Energy Intensity and Carbon Footprint in Sub-Saharan African Countries

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Abstract-* *This paper seeks to establish the effect of energy intensity on carbon footprint in SSA for the period of 2005-2022 using panel data. To account for endogeneity and unobserved heterogeneity across the 47 SSA countries, the study uses the Generalized Method of Moments (GMM) technique. The results show that energy intensity and carbon footprint are positively related, and the relationship is statistically significant; the increase in energy intensity by one-unit results in the increase of CO_2 emissions per capita by 0.003 metric tons. This implies that higher energy intensity, which is equivalent to lower energy efficiency increases carbon emissions in the region. The result confirms the IPAT hypothesis, which holds that efficiency increases energy and decreases emissions and inefficiency decreases energy and increases emissions. The evidence presented in this study is consistent with previous research done in the field of energy efficiency in SSA and stresses the importance of policies to improve energy efficiency. Since energy intensity is a major factor contributing to emissions, the study suggests that cleaner technologies and energy efficiency practices should be encouraged in the region to improve development sustainability.

Indexed Terms-* *Energy intensity, carbon footprint, Sub-Saharan Africa, GMM, energy efficiency

I. INTRODUCTION

The effects of energy use on the environment have received significant attention due to climate change and increased carbon footprint. Emissions related to energy consumption are the leading cause of the rise in the carbon footprint across the world, and as countries seek development, the significance of energy efficiency has become vital Shahzad et al. (2023). Energy intensity which is measured as the energy used per unit of output or per GDP is widely regarded as a key measure of energy efficiency. Lower energy intensity means better energy efficiency which in turn should mean less carbon emissions in theory. But in reality, there is a certain correlation between energy intensity and carbon footprint, where and when, but this correlation is different depending on the country's development level.

Energy intensity is a major determinant of carbon footprint in SSA which has low technological advancement, high energy intensity, and reliance on fossil energy. However, due to inadequate investment in infrastructure and policies, and limited access to new technologies the continent has been slow to shift to efficient energy sources. As the SSA is undergoing a process of industrialization and urbanization, the overall power demand has increased which, in turn, has led to severe environmental impacts mainly due to low energy efficiency.

The prior work on the link between energy intensity and the carbon footprint is inconclusive. While research on developed countries tend to show that as energy intensity declines carbon emissions also decline hence improved energy efficiency is a way of decreasing emissions, research that focuses on developing countries including SSA have found otherwise. For example, Li et al., 2023, and Shahzad et al., 2023, found that energy intensity has a negative effect on carbon emissions in Beijing and the leading RE countries, respectively. These studies shed light on how energy intensity improvements may be used to achieve carbon neutrality in the industrialized and technologically developed countries.

However, many researches carried out in developing zones often establish a direct relationship between energy intensity and carbon emission. Namahoro et al. (2021) and Khan et al. (2022) concluded that low energy intensity in developing countries have negative impact on environment which leads to more carbon emissions. This discovery holds special importance for

SSA because sectors like manufacturing, transportation, and agriculture in the region are notorious for their high energy inefficiency and growing emissions.

In SSA, energy intensity is still very high mainly because of technology lock-in, inadequate and limited access to modern energy infrastructure and excessive dependence on fossil fuels. This inefficiency does not only affect the region's economic growth, but it also generates a large amount of carbon emission. Namahoro et al., (2021) revealed that energy intensity increases in SSA countries with carbon emissions, which reveals that the region continues to face challenges with energy inefficiency.

High energy intensity in SSA coupled with increasing rates of urbanization and industrialization, therefore, remain an emerging policy concern. While developed countries have been able to reduce the energy intensity and hence their emissions through technology the same cannot be said of SSA. The energy sector in the region is still in its infancy, and there is very little spending on energy efficient technologies.

The overall purpose of this study is to examine the relationship between energy intensity and carbon footprint in SSA. Despite the fact that a number of studies have been conducted and published in the area of energy intensity and carbon emissions, the majority of these studies have been conducted on the developed countries or large emerging economies including China and India while very little is known on how energy intensity impacts on carbon emissions in SSA. This study aims at filling this gap by establishing a correlation between energy intensity and the carbon footprint of selected SSA countries and by identifying energy inefficiency factors in a bid to suggest ways of reducing the region's carbon footprint through better energy management.

