Renewable Energy Consumption and Carbon Footprint in Sub-Saharan African Countries

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Abstract- This paper examines the effect of renewable energy consumption on carbon footprint across 47 Sub-Saharan African (SSA) countries over the period 2005-2022. The study uses the Generalized Method of Moment (GMM) panel. The analysis establishes that carbon emissions in SSA are inherently sticky and that there is a strong and positive relationship between current and previous levels of carbon footprints. In addition, the negative and statistically significant coefficient of renewable energy consumption indicates that the promotion of renewable energy can help to decrease carbon emissions. Still, the coefficient is quite small which points to the fact that more stringent actions are needed for increase in the renewable energy sources share. This research provides input into the current discussion about the potential of renewable energy in combating climate change, especially in SSA where energy systems are in the process of being established. The analysis of the results of the study suggests that the public policymakers should enhance the investment in the renewable energy and put in place supportive policies and measures in order to foster faster transition from the conventional energy systems.

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

I. INTRODUCTION

As interest in climate change ramps up internationally, the focus on carbon emissions has become a core part of discussions in areas especially vulnerable to its impacts such as Sub-Saharan Africa (SSA) (Habiba et al., 2021). Carbon emissions are continually increasing, largely because of energy consumption modifications, which has prompted a more rigorous search for sustainable and renewable energy alternatives. The current situation has shown that renewable energy is an attractive answer to decreasing carbon emissions and to soften the consequences of global warming. The Sub-Saharan African region, which is rich in renewable energy resources, is an important case for examining the role of renewable energy consumption in lowering carbon emissions. Still, even as the concentration on renewable energy increases, the literature suggests conflicting evidence regarding the effects of REC on the carbon footprint in SSA and other areas.

The fundamental goal of this research is based on the need to tackle the complex relationship between renewable energy and carbon emissions in SSA, where energy poverty and a limited supply of clean energy options are persistent. Numerous studies into the connection between renewable energy consumption (REC) and carbon footprint (CFP) in various parts of the world have been conducted, yet their conclusions vary with local contexts, making it hard to effectively apply the findings to SSA. This research aims to bridge the existing gap by conducting an extensive analysis of the consequences of REC on CFP in SSA from 2005 to 2022. The necessity of the focus on the SSA is magnified because the region faces special challenges associated with energy access, economic growth, and sustainability.

Research suggests that the relationship between REC and CFP results in competing outcomes in empirical situations. Evidence backing the idea that renewable energy supports climate change reduction has been noted according to researchers, including Rahman et al. (2024) and Adedoyin et al. (2023), who have stated that it causes a drop in emissions of carbon. To serve as an example, Rahman et al. (2024) examined the environmental sustainability index of important fossil fuel-consuming countries and revealed that REC improves environmental quality, particularly in places that have low levels of CO_2 emissions. Like this, Adedoyin et al. (2023) illustrated Germany as an example that highlights the need for REC in presenting carbon footprints. Still, both studies are confined in their generalizability to regions outside of SSA, particularly where energy consumption patterns vary greatly from those of developed economies.

Other researchers have also made similar findings including Ali et al. (2022), Khezri et al. (2022), and Adebayo et al., (2022). In the study by Ali et al., (2022), REC and R&D expenditure in China influenced CFP decrease which provided evidence of the importance of technological advancements in energy conservation. Similarly, Khezri et al. (2022) also demonstrated that REC, coupled with urbanization and trade openness, is important in mitigating emissions in the Asia-Pacific region. However, these prior studies are restricted in that they may not necessarily be applicable to the SSA context where there is little energy infrastructure, and the energy is nonrenewable.

However, some of the previous research has suggested that REC may not necessarily result in lower levels of carbon emissions. For instance, Amin et al. (2023) established that biomass, a renewable energy source, did not affect carbon emissions in the household sector in China. Saidi and Omri (2020) also pointed out that in some countries like the Netherlands and South Korea, REC may lead to a rise in the carbon footprint because the cost of RE technologies is high Likewise, Da Silva et al. (2018) observed that in SSA, the expansion of renewable energy use may well lead to higher carbon emissions because of These conflicting results present several questions regarding the circumstances under which REC can help decrease the carbon footprint, especially in SSA where energy systems are relatively underdeveloped.

This research aims at adding to this discussion by analyzing the effects of REC on the carbon footprint in SSA, a region that has not been well explored in the literature. This is important because SSA is experiencing rising energy requirements, high levels of CO2 emissions, and enhanced susceptibility to climate change. In addition, this research aims at continuing the literature by assessing the period between 2005 and 2022, which captures the most recent trends in the energy sector and their effects on the environment.

