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THE RELATIONSHIP BETWEEN NET TRADE AND CARBON DIOXIDE EMISSIONS IN AFRICA

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Abstract: We study the net impacts of international trade on carbon dioxide (CO2) emissions in African countries at different income groupings and other driving forces of environmental impacts (CO2 emissions) using an augmented STIRPATN model. The continent experienced a large growth in carbon dioxide emissions of about 701.88% between 1960 and 2010, and this provoked our interest in the study. We identify the key driving forces to be net trade, population density, final consumption expenditure (annual growth), manufacturing sector and services sector. We also found that the services sector consistently show low-carbon emission impacts particularly in low middle income countries in Africa (LIMCA) and upper income countries in Africa (UICA). Indicating that a shift from highly depended manufacturing economies that suggest increasing-carbon economies in both LIMC and UICA to services economies is vital in order to strive for a low-carbon economies in the continent. The coefficient for net trade stands out explicitly significant and positive for all the income groupings. The findings show that the average effect of net trade over CO2, when the net trade changes across time and between countries increases by 1%, CO2 emissions increases by about 1.68%, 2.45% and 1.01% for LICA, LMICA and UICA respectively, when all other predictors are constant.

Keywords: International trade, CO_2 emissions, environmental impacts, population density.

I. INTRODUCTION

Important decisions facing the African community is the sustainability of the environment in the face of sustained increase in international trade. The evidence from change in the environment (heavy rainfall, flooding, erosion, deforestation, bush-burning, drought, land degradation, pollution, carbon dioxide emissions, etc.) consistently points to substantial environmental impacts in the long term. For example, the continent's total carbon dioxide emissions in 1960 was 145,972.275 kilotons and increased to 1,170,521.068 kilo tonnes in 2010 (World Bank Development Indicators data set, 2013). The continent experienced a large growth in carbon dioxide emissions of about 701.88% between 1960 and 2010. Thus, the openness of the economy is most likely one of the anthropogenic driver-triggers for future climate change. On the one hand, the controversy over whether such impacts exists or not remains inconclusive, and on the other hand, the disagreement over the size of the magnitude impacts by previous studies has not yet been well resolved even with descriptive, empirical and theoretical analyses on the much debated role of international trade on carbon dioxide emissions relationship.

Most research on international trade and carbon dioxide (CO_2) emissions concentrates on Environmental Kuznets Curve (EKC), but this study focus on the quantitative magnitude impacts of openness of the economy on CO_2 emissions in African countries. The neoclassical tradition maintained that although economic development has generated environmental impacts, further economic development through openness of the economy can solve these problems rather than increase them. This theory argued that the interaction between economic development and environmental impacts may produce an inverted U-Shaped curve (York, *et. al.* 2003[b]). This implies that during the first stage of economic development, environmental impacts increases, level-off and as further economic development takes place environmental impacts reduces. This linkage between economic development and environmental impacts is known as the environmental Kuznets curve (EKC), named after economist Simon Kuznets (see York, *et al.* 2003[b]). Other alternative perspectives include human ecology perspective, modernization: economy, democracy and the state perspective, ecology modernization perspective, political economy perspective and the world system perspective (see York, *et al.* 2003[b]). Little research considers technical disaggregation of technology that is, manufacturing sector (M_{it}), a component of GDP and services sector (S_{it}), another different component of GDP in an open economy. Thus, this research investigates how manufacturing sector (M_{it}) of technology differ with services sector (S_{it}) in the relationship between openness of the economy and CO_2 emissions. First, a conceptual framework of the structure of the nexus between openness of the economy and CO_2 emissions was synthesized from the manufacturing sector-to-services sector (Shi 2003). In addition, some researchers have paid attention to the relationship between openness of the economy, industrial pollution, mercury emissions and CO_2 emissions in developed countries, Brazil, Russia, India and China (see Li, *et al.* 2017; Liu, Zhou, and Wu, 2015; Liu, *et al.* 2015; Loftus, *et al.* 2015; Ouyang and Lin 2015; Xu and Lin 2015; Zhang, *et al.* 2014; Zhang and Choi, 2013). Little is known about how the openness of the economy influence CO_2 emissions in Africa. As a result, the literature on EKC is rich, but this study does not capture the intricacies of Environmental Kuznets Curve because African countries are yet to attain a reduction in environmental impacts due to increasing level of poverty in the continent.

The study is motivated by the continent's increasing trade relationship with the rest of the world. The continent has witnessed three simultaneous trends: increasing dependency on developed countries, China, India and Asian countries, an explosive growth in human population and a step increase in resource depletion and environmental degradation. These trends have accelerated since 1960, fuelling the debate on the linkages between the openness of the economy and environment (carbon dioxide emissions).