The literature features a rich body of works analysing the associations between energy intensity and carbon emissions in the developed and the emerging nations, however, relatively little research is dedicated to SSA. Most of the previous studies, for example, Shahzad et al., 2023, Rahman et al., 2022, Danish et al., 2020 are based on China, United States or other industrialized developed countries' energy structure and economy which is quite different from SSA. This leaves a gap in the global knowledge about the relationship between energy intensity and carbon emissions in low income developing countries with different economic characteristics and level of technology.

Furthermore, whereas some research has been conducted to understand the relationship between energy intensity and carbon footprint at the country level, for instance, Emir and Bekun (2020) and Appiah et al. (2019), there is limited research that investigates the impact of energy intensity across the SSA region. Further, this study found out that there is a lack of research on the influence of energy policy, institutional frameworks and technology on energy efficiency in SSA. This study intends to address this gap by assessing the impact that energy intensity has on carbon emissions in SSA and offer policy implications that would help the region move towards a more sustainable use of energy.

This study will add to the existing body of knowledge in the following ways: This study will further advance the understanding of energy intensity and carbon emissions in SSA region which has received limited attention in this research domain. This study will help to understand the impact of energy intensity on carbon emissions in the countries of the region by considering more countries for comparison. In addition, it will provide policy implications specific to the context of SSA that will address issues of energy intensity and carbon emissions.

II. DATA AND STYLISED FACTS

The research covers 2005 to 2022 and uses panel data from 47 countries in Sub-Saharan Africa (SSA). We studied the relationship between energy intensity level and carbon footprint (CFP) in SSA. The data on energy intensity level (EIL) (measured as energy used per real GDP), renewable energy consumption (REC) (measured as a per centage of total energy consumed) and carbon footprint (measured as CO_2 per capita in metric tons) were extracted from the World Development Indicators (Word Bank, 2023).

Table 1 provides summary statistics for three key variables: CFP (Carbon Footprint), EIL (Energy Intensity Level), and REC (Renewable Energy

Consumption). The summary includes the number of observations, the mean, standard deviation (Std. Dev.), minimum, and maximum values for each variable.

Table 1
Descriptive

Variable	*Observation*	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*
CFP	800	0.892	1.541	0.022	8.447
EIL	793	6.073	3.229	1.440	21.440
REC	793	63.246	26.840	0.700	97.400

Source: Researcher's Computation using Stata (2024)

Average individual carbon emission is 0.892 metric tons. This would imply that on the average SSA have a small impact on carbon emission and therefore have a small global warming potential. The sample standard deviation is 1.541, which also means that the variability of the carbon footprint values in the given sample is moderate. The values of carbon footprint are from 0.022 (minimum) to 8.447 (maximum). This range also demonstrates the spread of carbon footprints in relation to various observations where some of them have higher values of carbon emissions compared to others.

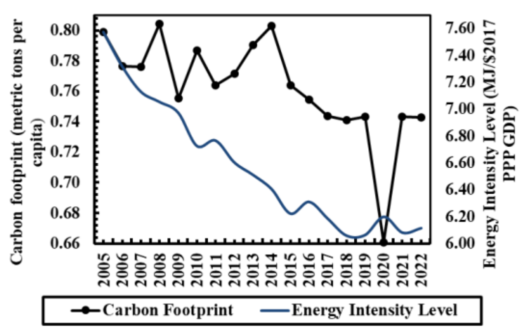
The average energy intensity level is 6.073 meaning the level of energy that is used normally in the sample in relation to the output produced. The mean of energy intensity level is 1.963, while the standard deviation is 3.229 which indicate that there is a large variation between countries and entities and some countries or entities are much more energy efficient than others. Minimum energy intensity level is 1.440 and the maximum energy intensity level is 21.440. This large range is due to the fact that some of the observations are record setting in terms of energy efficiency while others are record setting in terms of energy inefficiency.

The average share of renewable energy consumption is 63.246%, so, in average, renewable energy is a substantial part of the energy consumption in the sample. The standard deviation is 26.840 which represents a high variability of the share of renewable energy consumption in the sample.