The literature on renewable energy and carbon emissions is quite extensive and, therefore, produces mixed outcomes for different regions and time horizons. On one hand, literature has presented a lot of evidence that REC reduces carbon emissions, which is in accordance with the objective of reducing carbon impact. For instance, Rahman et al. (2024) established that REC leads to environmental sustainability in major fossil fuel consuming nations; however, they pointed out that the impact of REC may differ with the energy consumption patterns of the given country.

In a study on China, Ali et al. (2022) found that REC also, together with R&D spending, leads to the reduction of carbon emissions. The research recommended that more funds should be invested in renewable energy to reduce the carbon footprint. Nevertheless, regarding the practical relevance of the research, it is relevant in highly industrialized countries like China; hence, it is not relevant in less developed regions such as SSA. Also, Khezri et al. (2022) also found that REC, trade openness, and urbanization have a positive effect on carbon emissions in

However, there are other research which are in contrast to this finding because it show that REC may not always result in the reduction of carbon footprint. Amin et al. (2023) in their study found that biomass energy had no effect on carbon emissions in the household sector in China. Saidi and Omri (2020) found that in some OECD countries, REC led to increased carbon footprint because of suboptimal utilization of renewable energy technologies. In addition, Da Silva et al. (2018) noted that the use of renewable energy sources may contribute to emissions growth in SSA because of the use of poor quality and inefficient renewable energy sources. These results indicate that there is more to the REC-carbon footprint association than meets the eye, and that the dynamics of this association may depend on the REC region and the type of renewable energy sources used.

The literature also points to other factors which should be considered in the analysis of the effect of REC on carbon emissions including economic development, energy intensity, and population growth. For Likewise, the studies by Yuping et al. (2022)

This research seeks to fill this gap in the literature by assessing the relationship between REC and carbon footprint in SSA within the period between 2005 and 2022. Previous studies have offered some interesting ideas on the relationship between REC and carbon emissions, but the conclusions derived cannot be extended to SSA and may not adequately describe the characteristics of the region. Through this study, the role of REC in the reduction of the carbon footprint will be discussed in detail with regards to this region, which has implications for policy and sustainable development. The results of this study will provide a valuable input to the current discourse on the role of renewable energy in combating climate change and will be useful for the policy makers in SSA countries who are faced with the challenge of meeting energy needs, economic development and climate change.

II. DATA AND STYLISED FACTS

The paper examines the impact of renewable energy on carbon footprint for 47 Sub-Saharan Africa (SSA) countries between 2005 and 2022, using the Generalized Method of Moments (GMM). The data on renewable energy consumption (REC) (measured as a per centage of total energy consumed), energy intensity level (EIL) (measured as energy used per real GDP), and carbon footprint (measured as CO_2 per capita in metric tons) were extracted from the World Development Indicators (Word Bank, 2023).

Table 1
Descriptive

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

Source: Researcher's Computation using Stata (2024)

Table 1 provides summary statistics for three key variables: CFP (Carbon Footprint), REC (Renewable Energy Consumption) and EIL (Energy Intensity Level). The summary includes the number of observations, the mean, standard deviation (Std. Dev.), minimum, and maximum values for each variable.

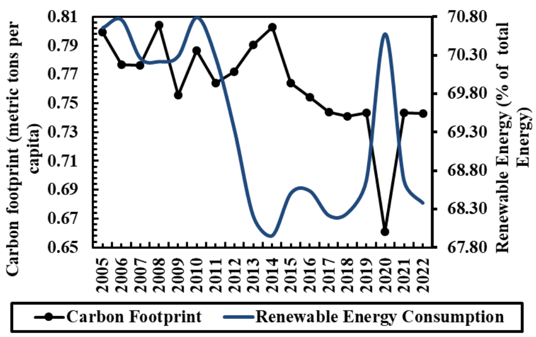
Average carbon emission is 0.892 metric tons. This would imply that on the average SSA have a small impact on carbon emission and therefore have a small global warming potential. The sample standard deviation is 1.541, which also means that the variability of the carbon footprint values in the given 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 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 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.

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. The minimum energy intensity level is 1.440 and the maximum energy intensity level is 21.440. This large range is since some of the observations are record setting in terms of energy efficiency while others are recording setting in terms of energy inefficiency.

