Acta Universitatis Danubius
ŒCONOMICA

Does Adulthood Obesity Promote Greenhouse Gas Emissions in Africa? Evidence from Panel Corrected Standard Error Models

Abayomi Samuel Oyekale[1]

Abstract: Obesity is one of the major public health epidemics that the world currently faces. The environmental implication of obesity is reflected in its impacts on greenhouse gas (GHG) emissions due to increased pressure on food production system, oxidative metabolism, and combustion of fossil fuels during transportation. However, few studies exist on the linkage between GHG emissions and obesity. This seeks to fill this gap by analyzing the effect obesity total GHG emission, carbon dioxides emissions, per capita carbon emissions, and emissions of carbon dioxide from liquid fuel. The data were from 45 African countries for the period 1990-2016. The data were analyzed with panel corrected standard error (PCSE) after positive feedbacks from cross-section dependence, and cointegration tests. The results showed that obesity, urban population, and GDP per capita were generally positively related to GHG emissions, while renewable energy, livestock production index and utilization had negative association. It was recommended that initiatives to reduce obesity promise some environmental benefits. Also, there is the need to promote renewable energy utilization and facilitate sustainable agricultural production, to reduce environmental damages.

Keywords: Obesity; Public Health; Greenhouse Gas Emission; Panel; Panel Corrected Standard Error Model; Africa

Jel Classification: Q5; Q53; Q54; Q56; Q57

[1] Department of Agricultural Economics and Extension, North-West University Mafikeng Campus, South Africa, Address: Mmabatho 2735, South Africa, Corresponding author: asoyekale@gmail.com.

1. Introduction

When Eunice Newton Foot in 1856 agitated on the implications of atmospheric carbon dioxide accumulation on global warming, many scholars may not have comprehended the depth of her environmental concerns (Koch et al.; 2021). Her mystic environmental impulse is now a global concern because the past few decades have witnessed environmental challenges that are associated with emission of greenhouse gases (GHGs) (Koch et al.; 2021). Specifically, the atmospheric reactions involving water vapours, carbon dioxide (CO_2), nitrous oxide (N_2O), methane (CH_4), ozone (O_3), and fluorinated gases are promoting a pervasive disequilibrium in some environmental parameters (United States Environmental Protection Agency, undated). Therefore, emission of GHG has been directly implicated in the current struggle against climate change, with such changes being witnessed in many climatic parameters. Climatologists have highlighted that the major contributors are carbon dioxide (77%), methane (14%), nitrous oxide (8%), and ozone (1%) (Koengkan & Fuinhas 2021a, 2021b). Moreover, the notion of environmental sustainability that had been highlighted in the Sustainable Development Goals (SDGs) is being sidelined by reluctancy of some countries to comply with the GHG emission reduction appeals as previously specified in the Kyoto Protocol (United Nations, 2023).

Besides the economic impacts of GHG emissions, their health consequences are likewise subjects of objective concern to policy makers and other stakeholders in the health sector. Specifically, while depletion of ozone layer has been traced to health problems like skin cancer, cataract, and melanoma, other manifestations of climate change such as drought can promote diarrhoea, while air pollution can enhance lung cancer, bronchitis, brain tumours and asthma (Paisley, 2023). In addition, the different manifestations of climate change can promote sedentary and food consumption lifestyles that can promote obesity, which is one of the major public health concerns the world currently faces. The trajectory of obesity epidemic assumed a different dimension since 1990, with pathetic doubling of adult obesity and stupendous quadrupling of adolescent obesity in 2022 (World Health Organization, 2024; Swinburn et al, 2019).

Available data have shown that in 2022, 12.5% of the global population was obese, with 890 million of adult population being obese and 2.5 billion were overweight. In 2022, the 75th World Health Assembly presented an accelerated plan to stop obesity among member states due to the growing economic impacts of the epidemic and the fundamental projection that about one billion adults will be obese by 2030 (World Health Organization, 2023). Moreover, international health policy makers are particularly worried because of the direct association between excessive body mass index (BMI) and concurrent incidences of some cardiovascular and non-communicable diseases (Akil & Ahmad, 2011). Therefore, obesity poses significant threat to the prescriptive mandates of target 3.4 in the Sustainable Development Goals (SDGs), which seeks to ensure a one-third reduction in global premature mortality (World Health Organization, 2023).

The relationships between obesity and environmental pollution have been largely understudied in the literature. Recently, however, some scholars have shown interest in understanding the nature of association between obesity and greenhouse gas emissions. Specifically, a school of thought emphasized the likelihood of obesity promoting climate change through increased emission of GHG. It was argued that obesity accounts for about 1.6% of global GHG emissions, contributing an equivalent of 700 megatons of carbon dioxide per year through the channels of increased metabolism, fossil fuel combustion and increased demand on food production (Magkos et al.; 2020). Moreover, the argument for higher emissions by obese people due to excessive oxidative metabolism is embedded in the physiological compositions and total energy expenditures. Therefore, it had been estimated that obese individuals may produce about 20% more carbon emissions than people with normal weight due to a higher oxidative metabolism, energy requirement, and higher combustion of fossil fuels during transportation (Magkos et al.; 2019). It had also been reported that compared to people with normal BMI with energy expenditure of 8,439kj/day, obese people will averagely expend 10,043 kJ/day (Ravussin, 1982).

Moreover, a projection by El-Khoury (1994) indicated that suppose obese individuals expend 30% more energy per day, in a year, they would have released an extra 81kg/y of carbon dioxide equivalent (El-Khoury, 1994). In addition, because metabolic energy requirement is directly related to body weight, obese individuals will require more energy than those with normal weight. This has significant implications for food production and associated GHG emissions from different input utilization and land use patterns (Walpole, 2012). Similarly, during transportation, fossil fuel utilization and associated emissions will be higher for obese individuals (Steinegger, 2019).

Michaelowa and Dransfeld (2008) submitted that emission of CO_2 by OECD countries could reduce by more than 10 million tonnes if average weight reduces by 5kg. Moreover, it was noted that in these countries, between 1990 and 2005, although a reduction in beef intake resulted in emission savings of about 20 million tonnes CO_2 equivalent, production of unhealthy foodstuffs that promote obesity increased emissions by more than 400 million tonnes. Although obesity is noted as a significant contributor to emission of GHGs, very scanty empirical evidences are available in the literature. This scenario reflects data paucity, especially those that are related to obesity. This study is therefore bridging an important gap in health/environmental literature by using panel data from highly representative samples of African countries to determine the effect of obesity on emission of GHGs. The estimation procedures are going to product robust estimators that can be reliably used for policy formulation.

2. Review of Literature

Empirical literature on the linkage between obesity and emission of GHGs is very scanty. However, there have been some classic reviews and conceptual framework propositions, many of which were not supported by empirical evidence due to data limitations. For instance, An et al. (2018) explored the relationships between obesity and carbon emissions, and a conceptual framework was proposed that linked obesity to GHG emissions along with other variables like urbanization, transportation, land use, and agricultural productivity. In their study, Swinburn et al. (2019) highlighted the association between carbon emission intensity and incidences of female obesity in South Asia and developed English-speaking countries. It was noted that South Asia has a carbon footprint of 2.2 and 5% incidence of female obesity, which can be compared to those developed Anglophone countries with 33% female obesity and a carbon footprint of 18.5.

In a review by Dietz and Pryor (2022), the relationships between obesity, undernutrition and climate change were discussed with focus on the USA. It was noted that the transportation system contributes to GHGs through fossil fuel combustion, and the emitted pollutant promotes obesity and other health problems. The use of fossil fuels for transportation systems also increases GHGs, rates of obesity, and ill health (Frank et al.; 2004). Myers et al. (2017) provided a conceptual linkage between obesity and GHG emissions. Webb and Egger (2014) submitted that obesity and climate change constitute global are dilemmas which affect each other. It was emphasized that some obesity risk factors are also associated with emission of GHGs. Therefore, interventions to prevent environmental degradation will have some positive impacts on human health.