The variation of renewable energy consumption is fairly broad and varies from 0,700% to 97,400%. This means that while some countries or entities are almost wholly dependent on renewable energy, others are not at all.

Therefore, the CFP variable reveals that the mean carbon footprint is still relatively small but there is a dispersion of emissions levels and some of them are significantly higher.

EIL further postulates that energy intensity is not constant, but rather differs, due to the differences in energy efficiency in the sample observations. REC goes on to explain that the average level of renewable energy consumption is high, but with significant volatility, meaning that some of the observations are significantly more dependent on renewable energy than others. These statistics do give a quick glimpse of the distribution of the sample by carbon emissions, energy efficiency, and reliance on renewable energy.



Source: Researcher's Computation using Microsoft Excel (2024)

Figure 1 Carbon Footprint and energy intensity level in SSA

Figure 1. The data obtained from 2005 to 2022 reveal that both the carbon footprint and energy intensity levels are gradually reducing due to the continued drive towards energy efficiency. The carbon footprint started at 0.80 in 2005 and has been fluctuating before a sharp decline to 0.66 in 2020, probably because of the COVID-19 crisis that led to a decline in GDP and

thus energy demand. After 2020, the carbon footprint was back to 0.74 and remained constant up to 2022.

The energy intensity level has also been reducing progressively from 7.58 in 2005 to 6.06 in 2019, which is attributed to increase in energy efficiency. After a slight rise to 6.20 in 2020 and may be attributed to changes in consumption patterns during the pandemic, the energy intensity level was at 6.12 by 2022. Even with the disruptions caused by the COVID-19 pandemic, there has been a steady move toward the disconnection of energy use from GDP growth, although the recent flattening of the curve may require additional improvements in energy intensity to reduce CO2 emissions.

III. METHODOLOGY

In theory, the STIRPAT model, introduced by Dietz and Rosa (1997), is a stochastic regression extension of the IPAT model that looks like this:

$$I = aP^{b1}A^{b2}T^{b3}e \quad (1)$$

Where α is a constant an erm, $\beta_1, \beta_2, \beta_3$ are the exponential terms for P, A, T, and e is the error term. The two sides of equation (1) are then log-transformed to equation (2):

$$\ln I = \alpha + b_1 \ln P + b_2 \ln A + b_3 \ln T + e \quad (2)$$

The STIRPAT model has undergone modifications and is currently a commonly employed tool for analysing the determinants of environmental change. The analysis of energy consumption issues, particularly those related to non-renewable energy consumption, has utilised this model due to its association with pollution as a byproduct of energy consumption. Moreover, researchers have enhanced its versatility by incorporating intricate factors depending on the specific subjective and the prevailing context.

Equation (2) is at this moment rewritten into equations (3):

$$CFP_{it} = b_{0i} + b_1 EIL_{it} + b_2 REC_{it} + \mu_{it} + \gamma_{it} + \varepsilon_{it} \quad (3)$$

Where CFP depicts carbon footprint, REC means renewable energy consumption. μ_{it} represents an unknown country specific while γ_{it} is an unknown year specific. Finally, ε_{it} is the error term.

The study adopted the generalized method of moment (GMM) technique to estimate equations 3. Usually, the cross-sectional approach is used most frequently to estimate factors affecting environmental quality. Cross-sectional estimations suffer from major drawbacks. For example, there could be an instance of an omitted variable bias whereby a component of economic growth unique to a country is related to the independent variables in cross-sectional analysis. The GMM technique accounts for endogeneity (Roodman, 2009).

IV. RESULTS

Cross-Sectional dependence test

Table 2 presents the results of the CSD tests.

Table 2

Friedman's CSD Test for N>T

Models	T-statistics	P-value
CFP = f(EIL)	9.674	1.000
CFP = f(REC)	8.423	1.000

Source: Researcher's Computation using Stata (2024)

The paper did not reject the null hypothesis of no CSD. This is evident by the p-value, which is not significant at any significant level for all the two cases. Therefore, the study employed a first-generation panel unit root test.