The study provides a quantitative assessment of the primary driving forces that determines carbon dioxide emissions loads in African countries at different income levels with emphasis on the role of net trade. The primary objective is to critically assess the relationship between net trade and carbon dioxide emissions to identify the key driving forces in African countries at different income countries. The study employ anthropogenic driver-triggers such as the population density, final consumption expenditure (annual growth), manufacturing sector and services sector as moderating roles to document by means of quantifying the magnitude impacts of net

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trade on CO_2 emissions, and to see by means of a panel dataset how international trade determines the concentration of carbon dioxide emissions loads. In our empirical analysis the study considers only Generalised Least Squares (GLS) estimator in order to overcome the problems of the errors (autocorrelation and heteroscedasticity) encountered in the study. The Random Effect (RE) Model/Generalised Least Squares (GLS)/Feasible Generalized Least Squares (FGLS) can handle temporal autocorrelation and heteroscedasticity (see Kristensen and Warwo 2003; Wooldridge 2010). These errors are: cross countries dependency due to common shocks in a given time period, the error variances are different across countries due to characteristics unique to the countries and the errors within the countries are temporally correlated (see Kristensen and Warwo 2003). The advantage GLS has over fixed effects and random effect is that it assumes that the variance-covariance matrix used to weight the data is known, and thus incorporates information about the errors and thereby overcome the inefficiency of fixed effects and random effects, and gives correct standard errors (see Balestra and Nerlove 1966; Kristensen and Warwo 2003; Baltagi 2008).

The following research questions address the contentious issues on the international and environment impacts nexus in Africa. We specifically ask what is the magnitude impact of net trade on carbon dioxide emissions in Africa? The study addresses this concern by using an empirical approach. The rest of this study is organised as follows: Section 2 discusses the literature review. Section 3 presents the methodology, data sources and the model in more detail and develop an augmented STIRPATN models used to identify the key driving forces that determine the magnitude impacts of net trade on CO_2 emissions, the estimation procedure and the model selection of GLS estimator used. Section 4 reports the findings for the STIRPATN model employed. Section 5 presents the concluding remarks.

II. LITERATURE REVIEW

2.1 Net trade and CO2 emissions: Evidence of relationship

Dietz and Rosa (1994a) offer a comparative analysis of studies with the argument that a single indicator of study and estimation based on it there from may be misleading due to many influencing factors. For example, Ehrlich and Holdren (1970, 1971, 1971a, 1972b) maintain that much of the environmental impact of a country may be displaced across its borders as a result of the mix between imports and exports and its place in the international division of labour. This study pointed out that the relationship between trade and environmental impacts can be controlled for in part by considering imports and exports with high environmental consequences. However, this position is flawed because substitution within a social system is not taken into account. It is argued that a country may have relatively low carbon dioxide emissions due to extensive use of nuclear hydroelectric power rather than fossil fuel. An obvious reference to the impacts of nuclear waste is reiterated by Dietz and Rosa (1994a); their study pointed out that the disposal of nuclear waste and the disruption of riparian ecosystems are environmental problems. It is argued that an adequate environmental indicator should take into account the effects of net trade and the possibility of displacing impacts. Dietz and Rosa (1994a) maintain that environmental impacts can be treated as latent variables while specific indicators such as carbon dioxide emissions, tropical wood imports or endangered species serve as observed indicators or proxies associated with the latent variables. In strict accordance with the world system theory, Shi (2003) asks whether the linkages between population and environmental impacts will be robust when the relationship between net trade and emissions is taken into account. This study argues that changes in emissions across countries may be influenced by imports and exports of dirtier products such as fuel. Shi (2003) examines the net trade-emission nexus by using non-trade output as a percentage of GDP as a predictor. It claimed that a large share of non-traded GDP may mean a smaller quantity of trade in dirtier industries. Thus, we expect that a country with relatively larger share of non-traded GDP will mitigate emissions than another whose share is relatively small. Shi′ s (2003) estimated results supported this a priori expectation.

Jorgenson (2009) investigates the transnational organization of production in the context of foreign direct investment and carbon dioxide emissions. The study used the method of fixed effects for a panel regression analysis of 37 less developing countries from 1975 to 2000, and examines the impact of secondary sector foreign investment on total carbon dioxide emissions and emissions per unit of production. The empirical findings suggest that foreign direct investment in manufacturing has a positive relationship with both outcomes. The results also indicate, level of economic development and export intensity all have a positive association with both response variables (total emissions and emissions per unit of production). The world system theory perspective foregrounds the importance of human-ecology and political economy perspectives when examining anthropogenic carbon dioxide emissions. In support of the findings in Jorgenson (2009) and Dietz and Rosa (1994a), Roberts, Grimes and Manale (2003) apply the world system perspective to environmental impacts. The research sampled 154 countries and investigated their contribution to the global economy and their internal class and political forces to estimate on how these factors influence the quantity of CO_2 emissions per unit of economic output. It would be correct to state that the findings are consistent with Satterthwaite's (2009) findings that semi-periphery and upper-periphery countries are the least efficient consumers of fossil fuels.

