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Panel heterogeneous distribution analysis of trade and modernized agriculture on CO_2 emissions: The role of renewable and fossil fuel energy consumption

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Abstract

In line with the global target of reducing climate change and its impact, this study explored the causal relationship between CO_2 emissions, modernized agriculture, trade openness, aggregate and disaggregate energy consumption in 14 African countries from 1990–2013 using a panel quantile estimation procedure. The empirical results showed that value addition to agricultural commodities declines CO_2 emissions in countries with high pollution levels. The study revealed a positive nexus between CO_2 emissions and energy consumption homogeneously distributed across quantiles. Trade openness was found to lower CO_2 emissions in countries with lower and higher levels of environmental pollution. While fossil fuel energy consumption was found to exacerbate CO_2 emissions, renewable energy consumption confirmed its mitigating effect on environmental pollution. The institution of climate-smart agricultural options will sustainably increase productivity and income while adapting to climate change by reducing greenhouse gas emissions. Diversification of energy technologies with clean and modern energy sources like renewables avoid the over-dependence on fossil fuels for agricultural purposes. Trade policies can stimulate flows of technology and investment opportunities for specialization in production and economies of scale. Hence, the consideration of policies that boost agricultural sector productivity and create an efficient market for international trade in Africa will help in improving livelihoods.

Keywords: Agricultural sustainability; renewable energy consumption; environmental pollution; panel quantile regression; disaggregate energy consumption; Africa.

1. Introduction

In recent studies, fossil fuel energy has been proven to cause environmental pollution and damage lands used for agricultural purposes. Renewable energy technologies such as biomass, solar, geothermal, wind and hydropower have been identified to benefit farmers in diverse ways (Owusu and Asumadu, 2016). Energy consumption contributes greatly to farming activities through economic, social and environmental means. However, zero-emission has been captured as the best guarantee for ensuring that the poor and vulnerable are spared from threatening impacts such as heat waves, poverty, food insecurity, crop failures, floods and water shortages (Bühler *et al*., 2015; Rao *et al*., 2016). Hence, a study that investigates the relationship between aggregate and disaggregate energy consumption, trade, and agriculture and evaluating their impact on carbon dioxide (CO_2) emissions is therefore imperative.

Energy is the most important resource for agricultural productivity. However, Africa is facing energy scarcity problems despite other problems of low productivity and soil conservation (Ortas and Lal, 2013). Increasing food production to meet the rising demand of the increasing population is another challenge. Nevertheless, energy scarcity remains a major obstacle to achieve sustainable agriculture and food security (FAO, 2014). Sustainable agriculture is related to an agriculture production system without damaging the environment for future generations and hampering food security (Farooq *et al*., 2009). Due to energy scarcity, fossil fuel-based energy generation is the current practice of agriculture in Africa—but, fossil fuel-based energy is expensive and causes carbon emissions and enhancing the climate change process. To mitigate climate change and reduce carbon emissions, there is a need to shift current fossil fuel-based energy generation to

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renewable-based energy generation. It is reported that energy scarcity can be solved using sustainable, clean and renewable energy sources which will ultimately become instrumental in the elimination of environmental damages and climate change (Owusu and Asumadu, 2016).

Energy is a useful commodity in agricultural processes in terms of crop production and agro-processing for value addition. Human, animal and mechanical energy are extensively used for crop production in agriculture. Energy requirements in agriculture are divided into two groups: direct and indirect (Todde *et al*., 2018). Direct energy is required to perform various tasks related to crop production processes such as land preparation, irrigation, threshing, harvesting and the transportation of agricultural inputs and farm produce. It is seen that direct energy is directly used on farms and on fields. In contrast, indirect energy consists of the energy used in manufacturing, packing, and transportation of fertilizers, pesticides, seeds and farm machinery. As the name implies, indirect energy is not directly used on the farm (Todde *et al*., 2018).

In a study by Bayrakcı and Koçar (2012), they classified the use of renewable energy sources in agricultural activities into five main groups namely: (1) solar energy used for greenhouse heating and cooling, lighting, product drying and farm field irrigation; (2) modern biofuels like bioethanol and biogas as well as various agricultural residues such as grain dust, wheat straw and hazelnut shells used as sources of energy; (3) geothermal energy used in aquaculture, barns, soil improvement, in greenhouse to heat the soil in open fields and to dry agricultural products; (4) wind energy used to generate electricity, irrigate fields and grind some crops; and (5) hydropower used for electricity production, irrigation, drinking water supplies and the facilitation of equitable sharing of water between farmers. However, the role of modernized agriculture, trade, renewable and fossil fuel consumption on environmental pollution has not been extensively investigated in agrarian economies in Africa.

In this paper, we examine the relationship between carbon dioxide emissions, modernized agriculture, trade openness, aggregate and disaggregate energy consumption. Relying on the vast literature on energy-growth and environmental Kuznets curve (EKC) (Farhani and Ozturk, 2015; Özokcu and Özdemir, 2017), we draw on some key and relevant macroeconomic factors besides energy consumption that has a plausible influence on carbon dioxide emission in Africa. Based on the literature we included trade openness in our analysis—trade openness is an important variable which affects environmental sustainability. Trade openness has three types of effect on the environment i.e. technique effect, scale effect and composition effect (Ling *et al*., 2015). In technique effect, when trade increases, technology improves, which in turn, decreases carbon dioxide emission. In scale effect, free trade increases trade volume and output, which subsequently results in a deleterious effect on the environment. In the composition effect, developing countries attract pollution-intensive industries which subsequently contribute to the deterioration of the environment. It indicates that the technique effect has a positive effect while the scale and composition effects have negative effects on environmental sustainability. The net effect of trade openness on the environment is ambiguous—as it depends on which of the three effects is dominant. Generally, scale and composition effects are dominant and both of which have an adverse impact on environmental pollution (Fontini and Pavan, 2014; Ling *et al*., 2015).

This study contributes to the existing literature by extending the long-run and the causal relationship between agriculture, trade openness, energy consumption and carbon dioxide emissions to a panel of selected African countries. Our paper differs from other similar studies (Azlina *et al*., 2014; Farhani and Ozturk, 2015; Özokcu and Özdemir, 2017) in the sense of spirit and letters. Contrary to previous attempts, we analyze the effect of country-fixed effects, cross-sectional dependence and conditional heterogeneity among variables across quantiles and panel units. These econometric techniques are useful in making unbiased statistical inferences that might influence policy implications and formulation.

The remainder of the paper is organized as follows: Literature review (Section 2)—outlines the nexus between carbon emissions, agriculture, trade and energy consumption and an overview of CO_2 emissions in Africa. Section 3 outlines the materials and method utilized in the study. Section 4 reports the empirical results and discussion. Section 5 concludes with policy recommendations.

2. Literature review

The use of cointegration, causality and panel quantile regression in recent studies on carbon emission and macroeconomic variables are increasing extensively (Ibrahim and Aziz, 2003; Chen and Huang, 2013; Sarkodie and Strezov, 2019), yet, investigation of this type and sophistication is sporadic and limited in the case of West Africa. This paper, to the best of our knowledge, contributes to the existing literature scope, since studies are scant in the case of West Africa. There are some studies which focused on other African countries, especially Northern Africa (Jebli and Youssef, 2015; Charfeddine and Mrabet, 2017). However, these studies show lack of consensus—due to the diverse findings emanating from the differences in sample size, model specification, estimation technique, etc. Most of these studies aimed at validating the EKC hypothesis while a few focused on quantifying the impacts of environmental pollution. In addition, these studies consider energy consumption and income as independent variables in the model specification while ignoring some useful variables leading to omitted bias. A review of the literature shows that the research related to the effects of agriculture on carbon dioxide emissions is still new but topical, hence, requires further scrutiny for new insights and policy direction (Tubiello *et al*., 2015). We use these studies as a guide for specifying the relationship between carbon dioxide emission and agriculture, trade openness and energy consumption.

2.1. The nexus between carbon emissions, agriculture, trade and energy consumption

The relationship between agriculture and carbon dioxide emissions has been studied and these indicate diverse outcomes. Studies have discussed the relationship between carbon dioxide emissions and agriculture (Özilgen and Sorgüven, 2011; Santiago-De la Rosa *et al*., 2017; Waheed *et al*., 2018). The study results stipulated that CO_2 emissions have a direct relationship with agriculture and its related services. The findings from these studies further showed that agriculture activities (pre-harvest, harvest and post-harvest activities) affect CO_2 emissions. A study on the nexus between the two variables from the perspective of OECD countries found bidirectional causality between CO_2 and agriculture (Alamdarlo, 2016). Two studies conducted in eastern Canada (Gagnon *et al*., 2016) and Turkey (Dogan, 2016) also discussed the causality between agricultural activities and CO_2 emissions. The results of these studies found no relationship between CO_2 emissions and agriculture.

