175	-0.3730	-0.0531	0.2314	0.6680
	(0.8707)	(0.5783)	(1.4274)	(1.2161)	(1.0890)	(0.9819)	(0.8763)	(0.8371)	(0.8530)	(0.9140)	(1.0876)
	[-0.813]	[1.519]	[-1.441]	[-1.377]	[-1.285]	[-1.133]	[-0.819]	[-0.446]	[-0.062]	[0.253]	[0.614]
lnPCIsq	0.1127	-0.0656	0.2135*	0.1849*	0.1643*	0.1430*	0.1134	0.0877	0.0638	0.0426	0.0099
	(0.0705)	(0.0468)	(0.1153)	(0.0984)	(0.0881)	(0.0794)	(0.0709)	(0.0677)	(0.0690)	(0.0739)	(0.0877)
	[1.599]	[-1.402]	[1.852]	[1.880]	[1.865]	[1.800]	[1.601]	[1.295]	[0.925]	[0.576]	[0.113]
lnEI	0.3980***	0.0008	0.3968**	0.3972**	0.3974***	0.3977***	0.3980***	0.3983***	0.3986***	0.3989***	0.3993***
	(0.1109)	(0.0736)	(0.1795)	(0.1548)	(0.1389)	(0.1248)	(0.1111)	(0.1063)	(0.1088)	(0.1163)	(0.1353)
	[3.590]	[0.011]	[2.211]	[2.565]	[2.860]	[3.185]	[3.583]	[3.746]	[3.664]	[3.431]	[2.951]
lnFD	0.2957***	0.1275*	0.0999	0.1554	0.1954	0.2369**	0.2943***	0.3443***	0.3907***	0.4320***	0.4953***
	(0.1030)	(0.0684)	(0.1703)	(0.1443)	(0.1291)	(0.1164)	(0.1038)	(0.0992)	(0.1011)	(0.1085)	(0.1305)
	[2.871]	[1.864]	[0.587]	[1.077]	[1.514]	[2.036]	[2.834]	[3.472]	[3.866]	[3.981]	[3.796]
LnNrr	0.0189	-0.0403	0.0808	0.0632	0.0506	0.0375	0.0194	0.0036	-0.0111	-0.0241	-0.0441
	(0.0536)	(0.0356)	(0.0874)	(0.0749)	(0.0671)	(0.0604)	(0.0538)	(0.0515)	(0.0525)	(0.0562)	(0.0663)
	[0.353]	[-1.132]	[0.924]	[0.845]	[0.754]	[0.621]	[0.360]	[0.069]	[-0.211]	[-0.429]	[-0.666]
Constant	-27.6310***	1.3786	-29.7485***	-29.1486***	-28.7161***	-28.2670***	-27.6467***	-27.1060***	-26.6041***	-26.1577***	-25.4726***
	(3.5405)	(2.3516)	(5.7500)	(4.9530)	(4.4428)	(3.9908)	(3.5497)	(3.3976)	(3.4780)	(3.7191)	(4.3425)
	[-7.804]	[0.586]	[-5.174]	[-5.885]	[-6.463]	[-7.083]	[-7.788]	[-7.978]	[-7.649]	[-7.033]	[-5.866]
Observations	437	437	437	437	437	437	437	437	437	437	437

*Note: Standard errors in ( ); t-statistics in [ ]; *** p<0.01, ** p<0.05, * p<0.1*

Source: Authors computations

5. Conclusion and Implications for Policy

The study examined the impact of population size on consumption-based carbon dioxide emissions using a balanced panel data of 19 Sub-Saharan African countries over the period 1975-2017. Consumption-based CO_2 emissions (ConCO2) were used as the explanatory variable, per capita income (PCI), square of per capita income (PCIsq), energy intensity (EI), financial development (FD), and natural resource rents (Nrr) are the control variables, while population size (PS) is the main explanatory variable.

The main estimation commenced with the Pesaran (2004, 2015) cross-section dependence (CD) test to confirm if CD exists in the variables, the results of which disclosed that CD exists in the variables of the model. The existence of CD in the variables necessitated the extension of analysis with traditional (first generation) econometric techniques by the adoption of second-generation analytical methods that take into account the presence of CD in the variables. The stationarity characteristics of the variables were checked using the Im et al. (2003) panel unit root test and the Peseran (2007) CD Augmented Dickey Fuller (CADF) panel unit root test. The results showed that the variables are stationary after the first difference. Subsequently, we checked for the existence of a long-run relationship among the series by adopting the Westerlund (2005) panel cointegration test, and the results established that cointegration exists among the series.