Koch et al. (2021) further provided a comprehensive conceptual framework showing the bidirectional relationships between climate change/GHG emission and obesity. It was indicated that climate change is promoted by fossil fuel usage, agricultural production, population growth, excessive consumption, and transportation. However, emission of GHGs contributes to obesity through air pollution that leads to endocrine dysregulation, elevated temperature that affects production of healthy food like fruits and vegetables, droughts and floods that reduce households' income, and elevated temperature that promotes sedentary lifestyle. The framework reveals that obesity, which is also promoted by other factors like race, metabolic syndrome, genetic composition, and sedentary lifestyles will eventually promote climate change through increased emission of GHGs.

Some studies have developed some integrated models that evaluated the impacts of agricultural systems, dietary requirements, and emission of GHGs (Willett et al.; 2019). Others have evaluated the carbon emission offsets of some dietary changes (Tilman and Clark, 2014; Springmann et al.; 2018). However, these authors failed to explore the health impacts of agricultural GHG emissions, which was the gap that was filled by Malley et al. (2021). Toti et al. (2019) also submitted that a significant environmental cost is associated with obesity. It was noted that excessive food intake that often leads to obesity places unnecessary pressure on the ecosystems from which food is produced, thereby promoting environmental degradation through agricultural intensification. Specifically, their analyses revealed that ecological footprints of metabolic food wastes were highest in European Union and North America and Oceania, with associated impacts being about fourteen times than what obtains in the SSA.

Some few studies have empirically analyzed the effect of obesity on GHG emissions. Koengkan and Fuinhas (2021a) analyzed the effect of overweight on energy consumption in some European countries using the quantile via moment's regression. The results showed that overweight increased energy consumption and emission of carbon dioxide. Zheutlin et al. (2014) analysed the bilateral effects of carbon dioxide emissions on obesity using county-level dataset for the USA. The results showed a significant positive marginal relationship between emissions of carbon dioxide and changes in the prevalence of obesity. Trentinaglia et al. (2021) explored the relationship between climate change and obesity using data covering adults and children in 134 countries, over 39 years. The results showed that as the BMI of children and women increased by 2% and 4%, respectively, average temperature increases by 1 degree centigrade.

The effects of some other economic variables on emission of GHGs had been studied in the literature. Several authors have explored the effect of economic development which had been proxied by GDP or per capita GDP. The assumption is that in absence of environmental benign technological innovations in every sector of the economy, economic growth will be accompanied by more emissions. However, some of these studies found the presence of Environmental Kuznet Curve (EKC) indicating the existence of an inverted-U relationship between environmental degradation and economic growth (Ansuategi & Escapa, 2002; Li et al.; 2016; Selden and Song, 1994; Roberts & Grimes, 1997; Albu, 2007; Ma et al.; 2009; Chuai et al.; 2012; Dong, 2014).

Some studies have found population to have different impacts on GHG emissions. Some reported that population reduced GHG emissions (Shah et al.; 2022;) while other found positive relationship (Adams et al.; 2017). Other studies integrated other attributes of population such as the distribution, quality, and age structure (Yu et al.; 2023; Zhou et al.; 2023; Fan et al.; 2021; Yang et al.; 2020; Zhang and Tan, 2016;

Yang et al.; 2015). Similarly, the degree of urbanization had been explored as a determinant of GHG emissions by some authors. Specifically, Sun and Huang (2020) found the existence of EKC between carbon emission efficiency and urbanization. Also, Li et al. (2019) concluded that carbon emission was promoted by urban population expansion.

The effect of foreign direct investment (FDI) on GHG emissions had been explored in the literature with mixed results. Specifically, foreign-invested companies leverage on horizontal (within industry) and vertical (between industries) opportunities for increased productivity (Anwar and Sun, 2014; Hale and Long, 2011). A study by Zhou et al.; 2018) found positive relationship between Chinese FDI and GHG emissions. Other studies with similar findings are Huang et al. (2022) and Wang et al. (2021). Some other authors have established the contributions of energy intensity (Lin and Raza, 2019; Adeleye et al. (2021a)), coal rent (Gyamfi et al.; 2021), financial development (Acheampong, 2019; Ali et al.; 2019; Omri et al.; 2019), globalization or trade openness (Ali et al.; 2019; Omri et al.; 2019), and renewable energy utilization (Nguyen and Kakinaka, 2019; Adeleye et al.; 2021a). In summary although several studies have been conducted on the determinants of GHG emissions, the role of obesity has not been fully explored. This study seeks to fill this gap in the literature by using the panel corrected standard error approach to determine the effect of obesity on GHG emission using data from 45 African countries.

3. Materials and Methods

3.1. The Data

This data used the data that were obtained from two secondary sources. The full descriptions of the data variables, their expected signs and sources are in Table 1. The dataset covered forty-five (45) countries, and they are Algeria, Angola, Benin, Botswana, Burkina Faso, Burundi, Cabo Verde, Cameroon, Central African Republic, Chad, Comoros, Congo, Côte d'Ivoire, Democratic Republic of Congo, Equatorial Guinea, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, São Tomé and Príncipe, Senegal, Seychelles, Sierra Leone, South Africa, Tanzania, Togo, Uganda, Zambia and Zimbabwe. Although obesity variable covered the period 1975-2020 (with gaps in 2017, 2018 and 2019), most of the variables from World Development Independent were available from 1990 upward. Therefore, the study covered the 1990 and 2016 periods.

Table 1. Selected Variables for the Analysis and their Sources

Variable	Expected Sign	Source
Dependent variables		
Total emission of GHG (kt of CO2 equivalent)	-	World Bank (2024)
Carbon dioxide emissions (kt)	-	World Bank (2024)
Per capita CO2 (metric ton per capita)	-	World Bank (2024)
CO2 emissions from liquid fuel consumption (kt)	-	World Bank (2024)
Independent variables		
Urban population	Positive	World Bank (2024)
Obesity in 18 years and above population (%)	Positive	iAHO and WHO (2024)
Renewable energy consumption (%)	Negative	World Bank (2024)
Per Capita GDP (current US $)	Positive	World Bank (2024)
Crop production index (2014-2016 = 100)	Positive	World Bank (2024)
Livestock production index (2014-2016 = 100)	Positive	World Bank (2024)

3.2. Empirical Models

Four separate models were estimated in this study. The study proposed a model of carbon dioxide emissions with focus on six independent variables. The models are stated as:

$$logTCO_{2it} = \alpha_0 + \alpha_1 logUP_{it} + \alpha_2 logGDP_{it} + \alpha_3 OBS_{it} + \alpha_4 CPI_{it} + \alpha_5 REN_{it} + \alpha_6 LPI_{it} + u_{it}.. \quad (1)$$

$$logCO_{2it} = \beta_0 + \beta_1 logUP_{it} + \beta_2 logGDP_{it} + \beta_3 OBS_{it} + \beta_4 CPI_{it} + \beta_5 REN_{it} + \beta_6 LPI_{it} + v_{it}.. \quad (2)$$

$$logPCO_{2it} = \pi_0 + \pi_1 logUP_{it} + \pi_2 logGDP_{it} + \pi_3 OBS_{it} + \pi_4 CPI_{it} + \pi_5 REN_{it} + \pi_6 LPI_{it} + k_{it}.. \quad (3)$$

$$logFCO_{2it} = \rho_0 + \rho_1 logUP_{it} + \rho_2 logGDP_{it} + \rho_3 OBS_{it} + \rho_4 CPI_{it} + \rho_5 REN_{it} + \rho_6 LPI_{it} + l_{it}.. \quad (4)$$

In equations 1-4, the $logTCO_2$is the log of total GHG emissions (CO_2 equivalent), $logCO_2$is the log of carbon dioxide emissions, $logPCO_2$ is the log of per capita carbon dioxide emission and $logFCO_2$is the log of emission of carbon dioxide from consumption of liquid fuels, $logUP$ is the log of urban population, $logGDP$is the log of per capita GDP, OBS is obesity (%), REN is the proportion of renewable energy in total energy consumption (%), CPI is the crop production index and LPI is the livestock production index.