Farhani *et al*. (2014) determined the nexus between CO_2 emissions and trade openness in Tunisia. The outcome of the study revealed that CO_2 emissions affect trade openness. Studies such as Al-Mulali and Ozturk (2015), Michieka *et al*. (2013), Omri *et al*. (2015), Shahbaz *et al*. (2013), Tamazian *et al*. (2009) and Yang and Zhao (2014) have discussed the causality between CO_2 emission and trade openness. These studies have been conducted from different perspectives and geographical locations. The outcome of these studies revealed that trade openness directly affects CO_2 emissions. Inferences made from the findings of these studies show that effective trade policies have the tendency to contribute greatly to economic development. Further studies conducted among BRICS countries, Vietnam and developing countries respectively revealed a bidirectional relationship among the two variables (Aziz *et al*., 2013; Zakarya *et al*., 2015; Khuong, 2017). In contrast, other studies revealed no relationship between CO_2 emission and trade openness (Halicioglu, 2009; Kohler, 2013; Farhani *et al*., 2014).

Causal linkages between CO_2 emissions and energy consumption have been studied extensively. Studies from Al-Mulali *et al*. (2015), Farhani and Ozturk (2015) and Yang and Zhao (2014), using the Granger causality test, revealed a unidirectional relationship running from CO_2 emissions to energy consumption, thus, CO_2 emissions affect energy consumption activities. Pao *et al*. (2011) and Sarkodie and Adom (2018) modeled the causality between pollutant emissions and energy consumption. The results revealed that effective energy consumption reduces CO_2 emissions and have no negative effect on economic development. Again, Lean and Smyth (2010) and Al-mulali and Binti Che Sab (2012) in their studies discussed the causality between CO_2 emissions and energy consumption. These studies showed a bidirectional relationship between CO_2 emissions and energy consumption (Lean and Smyth, 2010). They recommended an increase in renewable energy production to achieve a reduction in carbon dioxide emissions. However, a study conducted to show the relationship between CO_2 emissions and energy consumption in UAE using the autoregressive distributed lag regression model (ARDL) bound testing approach revealed no relationship among the variables (Sbia *et al*., 2014).

2.2. Overview of CO_2 emissions in Africa

Africa's fossil-fuel CO_2 emissions are low in both absolute and per capita terms as compared to Asia, Europe and North and South America. Africa's total emissions have increased twelve-fold since 1950, reaching 423.37 million metric tons of carbon dioxide in 2010 which is still less than the emissions for some single nations including Mainland China, the US, India, Russia and Japan (Wang *et al*., 2013). According to Statista, the carbon dioxide emissions in Africa as of 2010 are as follows: carbon dioxide of 929.69 million metric tons from fuel combustion, 423.37 million metric tons of CO_2 from electricity and heat production, 219.72 million metric tons of CO_2 from transport, 140.89 million metric tons from the manufacturing industries and construction, 39.84 million metric tons from other energy industries' own use and lastly, 48.3 and 57.57 metric tons are from residential sector and other sectors respectively. A small number of nations are largely responsible for African emissions from fossil fuels and cement production. It can also be seen that agriculture in almost all the countries have taken the bottom position which signifies that constant use of fossil energy has a negative impact on the agricultural sector of the selected countries. Though CO_2 emissions in Africa is not as severe as compared to China and the US, governments in Africa, through the intended nationally determined contribution (INDC), have put across strategic measures to mitigate greenhouse gas emissions within the continent (USAID, 2016).

3. Methodology

3.1. Data

Table 1 shows a description of the variables used in the study. Four data series are used spanning 1990–2013 in 14 African countries. The study employed 14 countries in Africa namely South Africa, Nigeria, DR Congo, Egypt, Zambia, Algeria, Tunisia, Cameroon, Tanzania, Zimbabwe, Sudan, Morocco, Kenya and Ghana. These selected 14 countries in Africa constitute the highest CO_2 emitters in the region. These developing economies in the region

Table 1 Variable definition

Variable	Definition	Unit	Source
CO_2	Carbon dioxide emissions	metric tons per capita	GCA (Global Carbon Atlas, 2018)
AVA	Agricultural Value Added	% of GDP	WDI (World Bank, 2018)
TRD	Trade	% of GDP	WDI (World Bank, 2018)
ENG	Energy Consumption	kg of oil equivalent per capita	WDI (World Bank, 2018)
FOS	Fossil Fuel Energy consumption	% of total	WDI (World Bank, 2018)
REN	Renewable Energy Consumption	% of total	WDI (World Bank, 2018)

Note: Country-specific data CO_2 was obtained from Global Carbon Atlas (GCA); AVA, TRD and ENG are obtained from World Development Indicators (WDI).

are becoming more advanced through rapid growth and industrialization. Agricultural modernization, effective trade and economic policies as well as a shift from fossil energy consumption to renewable energy are among the measures most African countries are utilizing to achieve steady economic growth. Though Angola, Rwanda, Uganda, Ethiopia and Libya are among the high emitters of CO_2 emissions in Africa, data unavailability and some cases of data uniformity did not permit us to include these countries in the study. With regards to geographical locations, Egypt, Algeria, Tunisia, Sudan and Morocco are in the Northern part of Africa. South Africa can be found in the Southern part of Africa. Ghana and Nigeria are in Western Africa and Kenya, Tanzania, Zambia and Zimbabwe can also be found in Eastern Africa. Lastly, Cameroon and DR Congo are in Central Africa. Country selection was based on data availability; nevertheless, the 14 countries represent all the five sub-regions in Africa. The six variables include carbon dioxide emissions (CO_2), agricultural value added (AVA), trade (TRD), energy consumption (ENG), renewable energy consumption (REN) and Fossil fuel energy consumption (FOS). The selection of the data series is based on the Agenda 2030 for Sustainable Development (United Nations, 2015).

3.2. Model estimation

The selection of econometric techniques for the model estimation was based on a number of factors which include the nature of data series (i.e. normal distribution, skewness, kurtosis, etc.), number of observations, stationarity of the variables, nature of cointegration and cross-sectional dependence. The linear relationship between carbon dioxide emissions, agricultural value added, trade and energy consumption of the proposed model can be expressed as:

$$CO_2 = f(AVA, ENG, TRD). \tag{1}$$

The linear relationship between carbon dioxide emissions, agricultural value added, trade and disaggregate energy consumption (renewable and fossil fuel energy) of the proposed model can be expressed as:

$$CO_2 = f(AVA, REN, FOS, TRD). \tag{2}$$

Prior to estimating the conditional distribution of the relationship across different quantiles, we first estimated the empirical basis of the model using Pedroni and Westerlund panel cointegration, panel fully modified ordinary least squares (FMOLS) and panel autoregressive distributed lag to investigate the long and short-run equilibrium relationships.

For brevity, the empirical specification of Equation 1 can be expressed as:

$$lnCO_{2i,t} = \beta_0 + \beta_1 lnAVA_{i,t} + \beta_2 lnENG_{i,t} + \beta_3 lnTRD_{i,t} + \varepsilon_{i,t}, \tag{3}$$

where $lnCO_{2i,\ t}$ is the logarithmic transformed carbon dioxide emissions, β_0 denotes the constant, $lnAVA_{i,\ t}$ is logarithmic transformed agricultural value added, $lnENG_{i,\ t}$ is the logarithmic transformed energy consumption, $lnTRD_{i,\ t}$ is logarithmic transformed trade, β_1-β_3 represent the estimated coefficients of the models and $\varepsilon_{i,\ t}$ denotes the white noise of individual countries i in time t.

After estimating the cointegration, panel FMOLS and panel ARDL long and short-run relationships, we further controlled for distributional heterogeneity using panel quantile regression (Sarkodie and Strezov, 2019). The linear quantile (Q) specification for Equations 1 and 2 is expressed as (Koenker and Hallock, 2001):

$$Q\left[\tau | X_i, \beta(\tau)\right] = \acute{X}_i \beta(\tau), \tag{4}$$

represents the vector of the coefficient to be estimated and τ denotes the -th quantile for individual i:

$$\hat{\beta}_n(\tau) = argmin_{\beta(\tau)} \left\{ \sum_i \rho_\tau \left(Y_i - \acute{X}_i \beta(\tau) \right) \right\}, \tag{5}$$

where $\hat{\beta}_n(\tau)$ represents the conditional quantile estimation analogous to the unconditional quantile regression estimation expressed in Equation 3, Y denotes the response variable (CO_2) and absolute function $\rho_\tau(.)$.

To verify the estimated panel quantile regression, the study adopts a goodness of fit test similar to the conventional R-squared expressed as (Koenker and Machado, 1999):

$$Q\left[\tau|X_i,\beta(\tau)\right]=\beta_0(\tau)+X_{i,1}^{\prime}\beta_1(\tau). \tag{6}$$

We test for the joint hypothesis of all coefficients of the estimated quantiles (0.05, 0. 1, …, 0.95) using the quantile process estimation technique expressed as the coefficient vector of the process (β):

$$\beta=\left(\beta(\tau_1)^{\prime},\beta(\tau_2)^{\prime},\ldots,\beta(\tau_k)^{\prime}\right)^{\prime}. \tag{7}$$

The robustness of the models is tested for heteroscedasticity using the slope equality test across quantiles, expressed as (Koenker and Bassett Jr., 1982):

$$H_0:\beta_1(\tau_1)=\beta_1(\tau_2)=\ldots=\beta_1(\tau_k). \tag{8}$$

The conditional panel quantile regression model based on the above algorithm can be expressed as:

$$Q_{lnCO_{2i,t}}\left[\tau|X_{i,t},\beta(\tau)\right]=\beta_{0,\tau}+\beta_{1,\tau}lnAVA_{i,t} +\beta_{2,\tau}lnENG_{i,t}+\beta_{3,\tau}lnTRD_{i,t}, \tag{9}$$

where β_0 is the constant, *ln* denotes log transformation, CO_2 is the response variable, *AVA*, *ENG* and *TRD* are the regressors, β's are the estimated coefficients and t is the period of the data series.