Panel unit root test

Table 3 presented the results of the Fisher-type unit-root test based on Augmented Dickey-Fuller tests, assuming that shocks are temporal and do not have a long-run effect on the series.

Table 3

Fisher-type unit-root test based on Augmented Dickey–Fuller tests

Series	Panel Mean & Drift (Level)			
	P	*Z*	*L*	*Pm*
CFP	244.132***	-9.027***	-9.157***	10.949***

EIL	350.057***	-11.476***	-13.381***	18.674***
REC	237.835***	-8.198***	-8.421***	10.490***

Note: ***, ** and * represent significance level at 1%, 5% and 10% respectively. The figures are the different *t*-statistics for testing the null hypothesis that the series has unit root. P stands for inverse chi-squared; Z denotes inverse normal; L means inverse logit while Pm signifiers modified inverse chi-squared. The number of panels is 47 with 17 number of periods.
Source: *Researcher's Computation using Stata (2024)*

The three series were all found to be stationary at level. Hence, all the series are characterized with I(0).
to test for the stated hypothesis.

Table 4
System GMM Results

Results		Diagnostics	
Variables	Coefficients	Category	Result
CFP_{t-1}	0.984*** (0.015)	Year Dummies	No
EIL	0.003** (0.001)	No. of Obs.	733
REC	-0.001** (0.000)	Wald Chi2 (2)	13585.730***
Constant	0.054** (0.023)	Groups/Instruments	47/20
		Arellano-Bond AR (1)	0.040
		Arellano-Bond AR (2)	0.387
		Hansen Test Prob.	0.421

Note: Standard errors are in parentheses, * means $p < 10\%$, ** signifiers $p < 5\%$, and *** indicates $p < 1\%$.
Source: Researcher's Compilation using Stata (2024)

From Table 4., The coefficient of CFP_{t-1} is 0.984 and it is significant at 1%. The positive coefficient signifies a positive relationship with carbon footprint, implying that an increase in one period lag of carbon footprint, increases carbon footprint in the current period. Specifically, for each metric ton per capital increase in the lagged value of carbon footprint, the current carbon footprint increases by 0.984 metric tons per capita. It further signifies that the current level of carbon footprint is close to the preceding period, and that the carbon footprint in the current period is almost the same as in the preceding period. Therefore, the carbon footprint in SSA is highly persistent and has a strong relationship with past values.

The coefficient of 0.003 for EIL is positive and statistically significant at 5% level. This implies a positive relationship between energy intensity and the carbon footprint in SSA. Specifically, a unit increase in energy intensity level results in an increase of carbon footprint by 0.003 metric tons of CO_2 per capita. This suggests that higher energy intensity, which means lower energy efficiency, leads to higher carbon emissions per unit of economic output. This validates the IPAT hypothesis that stated that energy efficiency through technological advancement reduces carbon emissions, and the reverse is the case. It is also in line with the works of Pang *et al.*, (2023), Zhang *et al.*, (2023), who concluded that energy intensity level exacerbates carbon footprint.

The instruments used were found to be appropriate, as the number of instruments were less than the number of the groups. The Hansen statistics was also found to be appropriate, as the p value was found not significant. The case was the same for the second order serial correlation results.

CONCLUSION AND RECOMMENDATION

The findings of this paper suggest that energy intensity is positively and significantly related to the carbon footprint in SSA. More so, a unit increase in energy intensity corresponds to an increase of 0.003 metric tons of CO_2 per capita suggesting that energy intensity which is an indicator of efficiency in energy utilisation increases carbon emissions in the region. This finding supports the IPAT hypothesis, which proposes that energy conservation through technology brings down carbon emission. The findings of the study are in line with other research scholars such as Pang et al. (2023) and Zhang et al. (2023) to conclude that energy intensity is an important factor that causes the carbon footprint. Furthermore, the instruments applied in the research analysis were considered acceptable; the Hansen statistic provided endorsement of the model; and no evidence of second order serial correlation was detected.

Energy efficiency policies should therefore be pursued as a cornerstone of policies in SSA including investing in clean energy technologies and encouraging the use of energy efficiency measures among growth sectors. This will not only reduce the effect of high energy intensity on carbon emission but enhance economic development with lesser emission rates of carbon.

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