3.3. Test for Multicollinearity

The need to examine the independent variables for multicollinearity compelled the use of variance inflation factor after an ordinary regression was conducted on the proposed model. A value greater than 4 normally raises a susception, while 10 and above indicates presence of significant multicollinearity (CFI, undated).

3.4. Cross-Section Dependence Test

Before the analyses were conducted, some tests were carried out to ensure proper guidance on the appropriateness of selected econometric model. The presence of cross-section dependence (CD) in panel data compromises estimation efficiency in dynamic panel estimators (Phillips & Sul, 2003). To avoid inconsistent estimators, CD test is to be carried out when the number of cross section (N) is greater than the data period (T) (De Hoyos and Sarafidis, 2006). This test is based on the propositions by Pesaran (2004 and 2007), and the test will be valid for balanced or unbalanced panels. Also, the command xtcdf was implemented in this study. The CD is expressed as:

$$CD = \sqrt{\frac{2T}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}} \qquad 5$$

Where $\hat{\rho}_{ij}$ is the residual's pairwise correlation coefficient.

3.5. Unit Root and Cointegration Tests

The presence of cross-sectional dependence in the selected variables compelled the conduct of unit root test using second generation approach. This study used the cross-sectional augmented Im, Pesaran, and Shin (CIPS) unit root test due to its second-generation nature (Pesaran, 2007). The expression of the test is specified as:

$$CIPS(N,T) = \bar{T} = N^{-1} \sum_{i=1}^{N} t_i(N,T) \qquad 6$$

In equation 2, t_i denotes the t-statistics of the cross-sectional estimation of the Augmented Dicky Fuller (ADF) regression. The null hypothesis for this test specifies that "all panels contain unit roots". The model was also tested for the presence of long-run equilibrium using the second-generation panel cointegration approach of Westlund (2007).

4. Results and Discussion

Table 2 shows the descriptive statistics for the data. The results revealed that in some of the variables, observations were missing. Average log of total emission was 4.04, and the log of CO_2 was 3.29. Average log per capita GDP was -0.51. The average obesity was 6.45%, the lowest was 1.10% and the highest was 28.30%.

Table 2. Descriptive Statistics of the Selected Variables

Variables		Mean	Std.	Min	Max	Observations
Log total emission of GHG	Overall	4.04	0.76	1.77	5.74	N = 1215
	Between		0.75	1.96	5.63	n = 45
	Within		0.13	2.52	4.41	T = 27
Log carbon dioxide emissions	Overall	3.29	0.76	1.65	5.65	N = 1212
	Between		0.74	1.84	5.53	n = 45
	Within		0.19	1.75	3.88	T-bar = 26.93
Log per capita CO_2	Overall	-0.51	0.61	-1.66	0.93	N = 1212
	Between		0.60	-1.48	0.85	n = 45
	Within		0.13	-1.82	-0.09	T-bar = 26.93
Log CO_2 emissions from liquid fuel consumption	Overall	3.12	0.63	1.68	4.89	N = 1209
	Between		0.61	1.84	4.63	n = 45
	Within		0.19	2.16	4.01	T-bar = 26.87
Log urban population	Overall	6.33	0.66	4.53	7.96	N = 1215
	Between		0.65	4.63	7.70	n = 45
	Within		0.14	5.86	6.70	T = 27
Obesity	Overall	6.45	4.52	1.10	28.30	N = 1215
	Between		4.03	2.46	21.38	n = 45
	Within		2.12	-0.51	14.49	T = 27
Renewable energy	Overall	1.72	0.48	-1.22	1.99	N = 1212
	Between		0.47	-0.53	1.98	n = 45
	Within		0.11	0.99	2.35	T-bar = 26.93
Log per capita GDP	Overall	2.90	0.48	2.00	4.30	N = 1185
	Between		0.42	2.25	3.98	n = 45
	Within		0.23	1.76	3.78	T-bar = 26.33
Crop production index	Overall	75.59	27.26	0.00	171.71	N = 1215
	Between		17.89	48.81	118.01	n = 45
	Within		20.74	-7.26	145.46	T = 27
Livestock production index	Overall	77.52	25.64	0.00	214.89	N = 1215
	Between		17.04	41.19	140.37	n = 45
	Within		19.33	3.10	152.04	T = 27

4.1. Multicollinearity Test

The variance inflation factor (VIF) was used to test for multicollinearity among the independent variables. The results of the analysis in Table 3 revealed that the overall VIF was 1.70, indicating that multicollinearity was not a problem in the model.

Table 3. Variance Inflation Factor of the Selected Variables

Variables	VIF	1/VIF
Obesity	2.45	0.41
Renewable energy consumption	1.89	0.53
Crop production index	1.62	0.62
Livestock production index	1.58	0.63
Per capita GDP	1.40	0.72
Urban population	1.27	0.79
Mean	1.70	

4.2. Preliminary Estimations

Following Adeleye et al. (2023), the variables were examined for existence of cross-section dependence. The results of the test are presented in Table 4. These results vividly rejected the null hypothesis of cross-section independence at 1 percent level of statistical significance. This implies the presence of cross-section dependence, and it necessitates crucial examination of the variables for stationarity and cointegration.

Table 4. Test for Cross-Section Dependence

Variable	CD-test	p-value	Decision
Total emission of GHG	103.953	0.000	Cross-section dependent
Carbon dioxide emissions	106.158	0.000	Cross-section dependent
Per capita CO_2 emissions	33.574	0.000	Cross-section dependent
CO2 emissions from liquid fuel	100.591	0.000	Cross-section dependent
Urban population	160.587	0.000	Cross-section dependent
Obesity	162.807	0.000	Cross-section dependent
Renewable energy consumption (%)	54.085	0.000	Cross-section dependent
Livestock production index	99.48	0.000	Cross-section dependent
Crop production index	90.741	0.000	Cross-section dependent
Per Capita GDP (current US $)	127.506	0.000	Cross-section dependent

4.3. Unit Root and Cointegration Tests

The results of the test for variable stationarity are presented in Table 5. The Table shows that the logs of all the included dependent variables were stationary at level [I(0)]. Among the independent variables, only urban population and obesity were not stationary at level. However, these variables showed stationarity at the first difference. In addition, the cointegration test result using the Westerlund approach was statistically significant ($p<0.01$).