3.2.1. Limitation of the study

There could be reverse feedback from carbon dioxide emissions to aggregate and disaggregate energy consumption, however, controlling for such endogeneity could be very challenging. Hence, the model specification may suffer from endogeneity issues, however, using the panel quantile regression technique can handle issues related to country-specific heterogeneity.

4. Results and discussion

4.1. Descriptive statistics

Table 2 provides a summary statistic of the variables and correlation matrix employed in the empirical analysis. All the variables, except REN, exhibit a long right tail, thus, shows a positive skewness with CO_2 having the longest right tail. The results indicate that agricultural value added, trade and renewable energy consumption have a negative correlation with carbon dioxide emissions. While Agricultural value added has a positive association with renewable energy consumption, it has a negative association with aggregate energy, fossil fuel and trade.

4.2. Panel unit root

The economic variables employed in the study may have stochastic trends and can lead to non-stationarity. The first and second generational panel unit root tests were employed to investigate whether variables are stationary or non-stationary. This study used three-panel unit root tests which are either first or second generation. The first generational unit root tests include Breitung (Breitung, 1999) and Hadri Lagrange multiplier (LM) (Hadri, 2000), while the second-generational unit root test include Pesaran's cross-sectionally augmented Dickey-Fuller (CADF) (Pesaran, 2007). The null hypothesis of Hadri LM test specifies that all the panel data series are stationary, while

Table 2 Descriptive statistical analysis

Statistic	AVA	CO_2	FOS	ENG	TRD	REN
Mean	20.8182	59.0694	44.5906	700.4535	59.3719	56.7940
Median	17.1142	12.2525	27.8607	551.4393	57.6348	77.5593
Maximum	56.5440	502.7008	99.9383	2913.1300	116.0484	98.3426
Minimum	2.0978	0.8134	1.6397	269.1488	11.0875	0.1405
Std. Dev.	11.9781	106.2300	35.9943	551.6848	19.3522	35.3960
Skewness	0.6228	2.6322	0.4397	2.6065	0.3180	−0.4663
Kurtosis	2.6435	9.3741	1.4234	9.2547	3.2506	1.4523
Jarque-Bera	23.4999	956.7879	45.6232	928.1599	6.5404	45.7158
Probability	0.0000	0.0000	0.0000	0.0000	0.0380	0.0000
Correlation						
AVA	1					
CO_2	−0.4980	1				
FOS	−0.6684	0.5499	1			
ENG	−0.5743	0.9319	0.4898	1		
TRD	−0.3128	−0.0808	0.2220	0.0481	1	
REN	0.6482	−0.5357	−0.9945	−0.4696	−0.2009	1

Table 3 Panel unit root tests

	Breitung		Hadri		Pescadf	
	Level	1st Diff	Level	1st Diff	Level	1st Diff
Variable						
CO_2	4.7600	−7.7984*	48.8550*	−2.2619	−1.5560	−2.8400*
ENG	2.3076	−8.4875*	44.0916*	−0.8640	−2.0260	−3.4270*
AVA	−0.4497	−8.3227*	32.3729*	−1.7459	−2.3360*	−3.8770*
TRD	−2.6826*	−8.6982*	22.0317*	−1.5513	−1.8900	−3.0320*
FOS	0.9778	−7.9826*	46.7647*	0.8884	−1.6750	−3.2180*
REN	0.9431	−4.0803*	46.3632*	1.8491**	−1.5960	−3.3410*

Note: *, ** denote significance at 1% and 5% level.

both Breitung and Pesaran's CADF (Pescadf) have the same null hypothesis indicating all the panel data series contain a unit root. Breitung test converts individual fixed effects and individual trends as regressors to make the standard t statistics function. Breitung and Hadri LM tests permit each panel to have its individual rho_i while the Im-Pesaran-Shin test does not necessitate a strongly balanced panel. Hadri proposed a test procedure to test the null hypothesis that all the individual series in the panel are stationary against the alternative of at least a single unit root (Hadri, 2000). Results from Table 3 indicate that the null hypothesis of a unit root by Breitung and Pescadf tests cannot be rejected in almost all the data series at level but rejected at first difference. The null hypothesis of stationarity by the Hadri LM test cannot be rejected at its level form in most of the variables but rejected at first difference. This signifies that the data series under investigation are integrated of order one.

4.3. Panel cointegration

Table 4 indicates the results of the Pedroni test for cointegration, ARDL and FMOLS regression analysis. Under the Pedroni test for cointegration, we reject the null hypothesis for Phillips-Perron *t* and augmented Dickey-Fuller *t* because the corresponding p-values are less than 5%, indicating the acceptance of the alternative hypothesis. However, we cannot reject the null hypothesis for Modified Phillips-Perron *t* with a probability value greater than 5%. Appendix Table A1 presents the results of the Westerlund cointegration and cross-sectional dependence tests for the disaggregate energy consumption model. The results show a variance ratio test statistic (2.9511) significant at 1% level ($p < 0.01$), hence, rejecting the null hypothesis of no cointegration (i.e. for the model: lnCO2 ~ (lnFOS, lnREN, lnAVA, lnTRD)) for the alternative hypothesis of some panels are cointegrated. We conclude that there exists a

Table 4 Pedroni's test for cointegration, ARDL and FMOLS regression

Cointegration	Coefficient	Std. Error	Statistic	p-value
Modified Phillips-Perron *t*	N/A	N/A	−0.1134	0.4549
Phillips-Perron *t*	N/A	N/A	−7.2143	0.0000*
Augmented Dickey-Fuller *t*	N/A	N/A	−8.2685	0.0000*
ARDL long run equation				
lnAVA	−0.2081	0.0469	−4.4377	0.0000*
lnENG	1.2377	0.0804	15.3894	0.0000*
lnTRD	0.1579	0.0785	2.0110	0.0454**
ARDL Short Run Equation				
ECT_{t-1}	−0.2509	0.0600	−4.1811	0.0000*
$\Delta lnCO_{2_{t-1}}$	−0.0917	0.0681	−1.3478	0.1789
ΔlnAVA	0.0237	0.1010	0.2345	0.8148
ΔlnENG	1.2624	0.4957	2.5465	0.0115**
ΔlnTRD	0.0016	0.0447	0.0353	0.9719
C	−1.1981	0.2702	−4.4348	0.0000*
FMOLS				
lnAVA	−0.3836	0.0503	−7.6249	0.0000*
lnENG	0.9647	0.0928	10.3984	0.0000*
lnTRD	0.4434	0.0482	9.2035	0.0000*
R^2	0.97		Adjusted R^2	0.97

Notes: [Model: $lnCO_2$ ~ (lnENG, lnAVA, lnTRD)]; *,** denote 1% and 5% significance level, N/A means not applicable.