Long-run estimates derived from Fixed Effects OLS with Driscoll and Kraay standard errors (FE-DK) prove that population size (PS), financial development (FD) and energy intensity (EI) significantly and positively promote consumption-based carbon emissions in SSA, while the effects of per capita income (PCI) and natural resource rents (Nrr) on consumption-based carbon emissions in SSA are not statistically significant. Also, the EKC hypothesis is rejected for the selected SSA economies. Estimates from the FMOLS, DOLS, and CCR estimations validate the results of the FE-DK.

For the reason that OLS estimations which assume normality condition, may provide inadequate information for policy when the modelled variables are not normally distributed, we adopted Machado & Silva (2019) method of moments quantile regression (MM-QR) technique to examine the distributional effects of explanatory variables on consumption-based carbon dioxide emissions.

Evidence based on the MM-QR estimations disclosed the following:

- Population size (PS) significantly and positively affects consumption-based CO_2 emissions (ConCO2) across the observed quantiles, with a more pronounced effect among economies at the lower quantiles.
- Energy intensity (EI) significantly promotes consumption-based CO_2 emissions (ConCO2) across the observed quantiles, with a more pronounced effect among economies at the upper or higher quantiles.
- The effect of financial development (FD) on consumption-based CO_2 emissions is positive and heterogeneous across the observed quantiles, with a more pronounced effect among economies at the upper quantiles but an insignificant effect among countries below the 40^{th} quantile.
- The effects of per capita income (PCI) and natural resources rents (Nrr) on consumption-based CO_2 are not significant across the observed quantiles.
- The study rejects the validity of the EKC hypothesis for the selected SSA economies given the signs and insignificance of the coefficients of PCI and PCIsq.

Therefore, the following measures are recommended to guide policy:

Given that population size significantly promotes consumption-based CO_2 emissions in SSA, countries in the sub-region, especially those at the lower quantiles, could benefit from policies targeted at ensuring that the size and quality of the population are managed on a continual basis. Strict implementation of existing birth control measures and the institution of a policy that prohibits early child marriage could be helpful in this direction. In addition, the populace in SSA countries should be given regular public environmental awareness and education to encourage attitudinal change in favour of environmentally sustainable production and consumption. This may involve revising the curricula of primary and secondary educational institutions to include subjects that are related to environmental education.

Again increased population size in SSA countries may give rise to more demand for goods, especially imported consumer goods, efforts should be made to ensure that only those goods that are eco-friendly are allowed to enter the SSA countries. Therefore, the government's efforts to ensure that every import is thoroughly inspected at entry points should be stepped up. Also, domestic manufacturing of consumer goods that meet the need for green technologies, particularly those with low energy-use content, is important. Domestic producers can be helped by government endorsement of locally produced goods. This government action, particularly when continued over time, has a propensity to impact the private sector's demand pattern in favour of locally produced commodities. This, if sustained, has the potential to reduce carbon imports while also increasing demand for locally manufactured consumables with an acceptable amount of green technology.

Besides, given that energy intensity has a positive and statistically significant effect on consumption-based CO_2 emissions in SSA, countries in the sub-region, especially those at the upper quantiles, could benefit from policies that are aimed at reducing the energy intensity level of primary energy in economic activities. Such measures may include switching dependence from non-renewable energy sources (for example, fossil fuel energy) to renewable energy sources (for example solar energy) in economic activities. This may require stepping up research and development (R&D) activities in the countries of the SSA region. Therefore, governments of the SSA countries can support private sector R&D activities through provision of funds and incentives such as tax breaks among other things. In addition, there is the need to substitute old and energy inefficient technologies with modern and energy-efficient ones in economic activities so as to reduce energy intensity in the sub-region. The SSA countries can realize this via the establishment of efficiency standards that will pertain to the factory floors in the SSA sub-region and by-passing laws on the maximum age of manufacturing plants and machineries with the aim of doing away with outdated machines.

Lastly, since financial development positively drives consumption-based carbon dioxide emissions in the selected SSA economies, measures that ensure that financial institutions in the SSA prioritize funding for those economic endeavours that promote the clean environment should be targeted. In this regard, the governments of SSA countries through their central banks can institute credit guidelines that favour credit allocation to economic agents that comply with environmental quality standards while discouraging credit extension to agents that violate environmental quality standards. Furthermore, the governments of the SSA countries can provide subsidies and credit guarantees to banks for the funding of green projects in the sub-region.

It will be helpful for the purpose of further studies, to replicate this work in other regions or sub-regions. Also, additional control variables, different from the ones used in this study, and interaction terms between the population and other variables such as energy intensity and financial development variables can be incorporated into the analysis. In addition, the impact of economic activities in SSA disaggregated into sectors such as agriculture, manufacturing, and services (or tourism) can be undertaken to see which sectors contribute more to CO_2 emissions in the sub-region.

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