Table 5. Test for Unit Root and Cointegration

Variable	Level data	First difference	Decision
	z-t-tilde-bar		
Total emission of GHG	-7.38***	-	I(0)
Carbon dioxide emissions	-5.47***	-	I(0)
Per capita CO_2 emissions	-5.59***	-	I(0)
CO_2 emissions from liquid fuel	-5.61***	-	I(0)
Urban population	-0.90	-5.32***	I(1)
Obesity	11.27	-22.72***	I(1)
Renewable energy consumption (%)	-4.38***	-	I(0)
Livestock production index	-4.82***	-	I(0)
Crop production index	-7.70***	-	I(0)
Per Capita GDP (current US $)	-4.59***	-	I(0)
Westerlund Cointegration Test			
Variance ratio	-3.69***		Cointegration exists

4.4. Results of the Panel Corrected Standard Error (PCSE) Models

Tables 6, 7, 8 and 9 present the results of PCSE models with total GHG emissions, total carbon dioxide emissions, per capita carbon dioxide emissions and carbon dioxide emissions from the use of liquid fuels respectively as the dependent variables. For each of the dependent variables, nine separate models were estimated based on different assumptions on the error structure and the form of autocorrelation. The results in columns 1-3 assumed heteroscedastic and panel correlation, those in columns 4-6 assumed heteroscedasticity, and those in columns 7-9 assumed panel independence. Similarly, for each of these assumptions, three assumptions about the form of autocorrelation were made. These were no autocorrelation, AR (1) and Panel AR(1). The results showed that across all the assumed error structures, the results with no autocorrelation were the best going by the statistical significance of the explanatory variables. This is in accordance with the findings of Adeleye et al. (2023). It should also be noted that all the estimated models showed statistical significance ($p<0.01$).

The results in Table 6 revealed that across the estimated models, obesity showed positive and significant impacts on total GHG emissions in the models with no form of heteroscedasticity. However, in the other results in Tables 7, 8 and 9, obesity parameters showed positive and statistical parameters. In Table 7, at the worst scenario and taking other variables constant, a 1 percent increase in obesity will lead to 0.0471% increase in carbon dioxide emissions. Similarly, for Table 8, a 1 percent increase in obesity will lead to 0.063 percent increase in per capita carbon dioxide emissions. These results are consistent with those of Koengkan and Fuinhas (2021b), Zheutlin et al. (2014), Swinburn et al. (2019), Trentinaglia et al. (2021) and Squalli (2014). The main channels through which obesity contributes to emission of GHGs have been highlighted in literature with emphases on increased emissions from fossil fuels through transportation, increase agricultural production and increase in oxidative metabolism (An et al. 2018; Dietz and Pryor, 2022; Frank et al.; 2004; Koch et al.; 2021).

Table 6. Panel Corrected Standard Error Model for Total Greenhouse Gas Emissions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Form of Autocorrelation	None	AR(1)	Panel AR (1)	None	AR(1)	Panel AR (1)	None	AR(1)	Panel AR (1)
Error Structure	Heteroscedastic and Panel Correlation			Heteroscedastic			Panel Independence		
Obesity	0.014***	-0.007*	-0.0008	0.0141***	-0.007	-0.0008	0.014***	-0.007**	-0.0008
	-7.522	(-1.738)	(-0.163)	-4.815	(-1.561)	(-0.177)	-4.511	(-1.992)	(-0.276)
Urban Population	1.004***	1.000***	0.856***	1.004***	1.000***	0.856***	1.004***	1.000***	0.856***
	-270.4	-42.03	-25.35	-63.7	-34.09	-20.5	-64.63	-35.43	-32.01
Renew. energy	-0.120***	-0.182***	-0.190***	-0.120***	-0.182***	-0.190**	-0.120***	-0.182***	-0.190***
	(-8.117)	(-6.802)	(-6.104)	(-4.899)	(-3.270)	(-2.296)	(-4.589)	(-5.702)	(-5.372)
. Livestock product	0.001***	0.000175	0.000167	0.00101**	0.00018	0.000167	0.00101**	0.000175	0.000167
	-3.419	-0.78	-0.773	-2.501	-0.803	-0.817	-2.237	-0.894	-0.922
Crop production	-0.003***	3.89E-05	4.50E-06	-0.003***	3.89E-05	4.50E-06	-0.003***	3.89E-05	4.50E-06
	(-8.088)	-0.346	-0.0399	(-6.642)	-0.336	-0.0429	(-6.039)	-0.294	-0.037
Per capita GDP	-0.0549***	-0.00063	0.0145	-0.0549**	-0.00063	0.0145	-0.0549**	-0.00063	0.0145

	(-4.141)	(-0.0438)	-0.929	(-2.214)	(-0.0286)	-0.673	(-2.435)	(-0.0344)	-0.862
Constant	-1.912***	-1.939***	-0.934***	-1.912***	-1.939***	-0.934***	-1.912***	-1.939***	-0.934***
	(-46.93)	(-14.07)	(-4.662)	(-17.00)	(-9.903)	(-3.206)	(-14.61)	(-10.38)	(-5.070)
Observations	1,184	1,184	1,184	1,184	1,184	1,184	1,184	1,184	1,184
R-squared	0.829	0.94	0.978	0.829	0.94	0.978	0.829	0.94	0.978
Number of panel	45	45	45	45	45	45	45	45	45
Rho	-	0.95506	.		0.95506	.	.	0.95506	.
Chi2	339972.44.	2532.1	1251.93	6134.45	1375.95	520.68	5744.29	1396.37	1087.37
Ch2p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7. Panel Corrected Standard Error Model for Carbon Dioxide Emissions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Form of Autocorrelation	None	AR(1)	Panel AR (1)	None	AR(1)	Panel AR (1)	None	AR(1)	Panel AR (1)
Error Structure	Heteroscedastic and Panel Correlation			Heteroscedastic			Panel Independence		
Obesity	0.0471***	0.0272***	0.0347***	0.0471***	0.0272***	0.0347***	0.0471***	0.0272***	0.0347***
	(23.54)	(7.747)	(10.22)	(10.81)	(5.087)	(6.756)	(13.97)	(6.124)	(8.223)
Urban Population	0.882***	0.869***	0.811***	0.882***	0.869***	0.811***	0.882***	0.869***	0.811***
	(117.2)	(57.50)	(28.96)	(44.61)	(27.26)	(20.53)	(52.71)	(28.55)	(24.45)

Ren energy	-0.279***	-0.401***	-0.488***	-0.279***	-0.401***	-0.488***	-0.279***	-0.401***	-0.488***
	(-17.56)	(-11.60)	(-10.16)	(-7.319)	(-6.059)	(-4.568)	(-9.932)	(-10.40)	(-10.32)
Livestock product	-0.0009***	-0.0002	-8.09e-05	-0.0009*	-0.0002	-8.09e-05	-0.0009*	-0.0002	-8.09e-05
	(-3.046)	(-0.909)	(-0.492)	(-1.935)	(-0.616)	(-0.345)	(-1.876)	(-0.584)	(-0.337)
Crop production	-0.0001	0.0002*	0.0002*	-0.0001	0.0002	0.0002	-0.0001	0.0002	0.0002
	(-0.232)	(1.687)	(1.814)	(-0.251)	(1.358)	(1.521)	(-0.235)	(1.139)	(1.215)
Per capita GDP	0.163***	0.0572***	0.0460**	0.163***	0.0572*	0.0460	0.163***	0.0572**	0.0460**
	(8.077)	(2.948)	(2.296)	(4.640)	(1.852)	(1.548)	(6.702)	(2.414)	(2.013)
Constant	-2.507***	-1.871***	-1.322***	-2.507***	-1.871***	-1.322***	-2.507***	-1.871***	-1.322***
	(-19.27)	(-13.19)	(-7.047)	(-15.79)	(-8.487)	(-4.911)	(-17.80)	(-8.984)	(-5.938)
Observations	1,184	1,184	1,184	1,184	1,184	1,184	1,184	1,184	1,184
R-squared	0.803	0.879	0.961	0.803	0.879	0.961	0.803	0.879	0.961
Number of panel	45	45	45	45	45	45	45	45	45
F	.	.	.	.	.	.	.	.	.
Chi2	199853.57	3761.88	1639.52	3200.56	1075.84	911.44	4839.54	1320.11	1143.61
Ch2p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