Table 5 Country-specific short-run equilibrium relationships

Country	Variable	Coefficient	Std. error	t-Statistic	Prob.
Algeria	ECT_{t-1}	−0.2245	0.0128	−17.5510	0.0004*
	$\Delta lnCO_{2_{t-1}}$	−0.4143	0.0268	−15.4427	0.0006*
	ΔlnAVA	0.2050	0.0158	12.9740	0.0010*
	ΔlnENG	−0.1962	0.1844	−1.0637	0.3655
	ΔlnTRD	0.0381	0.0532	0.7159	0.5257
	C	−0.8845	0.2180	−4.0565	0.0270**
Cameroon	ECT_{t-1}	−0.4086	0.0169	−24.1734	0.0002*
	$\Delta lnCO_{2_{t-1}}$	−0.0781	0.0825	−0.9469	0.4135
	ΔlnAVA	0.4299	0.5136	0.8372	0.4639
	ΔlnENG	−1.2209	2.5778	−0.4736	0.6681
	ΔlnTRD	−0.3109	0.1302	−2.3876	0.0970***
	C	−2.3679	0.6228	−3.8020	0.0320**
DR Congo	ECT_{t-1}	−0.2504	0.0126	−19.8554	0.0003*
	$\Delta lnCO_{2_{t-1}}$	0.1002	0.0411	2.4382	0.0927***
	ΔlnAVA	0.1740	0.0498	3.4943	0.0396**
	ΔlnENG	0.7484	1.0735	0.6971	0.5359
	ΔlnTRD	0.0617	0.0125	4.9177	0.0161**
	C	−1.6166	0.5394	−2.9972	0.0578***
Egypt	ECT_{t-1}	−0.2147	0.0094	−22.9437	0.0002*
	$\Delta lnCO_{2_{t-1}}$	−0.3157	0.0328	−9.6140	0.0024*
	ΔlnAVA	0.1374	0.0501	2.7452	0.0710***
	ΔlnENG	−0.0412	0.0831	−0.4964	0.6537
	ΔlnTRD	0.1487	0.0172	8.6707	0.0032*
	C	−0.6303	0.1079	−5.8438	0.0100*
Ghana	ECT_{t-1}	−0.0572	0.0020	−28.4905	0.0001*
	$\Delta lnCO_{2_{t-1}}$	−0.0900	0.0245	−3.6813	0.0347**
	ΔlnAVA	−0.7122	0.0430	−16.5627	0.0005*
	ΔlnENG	0.1311	0.0915	1.4326	0.2474
	ΔlnTRD	−0.2295	0.0156	−14.6959	0.0007*
	C	−0.2505	0.0546	−4.5906	0.0194**
Kenya	ECT_{t-1}	−0.2326	0.0032	−72.8593	0.0000*
	$\Delta lnCO_{2_{t-1}}$	0.1457	0.0148	9.8357	0.0022*
	ΔlnAVA	0.4878	0.0728	6.7043	0.0068*
	ΔlnENG	4.7019	0.9832	4.7822	0.0174**
	ΔlnTRD	−0.1596	0.0188	−8.4984	0.0034*
	C	−1.2175	0.0991	−12.2817	0.0012*
Morocco	ECT_{t-1}	−0.5666	0.0119	−47.6003	0.0000*
	$\Delta lnCO_{2_{t-1}}$	−0.3235	0.0135	−23.9365	0.0002*
	ΔlnAVA	0.0728	0.0014	53.8533	0.0000*
	ΔlnENG	0.0512	0.0288	1.7811	0.1729
	ΔlnTRD	0.0027	0.0045	0.5951	0.5937
	C	−2.1884	0.2447	−8.9420	0.0030*
Nigeria	ECT_{t-1}	−0.1174	0.0038	−30.9457	0.0001*
	$\Delta lnCO_{2_{t-1}}$	0.3534	0.0332	10.6592	0.0018*
	ΔlnAVA	−0.4390	0.0327	−13.4374	0.0009*
	ΔlnENG	2.5051	1.5288	1.6386	0.1998
	ΔlnTRD	0.0529	0.0117	4.5170	0.0203**
	C	−0.4492	0.0612	−7.3424	0.0052*
South Africa	ECT_{t-1}	−0.8233	0.0548	−15.0338	0.0006*
	$\Delta lnCO_{2_{t-1}}$	−0.1588	0.0118	−13.4858	0.0009*
	ΔlnAVA	−0.0225	0.0060	−3.7771	0.0325**
	ΔlnENG	0.3102	0.0757	4.1000	0.0263**
	ΔlnTRD	−0.0546	0.0051	−10.7657	0.0017*
	C	−3.3740	0.8708	−3.8746	0.0304**
Sudan	ECT_{t-1}	−0.0067	0.0028	−2.3812	0.0975***
	ECT_{t-1}	0.2763	0.0463	5.9671	0.0094*
	$\Delta lnCO_{2_{t-1}}$	−0.6058	0.0812	−7.4649	0.0050*
	ΔlnAVA	1.8139	0.3932	4.6134	0.0192**
	ΔlnENG	0.0453	0.0168	2.6985	0.0739***
	ΔlnTRD	0.0061	0.0772	0.0791	0.9420
Tanzania	ECT_{t-1}	0.0131	0.0065	2.0043	0.1387

Table 5. Continued

Country	Variable	Coefficient	Std. error	t-Statistic	Prob.
	$\Delta lnCO_{2_{t-1}}$	−0.0903	0.0476	−1.8966	0.1541
	ΔlnAVA	0.4996	0.1130	4.4216	0.0215**
	ΔlnENG	1.9227	2.0350	0.9448	0.4145
	ΔlnTRD	0.2787	0.0353	7.8937	0.0042*
	C	0.1412	0.2334	0.6053	0.5877
Tunisia	ECT_{t-1}	−0.1400	0.0172	−8.1500	0.0039*
	$\Delta lnCO_{2_{t-1}}$	−0.4749	0.0181	−26.2014	0.0001*
	ΔlnAVA	−0.0278	0.0046	−6.0938	0.0089*
	ΔlnENG	0.1933	0.0310	6.2334	0.0083*
	ΔlnTRD	0.0702	0.0108	6.4737	0.0075*
	C	−0.7302	0.5154	−1.4168	0.2515
Zambia	ECT_{t-1}	−0.2839	0.0303	−9.3640	0.0026*
	$\Delta lnCO_{2_{t-1}}$	0.0606	0.0296	2.0469	0.1332
	ΔlnAVA	−0.0323	0.0035	−9.3115	0.0026*
	ΔlnENG	5.1954	0.7008	7.4132	0.0051*
	ΔlnTRD	0.2227	0.0299	7.4378	0.0050*
	C	−2.0239	1.6015	−1.2637	0.2956
Zimbabwe	ECT_{t-1}	−0.1994	0.0233	−8.5738	0.0033*
	$\Delta lnCO_{2_{t-1}}$	−0.2750	0.0577	−4.7620	0.0176**
	ΔlnAVA	0.1647	0.0180	9.1351	0.0028*
	ΔlnENG	1.5583	0.9460	1.6472	0.1981
	ΔlnTRD	−0.1442	0.0385	−3.7487	0.0331**
	C	−1.1880	0.8316	−1.4286	0.2484

Notes: [Model: $lnCO_2$ ~ (lnENG, lnAVA, lnTRD)]; *,**,*** denote 1, 5 and 10% significance level.

long-run relationship between the data series among the high CO_2 emitters in Africa.

4.4. *Long and short-run relationship*

Table 4 further analyzed the long and short-run equilibrium relationships. The ARDL model was estimated based on 308 observations with two maximum dependent lags and dynamic regressors automatically selected with Akaike information criterion (AIC), resulting in ARDL(2, 1, 1, 1) as the selected model. In the long-run, the coefficient for agricultural value added (AVA) is ~ − 0.21% and statistically significant at 1% level, while the long-run coefficients on energy consumption (ENG) and trade openness (TRD) are 1.24% and 0.16% respectively. In the short-run, agricultural value added, energy consumption and trade openness have coefficients ~0.02% ($p > 0.05$), 1.26% ($p < 0.05$) and 0.0021% ($p > 0.05$) respectively. Energy consumption is positive and significant at 5%, whereas agricultural value added and trade openness are positive but statistically insignificant.

Based on Pedroni's technique (Pedroni, 2001), we estimated the fully modified OLS (FMOLS) for heterogeneous cointegration panels. The Panel FMOLS pooled estimation technique was used to examine the proposed model with 322 total panels (balanced) observations. The coefficient covariance was computed using the default method and long-run covariance estimates using Bartlett kernel, Newey-West fixed bandwidth. The first-stage residuals used heterogeneous long-run coefficients, with empirical results presented in Table 4.

Except for AVA, the coefficients in the FMOLS model estimation are positive and statistically significant at 1% significance level. These coefficients can be construed as elasticities because the variables are expressed in natural logarithm. The outcome indicates that a 1% increase in agricultural value added decreases carbon dioxide emissions by 0.38%; a 1% increase in energy consumption increases carbon dioxide emissions by 0.96% and a 1% increase in trade openness increases carbon dioxide emissions by 0.44%. The empirical results are consistent with Shahbaz *et al.* (2016, 2018). To compare our results with previous studies that utilized FMOLS technique, Liu *et al.* (2017) indicated that a 1% increase in agricultural value added decreases per capita carbon emissions by 0.53%, whereas a 1% increase in per capita non-renewable energy increases per capita carbon dioxide emissions by 0.52% among four ASEAN countries. Asumadu-Sarkodie and Owusu (2017) revealed that a 1% increase in agricultural machinery decreases carbon dioxide emissions by 0.09% based on the Ghanaian economy. A study by Sarkodie and Owusu (2017) showed that a 1% increase in the total energy production from combustible renewables and waste increases carbon dioxide emissions by 307.9 kt in the long run. Evidence from Asumadu-Sarkodie and Owusu (2016), using Nigeria as a case study, showed that a 1% increase in energy consumption increases carbon dioxide emissions by 3%. Table 5 shows the country-specific short-run equilibrium relationships. The investigation of the country-

Table 6 Panel quantile estimation results with inclusion of aggregate energy consumption