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. shows the line plot of carbon emission of SSA and renewable energy generation. The chart depicts a negative correlation between the two series in most of the period. For instance, the upsurge in the use of renewable energy from 70. 4 percent of total energy consumed reduces carbon emission from 0.80 to 0.78 metric tons per capita. The reverse is the case between 2013 and 2014 when renewable energy consumption was down to 68.2 percent of total energy from 70.8, while carbon footprint grew from 0.77 to 0.81 metric tons per capita. This points to the possible outcomes to be expected in the empirical results.

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):

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

Where CFP depicts carbon footprint, REC means renewable energy consumption, EIL stands for energy intensity level. 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(REC)	8.423	1.000
CFP = f(EIL)	9.674	1.000

Source: Researcher's Computation using Stata (2024)

The paper did not reject the null hypothesis of no CSD in Table 2. 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***
REC	237.835***	-8.198***	-8.421***	10.490***
EIL	350.057***	-11.476***	-13.381***	18.674***

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.

CHOICE BETWEEN DIFFERENCE AND SYSTEM GMM

One of the challenges of GMM is the choice between the difference and the System GMM. However, the study used the approach of Bond et al., (2021), which suggests estimating fixed effect, pool ordinary least squares and difference GMM. Then the lagged coefficient of the dependent variable be compared. When the coefficient is below the fixed effect, the system GMM is appropriate, otherwise, the difference GMM would be used.

Table 4.

Choice Between DGMM and SGMM

	POLS	FIXED	DGMM
CFP_{t-1}	0.982*** (0.004)	0.850*** (0.068)	0.572*** (0.008)
REC	-0.001*** (0.000)	-0.003* (0.001)	-0.014*** (0.001)
EIL			0.075*** (0.007)
Constant	0.067*** (0.018)	0.304* (0.129)	

Note: Standard errors are in parentheses * means $p < 10\%$, ** signifiers $p < 5\%$, and *** indicates $p < 10\%$.

POLS stands for pooled ordinary least squares, Fixed indicates fixed effect and DGMM means difference generalized method of moments

Source: Researcher's Compilation using Stata (2024)

From Table 4, the coefficient of the dependent variable for the DGMM is 0.572, and it is statistically significant at 1 %. However, the coefficient is lower than the coefficient of the fixed effect model (lower bound) at 0.850. Therefore, in the case of model 1, the DGMM estimate is downward biased, hence the study adopted SGMM to test for the stated hypothesis.

Table 5

System GMM Results

Results		Diagnostics	
Variables	Coefficients	Category	Result
CFP_{t-1}	0.984*** (0.015)	Year Dummies	No
REC	-0.001** (0.000	No. of Obs.	733

	)		
EIL	0.003** (0.001)	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 5., 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 -0.001 for renewable energy consumption (REC) is negative and significant at 5% level, indicating an inverse relationship between renewable energy consumption and the carbon footprint in Sub-Saharan Africa (SSA). Specifically, a one-percentage-point increase in renewable energy consumption as a percentage of total energy reduces the carbon footprint by 0.001 metric tons of CO_2 per capita. This signifies that increasing the share of renewable energy consumption helps reduce the carbon footprint. This result aligned with numerous empirical studies, such as those by Rahman et al., (2024), Khezri et al., (2022), Adebayo et al., (2022), among others. However, the findings contradict the works of Amin et al., (2023) and Saidi and Omri (2020), who found no relationship between the two.

The instruments used were found to be appropriate, as the number of instruments was less than the number of the groups. The Hansen statistics were 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 suggest that CFP in Sub-Saharan Africa (SSA) is relatively sticky and there is a strong positive correlation between current and past levels of CFP. The value of 0.984 for the lagged dependent variable (carbon footprint) shows that carbon emissions in SSA are strongly autoregressive and do not greatly differ from one time period to the next. This persistence shows that the task of cutting carbon emissions in the region remains difficult. Also, the renewable energy consumption (REC) is also found to have a negative and statistically significant association with the carbon footprint. Stagnation in the share of renewable energy sources in the total energy consumption also indicates that a 1% increase in the share leads to only a relatively small decrease in CO_2 emissions; therefore, focusing on the transition to cleaner energy is important. These results are in line with previous research, although some earlier works have not established any correlation between REC and carbon emissions.

The authors recommend that policymakers in SSA should increase investments in renewable energy infrastructure and technologies to further decrease the region's carbon emissions. The relatively small but statistically significant effect of renewable energy consumption on emissions indicates that although

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