z-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8. Panel Corrected Standard Error Model for Per Capita Carbon Dioxide Emissions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Form of Autocorrelation	None	AR(1)	Panel AR (1)	None	AR(1)	Panel AR (1)	None	AR(1)	Panel AR (1)
Error Structure	Heteroscedastic and Panel Correlation			Heteroscedastic			Panel Independence		
Obesity	0.063***	0.044***	0.054***	0.063***	0.044***	0.054***	0.063***	0.044***	0.054***
	(28.46)	(11.06)	(14.75)	(12.69)	(7.723)	(10.41)	(16.96)	(9.013)	(12.30)
Urban Population	-0.102***	-0.119***	-0.198***	-0.102***	-0.119***	-0.198***	-0.102***	-0.119***	-0.198***
	(-9.563)	(-6.362)	(-6.260)	(-4.948)	(-3.201)	(-4.132)	(-5.551)	(-3.302)	(-5.024)
Ren energy	-0.293***	-0.437***	-0.500***	-0.293***	-0.437***	-0.500***	-0.293***	-0.437***	-0.500***
	(-15.44)	(-10.98)	(-10.25)	(-6.524)	(-5.688)	(-4.694)	(-9.543)	(-10.51)	(-10.33)
Livestock product	0.0002	1.96e-05	-6.86e-05	0.0002	1.96e-05	-6.86e-05	0.000281	1.96e-05	-6.86e-05
	(0.674)	(0.117)	(-0.402)	(0.533)	(0.0804)	(-0.283)	(0.528)	(0.0755)	(-0.277)
Crop production	-0.001***	0.0002*	0.0002**	-0.001***	0.0002	0.0002*	-0.001**	0.0002	0.0002
	(-2.592)	(1.703)	(2.062)	(-2.644)	(1.451)	(1.857)	(-2.412)	(1.122)	(1.420)
Per capita GDP	0.370***	0.084***	0.071***	0.370***	0.0843***	0.0713**	0.370***	0.0843***	0.0713***
	(16.86)	(4.207)	(3.737)	(8.924)	(2.684)	(2.353)	(13.92)	(3.484)	(3.023)
Constant	-0.771***	0.435***	1.085***	-0.771***	0.435*	1.085***	-0.771***	0.435*	1.085***

	(-4.313)	(2.659)	(5.114)	(-4.277)	(1.730)	(3.539)	(-5.005)	(1.815)	(4.137)
Observations	1,184	1,184	1,184	1,184	1,184	1,184	1,184	1,184	1,184
R-squared	0.642	0.381	0.500	0.642	0.381	0.500	0.642	0.381	0.500
Number of panel	45	45	45	45	45	45	45	45	45
Chi2	10692.98	623.94	812.02	1695.48	395.87	462.86	2125.69	395.87	508.33
Ch2p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9. Panel Corrected Standard Error Model for Emissions from Liquid Fuel Usage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Form of Autocorrelation	None	AR(1)	Panel AR (1)	None	AR(1)	Panel AR (1)	None	AR(1)	Panel AR (1)
Error Structure	Heteroscedastic and Panel Correlation			Heteroscedastic			Panel Independence		
Obesity	0.014***	0.020***	0.016***	0.014***	0.020***	0.016***	0.014***	0.020***	0.016***
	(9.763)	(3.283)	(3.240)	(5.471)	(3.447)	(3.234)	(5.584)	(4.370)	(4.560)
Urban Population	0.840***	0.805***	0.904***	0.840***	0.805***	0.904***	0.840***	0.805***	0.904***
	(130.4)	(29.32)	(19.64)	(58.04)	(26.19)	(21.05)	(68.13)	(29.15)	(40.22)
Ren energy	-0.348***	-0.250***	-0.304***	-0.348***	-0.250***	-0.304***	-0.348***	-0.250***	-0.304***
	(-25.73)	(-3.663)	(-2.828)	(-11.83)	(-4.296)	(-3.628)	(-16.84)	(-6.184)	(-7.669)
Livestock product	-0.0003	-0.0004	-0.0003	-0.0003	-0.0004	-0.0003	-0.0003	-0.0004	-0.0003

	(-1.066)	(-1.222)	(-0.876)	(-0.796)	(-1.271)	(-0.928)	(-0.940)	(-1.187)	(-0.964)
Crop production	0.0007**	0.0003*	0.0003*	0.0007**	0.0003*	0.0003*	0.0007**	0.0003	0.0003
	(2.242)	(1.862)	(1.922)	(2.045)	(1.788)	(1.773)	(2.078)	(1.489)	(1.574)
Per capita GDP	0.163***	0.098**	0.095**	0.163***	0.098***	0.095***	0.163***	0.098***	0.095***
	(13.35)	(2.224)	(2.412)	(7.318)	(2.580)	(2.676)	(9.135)	(3.478)	(4.080)
Constant	-2.188***	-1.955***	-2.434***	-2.188***	-1.955***	-2.434***	-2.188***	-1.955***	-2.434***
	(-28.63)	(-7.785)	(-6.431)	(-18.59)	(-8.324)	(-7.374)	(-21.04)	(-9.679)	(-14.66)
Observations	1,181	1,181	1,181	1,181	1,181	1,181	1,181	1,181	1,181
R-squared	0.848	0.855	0.969	0.848	0.855	0.969	0.848	0.855	0.969
Number of panel	45	45	45	45	45	45	45	45	45
Chi2	83805.12	1108.99	519.43	4379.42	865.56	575.71	6606.05	1150.13	2365.50
Ch2p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Tables 6, 7 and 9, the parameters of urban population showed positive sign and statistically significant (p<0.01). However, in terms of the results in Table 8, which are for per capita CO_2 emissions, urban population had negative association across all the models. The results are in consonance with that of Liu et al. (2021) and Zhou and Liu (2016) who reported positive urban population elasticity of total carbon emissions and negative urban population elasticity of per capita carbon emissions. The results in Tables 6, 7 and 9 imply that increase in urban population will lead to increase in all the forms of GHG emissions. Similar finding had been reported by Li et al. (2019) and Liu et al. (2021). In addition, Liu et al. (2017) reported that elasticity of urbanization was negative in developed provinces of China, as against positive values for less developed provinces. Moreover, the results in Table 8 imply that if urban population increases by one percent, per capita emissions will decline by some percentages. It is a reflection that although total emissions may increase with increase in urban population, there are some reductions in emission per capita when rural households are added. Specifically, urban population growth places significant pressure on environmental resources through industrial expansion (Wei & Ye, 2014), energy demand, land use changes (Meyer & Turner, 1992), waste generation and natural resource degradation (Agudelo-Vera et al.; 2011).

It is also important to examine the magnitude of the impacts that had been exerted by urban population on GHG emissions. The results for total emissions (Table 6) have the least parameter as 0.856 and the highest as 1.004. The implication is at the worst scenario, a 1 percent increase in urban population will produce a 1.004 percent increase in total GHG emissions, all other variables held constant. However, in the results in Table 7, the least parameter was 0.811 and the highest was 0.882. These imply that a 1 percent increase in urban population will result in 0.882 percent increase in CO_2 emissions, all other variables held constant. Similar parameter estimations were obtained for emissions from liquid fuels (Table 9) with the minimum being 0.805 and the maximum being 0.904. These result reveal that at most a 1 percent increase in urban population will result in 0.904 percent increase in CO_2 emissions from liquid fuel utilization. These results are in alliance with those of O'Neill et al. (2012). For the result with negative parameters, the minimum was -0.198, while the highest was -0.102. These indicate that in the best scenario, a 1 percent increase in urban population will produce a 0.198 percent decrease in per capita CO_2 emissions. Similar results were reported by Sharma (2011), while Wang and Li (2021) reported contrary finding.