Quantile	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
lnAVA	0.2303	0.5895*	−0.0922	0.1395	0.3313	0.2397	−0.0371	−0.2050	−0.4335	−0.3470*	−0.2861**
	[0.5249]	[0.1847]	[0.1931]	[0.1630]	[0.2139]	[0.3313]	[0.3397]	[0.3399]	[0.2803]	[0.1023]	[0.1004]
lnENG	2.6526*	3.0729*	2.4451*	2.6709*	2.8279*	2.6371*	2.0867*	1.7900*	1.6287*	2.0369*	2.1440*
	[0.6266]	[0.2313]	[0.2361]	[0.1894]	[0.2713]	[0.4338]	[0.4338]	[0.4251]	[0.3450]	[0.1017]	[0.1031]
lnTRD	−0.7889*	−0.2633**	−0.3096**	−0.0852	0.0947	0.1885	0.3494	−0.0235	−0.0238	−0.5680*	−0.7213*
	[0.2980]	[0.1443]	[0.1240]	[0.0969]	[0.1326]	[0.2062]	[0.3123]	[0.3262]	[0.4385]	[0.1250]	[0.1137]
Constant	−13.5667**	−18.6316*	−12.0774*	−14.8236*	−16.9202*	−15.6472*	−11.6470*	−7.2575***	−5.3344	−5.3610*	−5.4858*
	[5.8847]	[1.8929]	[2.2546]	[1.9685]	[2.8044]	[4.3911]	[4.4349]	[4.3238]	[3.4969]	[0.7182]	[0.7710]
Pseudo R-squared	0.1517	0.2012	0.3044	0.3566	0.3771	0.3784	0.3845	0.3907	0.3787	0.4399	0.4673
Adjusted R-squared	0.1440	0.1939	0.2981	0.3508	0.3714	0.3728	0.3789	0.3852	0.3731	0.4348	0.4625
S.E. of regression	2.2639	1.6655	1.3392	1.2064	1.1456	1.0919	1.0817	1.2656	1.4169	1.8923	1.9919
Quantile dependent var	0.6193	0.8429	1.2986	1.7120	2.0523	2.4985	2.9078	3.6952	4.5164	5.0159	5.8974
Sparsity	12.6771	5.5658	2.6913	2.3946	2.3697	2.5087	3.0913	4.3159	4.4818	4.5534	5.0537
Quasi-LR statistic	20.9241	60.9403	190.7234	254.9246	278.5004	273.815	238.2037	182.1465	173.4958	215.5876	213.8408
Prob (Quasi-LR stat)	0.0001*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*

Notes: (Model: $\ln CO_2 \sim (\ln ENG, \ln AVA, \ln TRD)$); *,**,*** denote significance at 1, 5 and 10% level; the bracket [] represents the standard error.

specific short-run equilibrium relationship for the estimated model stems from Pesaran (2004) CD-test for cross-sectional dependence presented in Appendix Table A2 (rows 3–4). The results show mixed outcomes, hence, confirming the existence of weak cross-sectional dependence.

The results indicate that the error correction terms (for example, $ECT_{t-1} = -0.22$ for Algeria) for Algeria, Cameroon, DR Congo and Egypt are negative and significant at $p < 0.01$. The short-run coefficient for carbon dioxide emissions in Algeria is −0.41% at $p < 0.01$. The short-run coefficient for carbon dioxide emissions in Cameroon is −0.07% at $p < 0.01$. DR Congo also has a short-run coefficient value of −0.10% for carbon dioxide emissions at $p < 0.10$. Egypt has a short-run coefficient value of −0.31% for carbon dioxide emissions at $p < 0.01$. In the subsequent analysis, it can be seen in the following countries: Ghana, Kenya and Morocco, that negative error correction terms ($ECT_{t-1} = -0.05$, -0.23 and -0.56) were found, respectively. A short-run coefficient value of 0.09%, 0.14% and 0.32% were also found. All these figures were negative and significant at 1% or 5% level. Nigeria and South Africa recorded a negative and statistically significant error correction term ($ECT_{t-1} = -0.11$ and -0.82) coupled with varied short-run corresponding coefficients. In the same way, except Tanzania with a positive and insignificant error correction term, Sudan, Tunisia, Zambia and Zimbabwe have a negative and significant error correction term at $p < 0.01$. The error correction term close to one indicates the speed of adjusting or correcting previous disturbances in carbon dioxide emissions to an equilibrium state. The weak cross-sectional dependence and the variations in the estimated country-specific short-run equilibrium relationship propelled the inclusion of country-specific fixed effects presented in Appendix Table A3. The results from Appendix Table A3 reveal that the signs on lnENG, lnAVA and lnTRD are in line with the estimated ARDL and FMOLS models, thus, confirming that country-specific fixed effects have to impact on the emission-aggregate energy consumption model. The differences between the panel of countries in the country-specific impact on carbon dioxide emissions can be attributed to the differences in trade, energy consumption and modernized agricultural practices.

Since aggregate energy consumption provides no information about the role of fossil fuel and renewable energy consumption, a disaggregate model was examined, with results presented in Table 7. Prior to the estimation of the disaggregate energy consumption model using panel quantile technique, a cross-sectional dependence test (Appendix Table A2, rows 5–7) and country-specific fixed-effect model (Appendix Table A3, rows 10–18) were estimated. The CD-test for cross-sectional dependence in Appendix Table A2 (rows 5–7) showed strict cross-sectional independence ($p < 0.01$), thus, indicating a strong correlation between the panel of countries. Evidence from the disaggregate energy consumption model in Appendix

Table 7 Panel quantile estimation results with inclusion of disaggregate energy consumption

Quantile	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
lnFOS	0.7850* [0.0453]	0.8041* [0.0578]	0.7551* [0.0549]	0.7428* [0.0451]	0.7999* [0.0476]	0.8371* [0.0498]	0.8364* [0.0646]	0.9372* [0.0661]	1.1013* [0.0623]	1.4662* [0.0890]	1.8442* [0.2072]
lnREN	−0.2800* [0.0335]	−0.3117* [0.0359]	−0.3436* [0.0247]	−0.3119* [0.0225]	−0.2445* [0.0259]	−0.1482* [0.0319]	−0.0312 [0.0408]	−0.0001 [0.0374]	0.0705*** [0.0380]	0.2831* [0.0421]	0.3901* [0.0598]
lnTRD	−0.3136* [0.0762]	−0.2056** [0.0879]	−0.0795 [0.0668]	−0.1386*** [0.0733]	−0.2241** [0.1075]	−0.4534* [0.1089]	−0.5618* [0.1308]	−0.6320* [0.1612]	−0.3260*** [0.1828]	0.2457 [0.2152]	−0.0927 [0.2983]
lnAVA	−0.1381 [0.1040]	0.0087 [0.1014]	0.0569 [0.0562]	−0.0646 [0.0645]	−0.2035** [0.0868]	−0.5502* [0.1415]	−1.0482* [0.1369]	−0.9691* [0.0631]	−0.8139* [0.0529]	−0.3194* [0.0692]	0.1511 [0.1208]
Constant	1.7831* [0.5221]	1.1112*** [0.5909]	0.8965* [0.2919]	1.5561* [0.3760]	2.0390* [0.5594]	3.7476* [0.6741]	5.5013* [0.5819]	−5.2981* [0.7382]	3.0444* [1.0395]	−1.9476*** [1.1490]	−2.9130** [1.4545]
Pseudo R-squared	0.5341	0.5375	0.5436	0.5346	0.5232	0.5160	0.5221	0.5206	0.4748	0.4182	0.3810
Adjusted R-squared	0.5285	0.5319	0.5380	0.5290	0.5174	0.5102	0.5164	0.5148	0.4685	0.4111	0.3735
S.E. of regression	1.3873	1.3124	1.2316	1.1297	1.0195	0.9113	0.9531	0.9948	1.0936	1.6305	2.2245
Quantile dependent var	0.6193	0.8429	1.2986	1.7120	2.0523	2.4985	2.9078	3.6952	4.5164	5.0159	5.8974
Sparsity	3.0775	2.0117	1.4669	1.4937	1.6156	1.8286	1.7552	1.9668	2.3274	3.9949	6.6578
Quasi-LR statistic	303.4594	450.5277	624.8604	612.6103	566.7660	512.2691	569.7939	532.5662	418.9139	233.5913	132.3332
Prob (Quasi-LR stat)	0.0001*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*

Notes: (Model: lnCO_2 ~ (lnFOS, lnREN, lnAVA, lnTRD)); *, **, *** Denotes 1%, 5% and 10% significance level.

Table 8 Quantile slope equality test using Wald test

Test summary		χ^2 **Statistic**[a]	**Prob.**	χ^2 **Statistic**[b]	**Prob.**	χ^2 **Statistic**[c]	**Prob.**
Wald test		102.9879	0.0000*	102.9357	0.0000*	102.8456	0.0000*
Quantiles	Variable	Restr. Value	Prob.	Restr. Value	Prob.	Restr. Value	Prob.
0.05, 0.1	lnAVA	−0.3593	0.4803	−0.3593	0.4810	−0.3593	0.4804
	lnENG	−0.4203	0.4791	−0.4203	0.4790	−0.4203	0.4802
	lnTRD	−0.5256	0.0758***	−0.5256	0.0748***	−0.5256	0.0756***
0.1, 0.2	lnAVA	0.6817	0.0011*	0.6817	0.0011*	0.6817	0.0011*
	lnENG	0.6278	0.0198	0.6278	0.0197**	0.6278	0.0196**
	lnTRD	0.0463	0.7696	0.0463	0.7697	0.0463	0.7696
0.2, 0.3	lnAVA	−0.2317	0.1317	−0.2317	0.1318	−0.2317	0.1316
	lnENG	−0.2257	0.2150	−0.2257	0.2152	−0.2257	0.2149
	lnTRD	−0.2243	0.0237**	−0.2243	0.0236**	−0.2243	0.0236**
0.3, 0.4	lnAVA	−0.1919	0.1732	−0.1919	0.1732	−0.1919	0.1733
	lnENG	−0.1570	0.3566	−0.1570	0.3567	−0.1570	0.3568
	lnTRD	−0.1799	0.0412**	−0.1799	0.0412**	−0.1799	0.0412**
0.4, 0.5	lnAVA	0.0917	0.6813	0.0917	0.6813	0.0917	0.6813
	lnENG	0.1908	0.5158	0.1908	0.5158	0.1908	0.5158
	lnTRD	−0.0938	0.5097	−0.0938	0.5097	−0.0938	0.5097
0.5, 0.6	lnAVA	0.2768	0.2667	0.2768	0.2667	0.2768	0.2667
	lnENG	0.5504	0.0802***	0.5504	0.0802***	0.5504	0.0802***
	lnTRD	−0.1609	0.5238	−0.1609	0.5238	−0.1609	0.5238
0.6, 0.7	lnAVA	0.1679	0.5490	0.1679	0.5488	0.1679	0.5491
	lnENG	0.2967	0.3925	0.2967	0.3922	0.2967	0.3926
	lnTRD	0.3728	0.1992	0.3728	0.1996	0.3728	0.1996
0.7, 0.8	lnAVA	0.2284	0.4378	0.2284	0.4374	0.2284	0.4377
	lnENG	0.1613	0.6675	0.1613	0.6676	0.1613	0.6678
	lnTRD	0.0004	0.9992	0.0004	0.9992	0.0004	0.9992
0.8, 0.9	lnAVA	−0.0865	0.7333	−0.0865	0.7333	−0.0865	0.7334
	lnENG	−0.4082	0.1967	−0.4082	0.1970	−0.4082	0.1969
	lnTRD	0.5441	0.1752	0.5441	0.1761	0.5441	0.1754
0.9, 0.95	lnAVA	−0.0609	0.5080	−0.0609	0.5079	−0.0609	0.5085
	lnENG	−0.1072	0.2659	−0.1072	0.2678	−0.1072	0.2662
	lnTRD	0.1534	0.2289	0.1534	0.2278	0.1534	0.2275

Notes: [Model: lnCO_2 ~ (lnENG, lnAVA, lnTRD)]; *,**,*** denote significance at 1, 5 and 10% level; [a, b, c] denote the estimated equation quantile tau = 0.05, 0.50 and 0.95.

Table A3 (rows 10–18) shows that an increase fossil fuel energy consumption and trade openness by 1% increases carbon dioxide emissions by 0.81% and 0.16%, respectively. The empirical results of trade openness are consistent with the aggregate model while fossil fuel energy consumption is consistent with Rafiq *et al*. (2016b). In contrast, an increase in agricultural value added and renewable energy consumption declines carbon dioxide emissions by 0.49% and 0.36%—consistent with the aggregate energy model and Liobikienė and Butkus (2019) and Rafiq *et al*. (2016a).

4.5. Panel quantile estimation

In order to address the limitations of both panel FMOLS and ARDL estimation methods, a panel quantile estimation proposed by Koenker and Hallock (2001) was employed to control for conditional distribution and heterogeneity across quantiles. The panel quantile regression (tau = 0.05–0.95) included 336 observations, MCMB-A bootstrapping method (robust against heteroscedasticity) with 10,000 replications and a maximum of 500 iterations (Knuth random generator with seed = 2125545295) to estimate coefficient covariance, sparsity was estimated with Kernel (Epanechnikov) using residuals and the Hall-Sheather bandwidth method to successfully identify the unique optimal solution. The empirical results of the panel quantile estimation are presented in Table 6. The empirical results from Table 6 confirm the heterogeneous distribution of the impact of agricultural value added and trade on carbon dioxide emissions across quantiles. lnAVA is positive and significant at 0.1 quantiles, but returns insignificant afterwards until negative and significant at 0.9 to 0.95 quantiles. Thus, agricultural value-added declines carbon dioxide emissions in countries with high pollution levels in Africa. The integration of technology in the form of value-addition to agricultural production systems plays a vital role in rural development, especially in agrarian economies. Agricultural value-added improves the economic viability of agricultural production by creating new

Table 9 Symmetric quantiles test using Wald test

Test summary		χ^2 Statistic[a]	Prob.	χ^2 Statistic[b]	Prob.	χ^2 Statistic[c]	Prob.
Wald test		103.0418	0.0000*	102.7060	0.0000*	103.0590	0.0000*
0.05, 0.95	lnAVA	−0.5351	0.4953	−0.5351	0.4952	−0.5351	0.4953
	lnENG	−0.4775	0.6279	−0.4775	0.6276	−0.4775	0.6283
	lnTRD	−1.8872	0.0001*	−1.8872	0.0001*	−1.8872	0.0001*
	C	12.2620	0.2054	12.2620	0.2053	12.2620	0.2055
0.1, 0.9	lnAVA	−0.2368	0.7103	−0.2368	0.7104	−0.2368	0.7104
	lnENG	−0.1643	0.8423	−0.1643	0.8424	−0.1643	0.8424
	lnTRD	−1.2082	0.0040*	−1.2082	0.0040*	−1.2082	0.0040*
	C	7.3019	0.3763	7.3019	0.3765	7.3019	0.3766
0.2, 0.8	lnAVA	−1.0050	0.0638***	−1.0050	0.0637	−1.0050	0.0639***
	lnENG	−1.2003	0.0887***	−1.2003	0.0886***	−1.2003	0.0888***
	lnTRD	−0.7103	0.1623	−0.7103	0.1628	−0.7103	0.1623
	C	13.8826	0.0484**	13.8826	0.0484**	13.8826	0.0484**
0.3, 0.7	lnAVA	−0.5449	0.2575	−0.5449	0.2575	−0.5449	0.2576
	lnENG	−0.8132	0.1899	−0.8132	0.1898	−0.8132	0.1899
	lnTRD	−0.4856	0.1896	−0.4856	0.1899	−0.4856	0.1897
	C	9.2133	0.1386	9.2133	0.1387	9.2133	0.1387
0.4, 0.6	lnAVA	−0.1851	0.6422	−0.1851	0.6422	−0.1851	0.6422
	lnENG	−0.3596	0.4865	−0.3596	0.4865	−0.3596	0.4865
	lnTRD	0.0671	0.8269	0.0671	0.8269	0.0671	0.8269
	C	2.7274	0.5998	2.7274	0.5998	2.7274	0.5998

Notes: *,**,*** denote significance at 1, 5 and 10% level; [a, b, c] denote the estimated equation quantile tau = 0.05, 0.50 and 0.95.

opportunities that help in reducing environmental pollution. Value-added agricultural production enhances income levels and risk diversification benefits for climate susceptible agricultural production systems (Cowan, 2003).

Table 6 reveals that the nexus between carbon dioxide emissions and energy consumption is positive and homogeneously distributed across quantiles—this corroborates the results from the panel FMOLS and ARDL (both long and short-run). Therefore, an increase in energy consumption spurs carbon dioxide emissions in low and high polluting countries in Africa. The positive impact of energy consumption on environmental pollution is not due to renewable energy technologies but may be attributed to the overreliance on traditional biomass like fuelwood and charcoal, which constitutes a greater proportion of energy consumption in Africa, especially in rural communities. A similar study found energy consumption as the main driver of environmental pollution (Zhu *et al*., 2016), consistent with our results.

The coefficient on trade is negative and statistically significant in lower (0.05–0.20) and higher quantiles (0.90–0.95), but heterogeneous and insignificant across 0.30–0.85 quantiles. Meaning that trade openness lowers carbon dioxide emissions in countries with lower and higher environmental pollution—consistent with a study in Asia (Zhu *et al*., 2016).

The results of the panel estimation showing the disaggregate energy model are presented in Table 7. The following highlights are derived from the panel quantile regression: (1) the sign on lnFOS is positive and statistically significant from 0.05–0.95 quantiles; (2) the sign on lnREN is negative and significant from 0.05–0.50 quantile, turns positive and insignificant at 0.60–0.70 quantile and becomes significantly positive from 0.80–0.95 quantile; (3) the significant negative sign on lnTRD runs from 0.05–0.80 quantile before it turns insignificant positive from 0.90–0.95 quantile; and (4) the sign on lnAVA is insignificant and varies from 0.05–0.30 quantile, turns significant negative from 0.40–0.90 and turns insignificant positive at 0.95 quantile. Apart from lnFOS, the variations in the estimated results confirm the Conditional distribution and Heterogeneity across quantiles. The empirical results show that an increase in fossil fuel energy consumption increases carbon dioxide emissions in both low and high CO_2 emitters. Burning of fossil fuels for electricity and heat generation, transportation, agricultural activities and industrial production has been the backbone of economic development, but its impact on environmental pollution is alarming. Hence, reducing the final energy consumption through enhanced energy efficiency, the inclusion of carbon capture and storage technologies, fuel-switching and behavioral changes would help stabilize the CO_2 equivalent concentrations (Bruckner *et al*., 2014). In contrast, an increase in renewable energy consumption declines emissions in low CO_2 emitters but increases carbon dioxide emissions in high CO_2 emitters. This is inline with a similar study that found a huge impact of renewable energy from low and lower middle income countries in negating environmental pollution compared to uppermiddle and higher income