Renewable energy utilization is another important determinant of carbon dioxide emissions. The campaigns towards GHG emissions are strictly motivated towards more utilization of renewable energies. In the results presented in Tables 6, 7, 8 and 9, the parameters of renewable energy are with negative sign and statistically significant ($p<0.01$). These findings reveal that in Table 6, in the worse scenario, a 1 percent increase in renewable energy utilization will lead to 0.120 percent decrease in total emissions of GHGs. Similarly, in Table 7, a 1 percent increase in renewable energy utilization will lead to 0.279 percent reduction in emissions of carbon dioxide. Table 8 also reveals that a 1 percent increase in renewable energy utilization will in the worst scenario result in 0.293 percent reduction in per capita emissions of carbon dioxide. Also, Table 9 reveals that in the worst scenario, taking other variables constant, a 1 percent increase in renewable energy utilization will reduce emission of carbon dioxide from liquid fuel by 0.250 percent.

These findings are consistent with findings by Lin and Raza (2019), Adeleye et al. (2021a), Shaheen et al. (2020), Sarkodie and Strezov (2018), Neagu and Teadoru (2019) and Nguyen and Kakinaka (2019). Amponsah et al. (2014) highlighted the GHG emission efficiency of renewable energy when compared with that conventional fossil fuels. Similar conclusion was reached by Lima et al. (2020) and Wang et al. (2019) who indicated that promotion of renewable energy utilization is a cost effective and fundamental way to reduce the consequences of climate change.

Livestock and crop production play a significant role in human-induced GHG emissions. Specifically, emissions from livestock account for about 14.5 percent of global emissions (Sakadevan & Nguyen, 2017). Emissions from livestock production are derived from fermentations, fertilizer application and decomposition of manures (O'Mara, 2011). The parameters of livestock production index did not show statistical significance ($p>0.05$) in the results presented in Tables 8 and 9. However, in Tables 6 and 7, the variable had positive and negative parameters, respectively. These parameters were statistically significant ($p<0.05$) in the model with no autocorrelation assumption. The results showed that a 1 percent increase in the livestock production index will increase total GHG emissions by 0.001 percent. However, in Table 7, the result implies that a 1 percent increase in livestock production index will reduce carbon dioxide emissions by 0.0009 percent. In the results for crop production index, statistical significance was not obtained in Table 7. Moreover, in term of consistency, only the parameters estimated for columns 1, 4 and 7 – which were the models for no form of autocorrelation - showed statistical significance ($p<0.05$) in Tables 6, 8 and 9. Table 6 shows that a one percent increase in crop production index reduced total GHG emissions by 0.003%. However, in Table 8, a 1 percent increase in crop production index reduced per capita CO_2 emissions by 0.001%. In Table 9, the estimated parameters were with positive sign indicating that a 1 percent increase in crop production index will produce increase emissions from liquid fuel by 0.0007%.

In a similar analysis, Appiah et al. (2018) found positive association between crop and livestock production indices and GHG emissions in emerging economies. In another study, Ayyildiz and Erdal (2021) also found that livestock production index promoted the rate of carbon dioxide emissions in high-income, upper-middle income and lower-middle income countries by 39 percent, 49 percent, and 28 percent, respectively. Sarkodie and Owusu (2017) also reported that in using Ghanaian dataset, carbon dioxide emissions increased by 0.52 percent and 0.81 percent if crop production index and livestock production index increased by 1 percent, respectively.

The results in Tables 7-9 further revealed that per capita GDP showed statistical significance ($p<0.01$) in all the models with positive sign. In Table 7, a 1 percent increase in the per capita GDP will increase carbon dioxide emissions by 0.163. Similarly, in Tables 8 and 9, a 1 percent increase in per capita GDP will increase per capita carbon dioxide emission and carbon emission from liquid oil by 0.370 percent and 0.163 percent, respectively. In Table 6, however, total GHG emissions was negatively associated with GDP per capita. The results are in harmony with some previous findings. Definitely, the impact of GDP on carbon emission had been widely reported in the literature with mixed results. While some authors emphasized the positive contributions of GDP (Tucker, 1985; Huang et al.; 2008). others emphasized compliance with EKC (Vasylieva et al.; 2019).

5. Conclusion

Obesity is a growing public health problem in Africa. The need to urgently address this problem is borne not only due to its impacts on Africa's demographic transitions, but also due to its relationships with global environmental sustainability through contributions to GHG emissions. This study highlighted some empirical evidences of the effect of obesity and other important economic indicators on emission of GHGs. The empirical investigations are robust due to adoption of most appropriate econometric approaches through detection of cross-section dependence, cointegration and correction for heteroscedasticity. The results have clearly underscored the need to address obesity, given its positive impacts on the different indicators of GHG emissions. This can be approached from different perspectives, including awareness creation on the current severity of obesity in Africa, promotion of education on the health risks and welfare implications of obesity, and encouragement of adequate nutrition and healthy lifestyles. The study also extends its policy insights into other variables that are associated with GHG emissions. One of the policy implications from these variables include promotion of technological and investment initiatives to facilitate adoption of renewable energies. This initiative is bound to reduce GHG emission intensity, thereby promoting green growth. This is a critical factor because per capita GDP and some agricultural production indicators were positively associated with GHG emissions. The onus therefore rests on African leaders to fathom some development pathways that promote economic growth and agricultural development in a manner that is environmentally and economically sustainable. Such initiative should also evaluate the trend of urbanization and associated GHG emissions. This will ensure that the inventory of urban development and associated environmental consequences are properly considered for the ultimate achievement of some Sustainable Development Goals (SDGs).

Conflict of Interest

The author declares no conflict of interest.

References

*** United States Environmental Protection Agency. *Global greenhouse gas emissions data.* Available online: https://www.epa.gov/ghgemissions/global-greenhouse-gas-emissions-data (accessed on 20th March, 2024).

Adeleye, B.N.; Akam, D.; Inuwa, N.; James, H.T. & Basila, D. (2023). Does globalization and energy usage influence carbon emissions in South Asia? An empirical revisit of the debate. *Environmental Science and Pollution Research,* 30(13), pp. 36190-36207.

Adeleye, B.N.; Akam, D.; Inuwa, N.; Olarinde, M.; Okafor, V.; Ogunrinola, I. et al. (2021a). Investigating growth-energy-emissions trilemma in South Asia. International Journal of Energy Economics and Policy, 11(5), pp. 112–120.

Adeleye, B.N.; Nketiah, E.; & Adjei, M. (2021b). Causal examination of carbon emissions and economic growth for sustainable environment: evidence from Ghana. *Estudios De Economia Aplicada* 39(8), pp. 1-18.

Agudelo-Vera, C.M.; Mels, A.R.; Keesman, K.J. & Rijnaarts, H.H. (2011). Resource management as a key factor for sustainable urban planning. *Journal of Environmental Management*, 92(10), pp. 2295-2303.

Akil, L. & Ahmad, H.A. (2011). Relationships between obesity and cardiovascular diseases in four southern states and Colorado. *Journal of Health Care Poor Underserved,* 22(4 Suppl), pp. 61-72.

Albu, L. L. (2007). Spatial econometrics-applications to investigate- Distribution of CO2 emission in Europe. *Journal of Economic Forecasting*, 8, pp. 45–56.

Amponsah, N.Y.; Troldborg, M.; Kington, B.; Aalders, I. & Hough, R.L. (2014). Greenhouse gas emissions from renewable energy sources: A review of lifecycle considerations. *Renewable and Sustainable Energy Reviews*, 39, pp. 461-475.

An, R.; Ji, M. & Zhang S. (2018). Global warming and obesity: a systematic review. *Obesity Review*, 19, pp. 150–163.

Ansuategi, A. & Escapa, M. (2002). Economic growth and greenhouse gas emissions. *Ecological Economics*, 40(1), pp. 23-37.