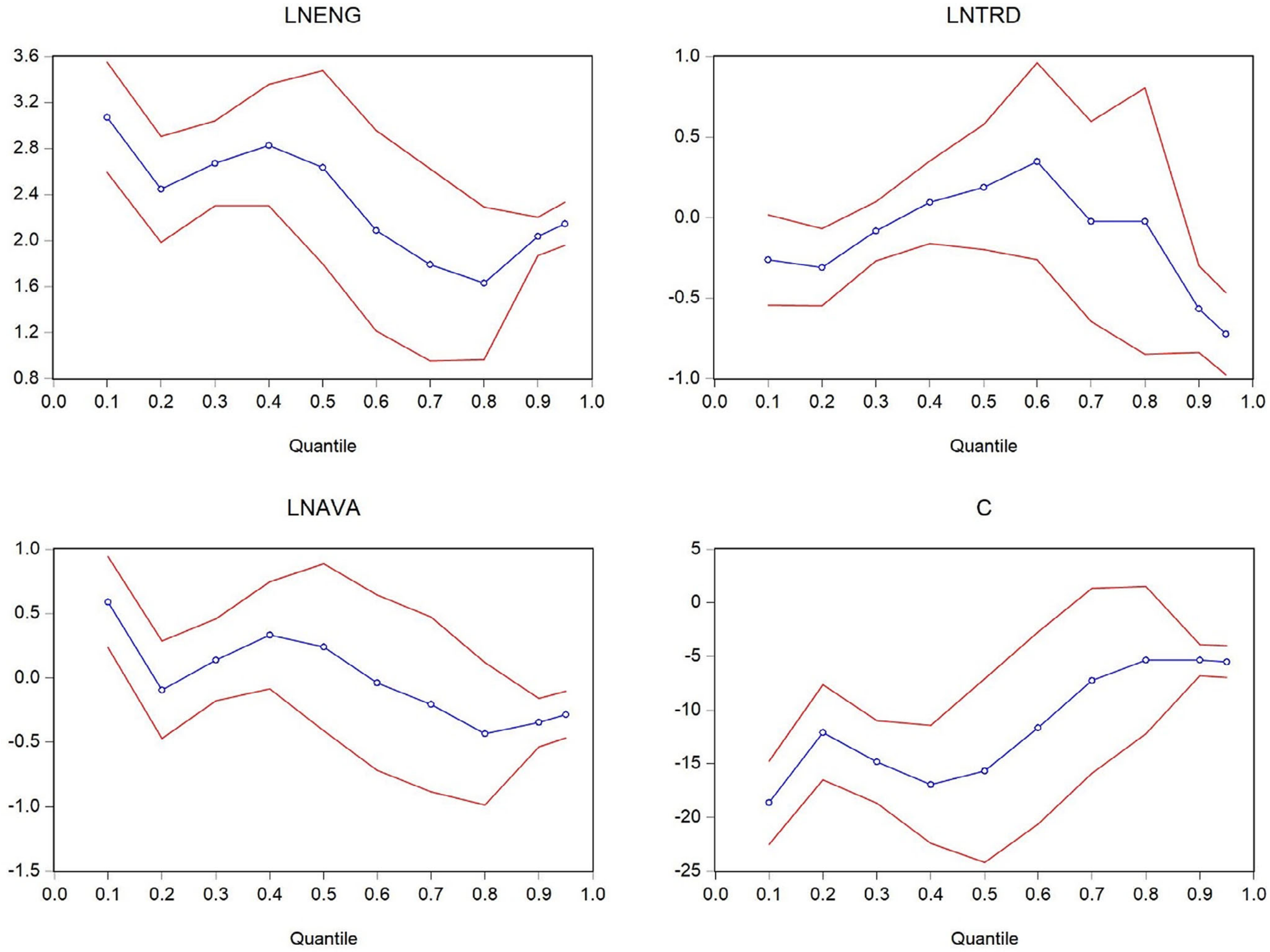

Figure 1. Quantile process coefficient estimation for 0.05–0.95 quantiles. *Notes*: (Model: $\ln CO_2$ ~ (lnENG, lnAVA, lnTRD)); the quantile specification plot is based on the results of the estimation equation and quantiles for all coefficients. The red line represents the 95% confidence interval.

countries (Liobikienė and Butkus, 2018). It appears that increasing the share of renewable energy technologies in the energy mix without repealing and replacing existing fossil fuel energy technologies would not yield the main target of emission reduction. For example, South Africa is the highest emitter of CO_2 emissions in Africa, with over 90% of energy mix from fossil fuel sources (Bekun *et al.*, 2019), hence, increasing the share of renewable energy sources of already existing renewable energy infrastructure will yield no results, but diversifying the 90% share of fossil fuel with clean and renewable energy technologies will act as a mitigating effect towards CO_2 emissions. As a policy implication, diversification of the energy portfolio through the inclusion of low-carbon energy technologies like nuclear, renewable energy and the improvements in fossil fuel energy consumption efficiency have a climate change abatement potential.

Koenker and Bassett Jr. (1982) and Newey and Powell (1987) proposed the use of inter-quantile estimation techniques such as slope equality and symmetry testing to examine the heterogeneous distribution of the estimated quantile parameters. Tables 8 and 9 and Appendix Tables A4 and A5 show the quantile process testing using quantile slope equality and symmetric quantile tests. The Wald test statistic compares all coefficients from the estimated equation quantiles from 0.05 to 0.95 for both quantile slope equality test and symmetric quantiles test. The empirical results in Table 8 show that the null hypothesis of homogeneity is rejected in the case of lnTRD (0.05, 0.1; 0.2, 0.3 and 0.3, 0.4 quantiles) and lnENG (0.1, 0.2 and 0.5, 0.6 quantiles). The null hypothesis of symmetry in Table 8 is rejected in the case of lnTRD (0.05, 0.95 and 0.1, 0.9), lnAVA (0.2, 0.8) and lnENG (0.2, 0.8). The two inter-quantile estimation techniques show heterogeneous results across quantiles. Homogeneity, heterogeneity, symmetry and asymmetry exist across different quantiles show the complexities of nexus testing in some cases, hence, requiring multiple estimation techniques as used in this study.

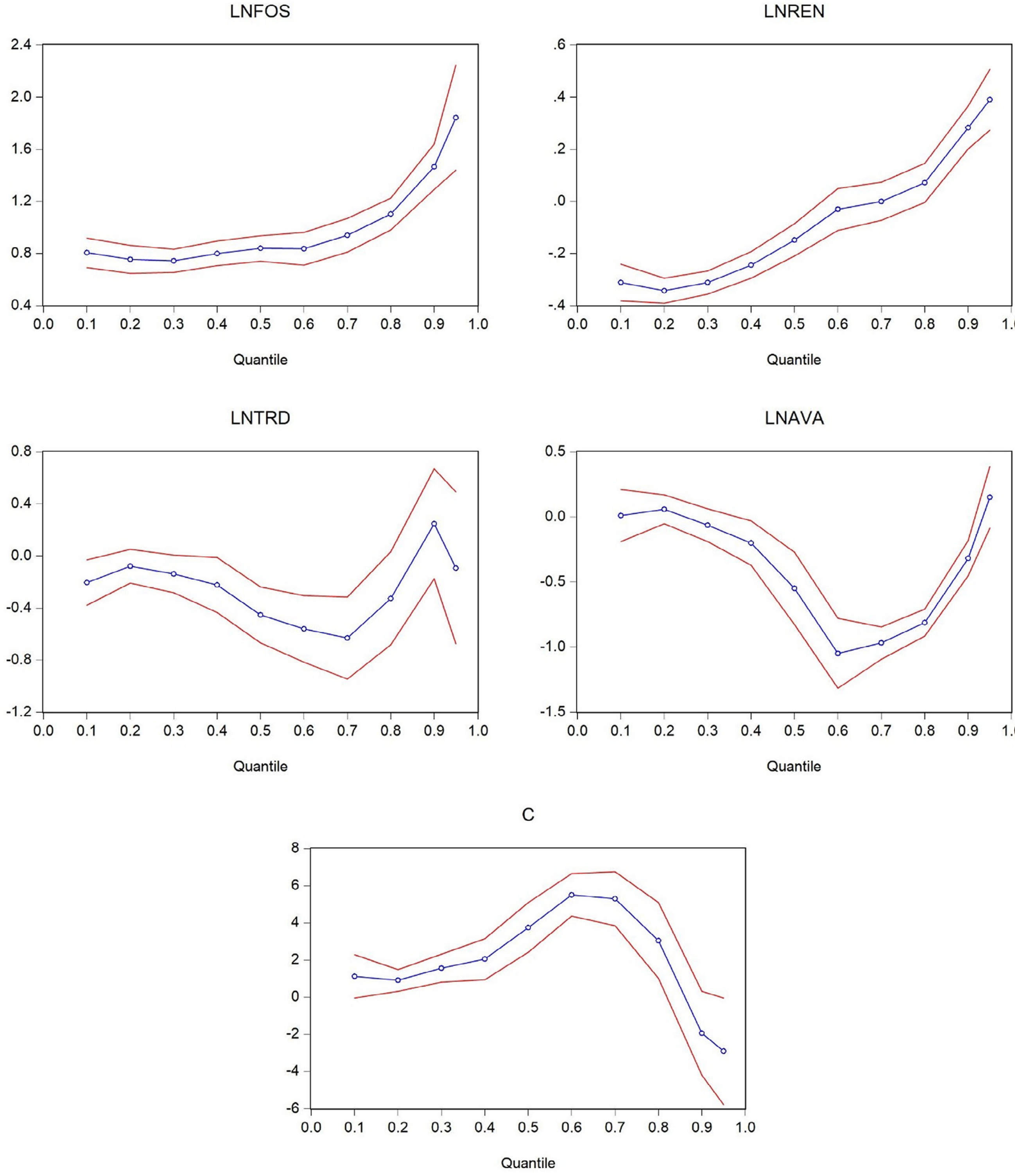

Figure 2. Quantile process coefficient estimation for 0.05–0.95 quantiles. *Notes*: (Model: $\ln CO_2$ ~ (lnFOS, lnREN, lnAVA, lnTRD)); the quantile specification plot is based on the results of the estimation equation and quantiles for all coefficients. The red line represents the 95% confidence interval.

4.6. Model validation

To verify the quality of the panel quantile regression, the study utilized goodness of fit tests (pseudo R-squared and adjusted R-squared), quasi-likelihood ratio (RL) test via sparsity estimation and coefficient testing proposed by Koenker and Machado (1999). The estimated model in Tables 6 and 7 reveals a pseudo R-squared ranging from

~0.15 to ~0.54 and the probability of quasi-LR statistically significant at 1% level. Figure 1 presents the quantile process coefficient estimation across quantiles. For brevity, we present the coefficient testing for 0.05, 0.50 and 0.95 quantiles. The quantile specification plot in Figures 1 and 2 is constructed based on the results from the estimation equation and quantiles for all coefficients. Evidence from Figure 1 shows that the estimated coefficients of the models are within the 95% confidence band, hence, validating the empirical analysis of the panel quantile regression.

5. Conclusion

The study examined the relationship between agriculture, trade openness, aggregate and disaggregate energy consumption (renewable and fossil fuel) and its effect on CO_2 emissions. The study employed data spanning from 1990 to 2013 in the top 14 emitters of CO_2 emissions in Africa. The long-run equilibrium relationship, fixed-effect and the FMOLS estimation techniques revealed a mitigating effect of agricultural value added on CO_2 emissions, while energy consumption and trade openness were found to escalate environmental pollution. The panel quantile estimation technique confirmed the conditional distribution and heterogeneity across quantiles in the nexus between CO_2 emissions, AVA, REN and TRD. The empirical analysis revealed that agricultural value-added declines carbon dioxide emissions in countries with high pollution levels in Africa. The nexus between carbon dioxide emissions and energy consumption was positive and homogeneously distributed across quantiles. However, trade openness was found to lower carbon dioxide emissions in countries with lower and higher environmental pollution. While an increase in fossil fuel energy consumption was found to increase CO_2 emissions in low and high CO_2 emitters in Africa, renewable energy consumption declines environmental pollution in low CO_2 emitters but increases carbon dioxide emissions in high CO_2 emitters. Though fossil fuels remain the backbone of sustained economic growth, its adverse impact on environmental pollution can be negated by diversifying the energy portfolio with clean and renewable energy technologies. Improving existing fossil fuel infrastructures with carbon, capture and storage technologies and enhanced energy efficiency would help stabilize the CO_2 equivalent concentrations in the atmosphere.

As a policy implication, agricultural sector reforms in Africa needs to focus on climate-smart and sustainable agricultural production. This approach can help increase productivity and income, adapt to climate change sensitivity and reduce greenhouse gas emissions. This approach can assist agricultural stakeholders to increase their productivity and reduce emissions. Studies have also predicted Africa's vulnerability to climate change and its related effect. This signifies that Africa's agricultural sector needs to engage in practices that encourage hybrid seeds that are drought and striga-tolerant, have a higher-yielding potential and can adapt well in all agro-ecological zones. Since trade openness has a tendency of contributing greatly to economic development, efficient regional trade policies can abate carbon dioxide emissions in countries with lower and higher environmental pollution. We recommend governments in Africa to enact policies that can boost the agricultural sector productivity and create an efficient market for international trade. Such policies can stimulate the flow of technology and investment opportunities for specialization in production and economies of scale. Though Africa contributes less to environmental deterioration than developed economies, the former suffers the highest environmental impacts because of poor living conditions, infrastructure deficiencies and poor disaster management control. Financial assistance coupled with technological subsidies should be enhanced — to adapt to the changing climatic conditions. Developing infrastructure and equipping them with better disaster management systems will help African economies that depend largely on agriculture. Special attention should be given to the adoption of modern energy technologies, like renewable energy, in order to reduce the over-dependence on fossil fuel for agricultural purposes which contributes to the rising levels of atmospheric CO_2 emissions.

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Conflicts of Interest

The authors declare no conflict of interest.

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Appendix

Table A1 Westurlund cointegration test

Westurlund[a]	**Statistic**	**p-value**
Variance ratio	2.9511	0.0016

Notes: (Model: $lnCO_2$ ~ (lnFOS, lnREN, lnAVA, lnTRD)).
[a] H_o: No cointegration vrs H_a: Some panels are cointegrated.

Table A2 Cross-sectional dependence test

Variable	**CD-test**	**p-value**	**average joint T**	**mean ρ**	**mean abs(ρ)**
Aggregate model					
$lnCO_2$	20.9880	0.0000*	24.0000	0.4500	0.6700
res	0.4850	0.6280	24.0000	0.0100	0.4400
Disaggregate model					
$lnCO_2$	20.9880	0.0000*	24.0000	0.4500	0.6700
res	7.9740	0.0000*	24.0000	0.1700	0.3900

Notes: (Aggregate Model: $lnCO_2$ ~ (lnENG, lnAVA, lnTRD)); (Disaggregate Model: $lnCO_2$ ~ (lnFOS, lnREN, lnAVA, lnTRD)); * denotes the rejection of the null hypothesis of cross-section independence, CD ~ N(0,1). P-values close to zero indicate data are correlated across panel groups.

Table A3 Country-specific fixed effect estimation results

$\mathbf{lnCO_2}$	**Coef.**	**Std. err.**	**t**	**P > t**
Aggregate model				
lnENG	0.9974	0.1425	7.0000	0.0000*
lnAVA	−0.4060	0.0784	5.1800	0.0000*
lnTRD	0.3997	0.0732	5.4600	0.0000*
_cons	−4.0177	1.0280	3.9100	0.0000*
sigma_u	1.16915		F(3,319)	54.81
sigma_e	0.28914		Prob>F	0.0000*
rho	0.94236		R-sq	0.5313
Disaggregate model				
lnFOS	0.8075	0.0538	15.0200	0.0000*
lnREN	−0.3621	0.0926	−3.9100	0.0000*
lnAVA	−0.4916	0.0597	−8.2400	0.0000*
lnTRD	0.1643	0.0576	2.8500	0.0050*
_cons	2.0768	0.4960	4.1900	0.0000*
sigma_u	0.9817		F(4,318)	128.89
sigma_e	0.2202		Prob>F	0.0000
rho	0.9521		R-sq	0.6614

Notes: (Aggregate Model: $lnCO_2$ ~ (lnENG, lnAVA, lnTRD)); (Disaggregate Model: $lnCO_2$ ~ (lnFOS, lnREN, lnAVA, lnTRD)); * denotes the rejection of the null hypothesis at 1% significance level.

Table A4 Quantile slope equality test

Test summary		χ^2 statistic	χ^2 d.f.	Prob.
Wald test		438.4129	12	0.0000
Restriction detail: b(tau_h) - b(tau_k) = 0				
Quantiles	Variable	Restr. value	Std. error	Prob.
0.25, 0.5	LNFOS	−0.0661	0.0524	0.2076
	LNREN	−0.1808	0.0309	0.0000
	LNTRD	0.3530	0.0986	0.0003
	LNAVA	0.5586	0.1239	0.0000
0.5, 0.75	LNFOS	−0.1473	0.0669	0.0277
	LNREN	−0.1621	0.0435	0.0002
	LNTRD	0.1258	0.1747	0.4714
	LNAVA	0.3681	0.1435	0.0103
0.75, 0.95	LNFOS	−0.8598	0.2034	0.0000
	LNREN	−0.3762	0.0641	0.0000
	LNTRD	−0.4866	0.3122	0.1190
	LNAVA	−1.0694	0.1208	0.0000

Notes: (Model: $\ln CO_2$ ~ (lnFOS, lnREN, lnAVA, lnTRD)). Test statistic compares all coefficients.

Table A5 Symmetric quantiles test

Test summary		χ^2 statistic	χ^2 d.f.	Prob.
Wald test		245.3661	10	0.0000
Restriction detail: b(tau) + b(1-tau) - 2*b(0.5) = 0				
Quantiles	Variable	Restr. value	Std. error	Prob.
0.05, 0.95	LNFOS	0.9551	0.2264	0.0000
	LNREN	0.4065	0.0915	0.0000
	LNTRD	0.5006	0.3547	0.1581
	LNAVA	1.1133	0.3044	0.0003
	C	−8.6250	1.9360	0.0000
0.25, 0.75	LNFOS	0.0813	0.0969	0.4014
	LNREN	−0.0187	0.0631	0.7671
	LNTRD	0.2272	0.2219	0.3058
	LNAVA	0.1905	0.2577	0.4599
	C	−1.6220	1.4273	0.2558

Notes: (Model: $\ln CO_2$ ~ (lnFOS, lnREN, lnAVA, lnTRD)). Test statistic compares all coefficients.