Anwar, S. & Sun, S. (2014). Heterogeneity and curvilinearity of FDI-related productivity spillovers in China's manufacturing sector. *Economic Modelling*, 41, pp. 23-32.

Appiah, K.; Du, J. & Poku, J. (2018). Causal relationship between agricultural production and carbon dioxide emissions in selected emerging economies. *Environmental Science and Pollution Research*, 25, pp. 24764-24777.

Ayyildiz, M. & Erdal, G. (2021). The relationship between carbon dioxide emission and crop and livestock production indexes: a dynamic common correlated effects approach. *Environmental Science and Pollution Research*, 28(1), pp. 597-610.

Chuai, X.W.; Huang, X.J.; Wang, W.J.; Wen, J.Q.; Chen, Q.; & Peng, J.W. (2012). Spatial econometric analysis of carbon emissions from energy consumption in China. *Journal of Geographical Sciences*. 22, pp. 630–642.

De Hoyos, R.E. & Sarafidis, V. (2006). Testing for cross-sectional dependence in panel-data models. *The Stata Journal*, 6(4), pp. 482-496.

Dietz, W.H. & Pryor, S. (2022). How can we act to mitigate the global syndemic of obesity, undernutrition, and climate change?. *Current Obesity Reports*, 11(3), pp. 61-69.

Dong, L. & Liang, H.W. (2014). Spatial analysis on China's regional air pollutants and CO2 emissions: Emission pattern and regional disparity. *Atmospheric Environment*, 92, pp. 280–291.

El-Khoury, A. E.; Sánchez, M.; Fukagawa, N. K.; Gleason, R. E. & Young, V. R. (1994). Similar 24-h pattern and rate of carbon dioxide production, by indirect calorimetry vs. stable isotope dilution, in healthy adults under standardized metabolic conditions. *Journal of Nutrition*, 124, pp. 1615-1627.

Fan, J.; Zhou, L.; Zhang, Y.; Shao, S. & Ma, M. (2021). How does population aging affect household carbon emissions? Evidence from Chinese urban and rural areas. *Energy Economics*, 100, p. 105356.

Frank, L.D.; Andresen, M.A. & Schmid, T.L. (2004). Obesity relationships with community design, physical activity, and time spent in cars. *Am J Prev Med,* 27(2), pp. 87-96.

Hale, G. & Long, C. (2011). Did foreign direct investment put an upward pressure on wages in China? *IMF Economic Review*, *59*, pp. 404-430.

Huang, W.M.; Lee, G.W. and Wu, C.C.; 2008. GHG emissions, GDP growth and the Kyoto Protocol: A revisit of Environmental Kuznets Curve hypothesis. *Energy Policy*, 36(1), pp. 239-247.

Huang, Y.; Chen, F.; Wei, H.; Xiang, J.; Xu, Z. & Akram, R. (2022). The impacts of FDI inflows on carbon emissions: Economic development and regulatory quality as moderators. *Frontiers in Energy Research*, 9, p. 820596.

Koch, C.A.; Sharda, P.; Patel, J.; Gubbi, S.; Bansal, R. & Bartel, M.J. (2021). Climate change and obesity. *Hormone and Metabolic Research*, 53(09), pp. 575-587.

Koengkan, M. & Fuinhas, J.A. (2021a). Does the overweight epidemic cause energy consumption? A piece of empirical evidence from the European region. *Energy*, 216, p. 119297.

Koengkan, M. & Fuinhas, J.A. (2021b). Is gender inequality an essential driver in explaining environmental degradation? Some empirical answers from the CO2 emissions in European Union countries. *Environmental Impact Assessment Review*, 90, p. 106619.

Leitão, N. C. & Balogh, J. M. (2020). The impact of energy consumption and agricultural production on carbon dioxide emissions in Portugal. *AGRIS on-line Papers in Economics and Informatics*, 12(1), pp. 49-59.

Li, L.; Hong, X.; Tang, D. & Na, M. (2016). GHG emissions, economic growth and urbanization: a spatial approach. *Sustainability*, 8(5), p.462.

Lima, M.A.; Mendes, L.F.R.; Mothé, G.A.; Linhares, F.G.; De Castro, M.P.P.; Da Silva, M.G. & Sthel, M.S. (2020). Renewable energy in reducing greenhouse gas emissions: Reaching the goals of the Paris agreement in Brazil. *Environmental Development*, 33, p. 100504.

Liu, J.; Li, M. & Ding, Y. (2021). Econometric analysis of the impact of the urban population size on carbon dioxide (CO_2) emissions in China. *Environment, Development and Sustainability*, 23(12), pp. 18186-18203.

Liu, Y.; Gao, C. & Lu, Y.; 2017. The impact of urbanization on GHG emissions in China: The role of population density. *Journal of Cleaner Production*, 157, pp. 299-309.

Ma,J.J.; Liu, X.; You, J.X. & Zhang, M.L. (2009). Spatial econometric analysis of China's provincial CO_2 emissions. *Proceedings of the 2nd International Joint Conference on Computational Sciences and Optimization*, Sanya, China, pp. 452-456.

Magkos, F.; Tetens, I.; Bügel, S.G.; Felby, C.; Schacht, S.R.; Hill, J.O.; Ravussin, E. & Astrup, A. (2020). The environmental foodprint of obesity. *Obesity*, 28(1), pp. 73-79.

Malley, C.S.; Hicks, W.K.; Kulyenstierna, J.C.; Michalopoulou, E.; Molotoks, A.; Slater, J.; Heaps, C.G.; Ulloa, S.; Veysey, J.; Shindell, D.T. & Henze, D.K. (2021). Integrated assessment of global climate, air pollution, and dietary, malnutrition and obesity health impacts of food production and consumption between 2014 and 2018. *Environmental Research Communications*, 3(7), p. 075001.

Meyer, W.B. & Turner, B.L.; 1992. Human population growth and global land-use/cover change. *Annual Review of Ecology and Systematics*, 23(1), pp. 39-61.

Michaelowa, A. & Dransfeld, B. (2008). Greenhouse gas benefits of fighting obesity. *Ecological Economics*, 66(2-3), pp. 298-308.

Myers, S. S.; Smith, M. R.; Guth S, Golden, C. D.; Vaitla, B.; Mueller, N. D. et al. (2017). Climate change and global food systems: potential impacts on food security and undernutrition. *Annual Review of Public Health*, 38, pp. 259-277.

O'Mara, F.P. (2011). The significance of livestock as a contributor to global greenhouse gas emissions today and in the near future. *Animal Feed Science and Technology*, 166-167, pp. 7-15.

O'Neill, B.C.; Liddle, B.; Jiang, L.; Smith, K.R.; Pachauri, S.; Dalton, M. & Fuchs, R. (2012). Demographic change and carbon dioxide emissions. *The Lancet*, 380(9837), pp. 157-164.

Paisley, A. (2023). *Why the climate crisis is a health crisis*. Available online: https://www.one.org/stories/climate-global-health-crisis/?gad_source=1&gclid=CjwKCAjwkuqvBhAQEiwA65XxQLFddR9Y9Nja5fCUhm6tVJYWuTHKPkO2zJSxmLA1RSExrVeaGzTXMRoCA8AQAvD_BwE (accessed on 20th March 2024).

Phillips, P. & Sul, D. (2003). Dynamic panel estimation and homogeneity testing under cross section dependence. *Econometrics Journal*, 6, pp. 217–259.

Ravussin, E.; Burnand, B.; Schutz, Y. & Jequier E. (1982). Twenty-four-hour energy expenditure and resting metabolic rate in obese, moderately obese, and control subjects. *American Journal of Clinical Nutrition*, 35, pp. 566-573.

Roberts, J.T. & Grimes, P.E. (1997). Carbon intensity and economic development 1962-1991: A brief exploration of the environmental Kuznets curve. *World Development*, 25, pp. 191-198.

Sakadevan, K. & Nguyen, M.L. (2017). Livestock production and its impact on nutrient pollution and greenhouse gas emissions. *Advances in Agronomy*, 141, pp. 147-184.

Sarkodie, S. & Owusu, P. (2017). The relationship between carbon dioxide, crop and food production index in Ghana: By estimating the long-run elasticities and variance decomposition. *Environmental Engineering Research*, 22(2), pp. 193-202.

Selden, T. M. & Song, D. Q. (1995). Neoclassical growth, the J-curve for abatement, and the inverted U-curve for pollution. *Journal of Environmental Economic Management*, 29, pp. 162-168.

Shah, S.A.A.; Shah, S.Q.A. & Tahir, M. (2022). Determinants of CO_2 emissions: exploring the unexplored in low-income countries. *Environmental Science and Pollution Research*, 29, pp. 48276–48284.

Sharma, S.S. (2011). Determinants of carbon dioxide emissions: empirical evidence from 69 countries. *Applied Energy*, 88(1), pp. 376-382.

Springmann, M.; Wiebe, K.; Mason-D'Croz, D.; Sulser, T.B.; Rayner, M. & Scarborough, P. (2018). Health and nutritional aspects of sustainable diet strategies and their association with environmental impacts: a global modelling analysis with country-level detail. *The Lancet Planetary Health*, 2(10), pp. 2542-5196.

Squalli, J. (2014). Is obesity associated with global warming? *Public Health*, 128(12), pp. 1087-1093.

Steinegger, R. (2017). Fuel economy as function of weight and distance. Winterthur, Switzerland: Zurich University of Applied Sciences (ZHAW Zürcher Hochschule für Angewandte Wissenschaften). https://digitalcollection.zhaw.ch/handle/11475/1896. Accessed November 26, 2019.

Sun, W. & Huang, C. (2020). How does urbanization affect carbon emission efficiency? Evidence from China. *Journal of Cleaner Production*, 272, p. 122828.

Swinburn, B. A.; Kraak, V. I.; Allender, S.; Atkins, V. J.; Baker, P. I.; Bogard, J. R.; Brinsden, H.; Calvillo, A.; De Schutter, O.; Devarajan, R. & Ezzati, M. (2019). The global syndemic of obesity, undernutrition, and climate change: the Lancet Commission report. *The lancet*, *393*(10173), pp. 791-846.

The integrated African Health Observatory (iAHO) and World Health Organization (WHO) (2024). *Displaying Indicators for AFRO Region*. Available online: https://aho.afro.who.int/ind/af?ind=439&cc=af&ci=1&dim=100&dom=Cardiovascular%20disease%20across%20NCDs (Accessed 12 February, 2024).

Tilman, D. & Clark, M. (2014). *Global diets link environmental sustainability and human health Nature* 515, pp. 518-522.

Toti, E.; Di Mattia, C. & Serafini, M. (2019). Metabolic food waste and ecological impact of obesity in FAO World's region. Frontiers in Nutrition, 6, p. 460769.

Trentinaglia, M. T.; Parolini, M.; Donzelli, F. & Olper, A. (2021). Climate change and obesity: A global analysis. *Global Food Security*, *29*, p. 100539.

Trentinaglia, M. T.; Parolini, M.; Donzelli, F. & Olper, A. (2021). Climate change and obesity: A global analysis. *Global Food Security*, 29, p. 100539.

Tucker, M. (1995). Carbon dioxide emissions and global GDP. *Ecological Economics*, *15*(3), pp. 215-223.

United Nations (2023). *Goal 13: Take urgent action to combat climate change and its impacts*.

Vasylieva, T.; Lyulyov, O.; Bilan, Y. & Streimikiene, D. (2019). Sustainable economic development and greenhouse gas emissions: The dynamic impact of renewable energy consumption, GDP, and corruption. *Energies*, 12(17), p. 3289.

Walpole, S.C.; Prieto-Merino, D.; Edwards, P.; Cleland, J.; Stevens, G.; & Roberts, I. (2012). The weight of nations: an estimation of adult human biomass. *BMC Public Health*, 12, p. 439.

Wang, Q. & Li, L. (2021). The effects of population aging, life expectancy, unemployment rate, population density, per capita GDP, urbanization on per capita carbon emissions. *Sustainable Production and Consumption*, 28, pp. 760-774.

Wang, S.; Tarroja, B.; Schell, L.S.; Shaffer, B. & Samuelsen, S. (2019). Prioritizing among the end uses of excess renewable energy for cost-effective greenhouse gas emission reductions. *Applied Energy*, 235, pp. 284-298.

Wang, Y.; Liao, M.; Xu, L. & Malik, A.; 2021. The impact of foreign direct investment on China's carbon emissions through energy intensity and emissions trading system. *Energy Economics*, 97, p. 105212.

Webb, G. J. & Egger, G. (2014). Obesity and climate change: can we link the two and can we deal with both together? *American Journal of Lifestyle Medicine*, 8(3), pp. 200-204.

Wei, Y.D. & Ye, X. (2014). Urbanization, urban land expansion and environmental change in China. *Stochastic Environmental Research and Risk Assessment*, *28*, pp. 757-765.

Willett, W.; Rockström, J.; Loken, B.; Springmann, M.; Lang, T.; Vermeulen, S.; Garnett, T.; Tilman, D.; DeClerck, F.; Wood, A. & Jonell, M. (2019). Food in the Anthropocene: the EAT–Lancet Commission on healthy diets from sustainable food systems. *The Lancet*, 393(10170), pp. 447-492.

World Health Organization (WHO) (2023). *WHO Acceleration Plan to Stop Obesity*. Available online https://iris.who.int/bitstream/handle/10665/370281/9789240075634-eng.pdf?sequence=1 (accessed on 18th March 2024).

World Health Organization, (2024). *Obesity and Overweight*. Available online: https://www.who.int/news-room/fact-sheets/detail/obesity-and-overweight#:~:text=In%202022%2C%201%20in%208,million%20were%20living%20with%20obesity (accessed on 18th March 2024).

Yang, T. & Wang, Q. (2020). The nonlinear effect of population aging on carbon emission-Empirical analysis of ten selected provinces in China. *Science of the Total Environment*, 740, p. 140057.

Yang, Y.; Zhao, T.; Wang, Y. & Shi, Z. (2015). Research on impacts of population-related factors on carbon emissions in Beijing from 1984 to 2012. *Environmental Impact Assessment Review*, 55, pp. 45-53.

Yu, Y.Y.; Liang, Q. M. & Liu, L.J. (2023). Impact of population ageing on carbon emissions: a case of China's urban households. *Structural Change and Economic Dynamics*, 64, pp. 86-100.

Zhang, C. & Tan, Z. (2016). The relationships between population factors and China's carbon emissions: does population aging matter? *Renewable and Sustainable Energy Reviews*, 65, pp. 1018-1025.

Zheutlin, A.R.; Adar, S.D. & Park, S.K. (2014). Carbon dioxide emissions and change in prevalence of obesity and diabetes in the United States: an ecological study. *Environment International*, 73, pp. 111-116.

Zhou Y. & Liu Y. (2016). Does population have a larger impact on carbon dioxide emissions than income? *Evidence from a cross-regional panel analysis in China. Applied Energy*, 180, pp. 800-809.

Zhou, Y.; Fu, J.; Kong, Y. & Wu, R.; 2018. How foreign direct investment influences carbon emissions, based on the empirical analysis of Chinese urban data. *Sustainability*, 10(7), p. 2163.

Zhou, Y.; Wang, H. & Qiu, H. (2023). Population aging reduces carbon emissions: Evidence from China's latest three censuses. *Applied Energy*, 351, p. 121799.