Li, Chen, Chen, Yang, Wei, Wang, Dong, and Chen, (2017) study provide evidence on the impact of trade on fuel related mercury emissions. It examines the aggregate energy consumption and environmental emissions. The study's empirical evidence on the nexus between trade and emissions in the study is much less convincing. The literature employs a three-scale input-output analysis which accommodates variation in circumstances regarding local, domestic and international activities and evaluated the embodiment fluxes of fuel related mercury emissions in Beijing in 2010, given the mercury intensities for average national and world economies. The gap in the study is that it treats manufacturing sector (M_{it}), a component of GDP and services sector (S_{it}), another different component of GDP as the same (technology). The results found that international trade is a major contributor of Beijing environmental emissions (Beijing mercury emissions final fuel consumption were 7.79t in 2010, higher by about 3/4 of which is linked to domestic and openness of the economy). However, capital formation, it was argued accounted for the highest level of environmental emissions due to massive infrastructural development in the capital city. The implication is that modernization is a driver-trigger in the analysis of environmental impacts. The specification used by Liu, Mao, Ren, Yi, Li, Guo and Zhang (2015) is a system dynamic model to estimate energy consumption and carbon dioxide emissions in China for the period 2008-2020.

Using macro-data, the literature clearly shows that CO_2 emissions per GDP amelioration by about 40-45% of 2005 level could be attained in 2020 in China. Even though the structure conducted scenario simulation to determine the impacts of economic growth rates on the energy consumption and carbon dioxide emissions, some vital variables (population dimensions, technology) were neglected in the determination of environmental impacts. Consumption is not the only driving forces of environmental impacts. Xu and Lin (2015) analyse the driver-trigger of carbon dioxide emissions in China's transport sector. A nonlinear inverted U-shaped curve was found to exist suggesting evidence of Environmental Kuznets Curve (EKC) in the sector, as in economic growth depending heavy on road and air transport in the early stage, but deepening on emission-free train-transport at the later stage due to the speed of technological progress at different times. Urbanization is also found to exhibit pattern of EKC. Zhang, Wu, Liu, Huang, Un, Zhou, Fu and Hao (2014) use a PEMs method to collect 60 light-duty passenger vehicles (LDPVs) data on-road fuel consumption and CO2 emissions for China. The study found about 30% gap between on-road fuel consumption and type-approval values. The results among many others, found diesel LDPVs to have a 22% energy saving advantage against gasoline counterparts while the literature also reports a strong correlation between fuel consumption and average speed, that is, a reduction in traffic congestion has effect of mitigating distance-based fuel consumption. Loftus, Cohen, Long, and Jenkins (2015) carried out feasibility studies on global decarbonisation argue that historical carbon intensity and energy intensity rates need to improve and normalized energy technology capacity deployment rates are important benchmarking comparators to examine the relative feasibility of global decarbonisation scenarios for decision makers. Zhang and Choi (2013) explore the feasible application of the SBM-DEA approach for energy efficiency in China, and the evidence shows that most regions in China are not efficient in environmental-friendly low energy carbon economy. This is due to environmental energy inefficiency to pure energy inefficiency, and research and development is therefore recommended for the future. Ouyang and Lin (2015) investigate the drivers of energy-related carbon dioxide emissions in China's industrial sector. The study argues that there is a long-run relationship between industrial carbon dioxide emissions and the influencing variables (CO_2 emissions per unit of energy consumption, industrial value added, labor productivity and fossil fuel consumption). The industrial CO_2 emissions are identified as the key determinant to the coal-dominated energy structure in the country. Liu, Zhou and Wu (2015) examine the relationship between population, income and technology on energy consumption and industrial pollutant emissions. The research did not find evidence of Environmental Kuznets Curve (EKC) hypothesis. The lack of EKC may be explained by the fact that industrial pollution emissions is very substantial. In addition, the impact of population density, income and technology on energy consumption and pollutant emissions varies at different level of development.

A common finding in these more recent studies is that an inverted U-Shaped curve which indicate the presence of Environmental Kuznets Curve exist. Meaning that emission impacts fall in greater proportion to an increase in driving forces during the first phase, but as economic development improves due to many factors (e.g. openness of the economy) in the second phase emission impacts increases, but less rapidly to changes in the driving forces.

2.2 Dumping of nuclear waste on African soil

Anyinam (1991) investigates transfer of nuclear toxic waste between industrialised nations and developing countries; the evidence suggests that the global community face environmental crisis, arising from the planet being choked by the waste by-products of development. The industrialized countries face the problem of what to do with the *millions of tons of waste materials produced* every year. The works of Anyinam (1991) reports that the industrialised countries are now closely watched regarding activities of waste management agents by pressures groups such as the concerned individuals, environmental groups, etc. with the slogan *not-in-my-backyard movement*. However, the search for dumping sites for waste disposal has intensified and extended beyond regional and national boundaries. The study argues that attempts to dump hazardous wastes on developing countries were made in the 1980s, with the African continent as the prime hunting ground. The increasingly intense public opposition to the toxic waste disposal in the US and Europe, the waste management companies (WMC) and illegal waste traders (IWT) leads to Africa and other developing countries in Asia and Latin America becoming alternative dump sites. According to Alston and Brown (1993, p.185), the target is "the politically and economically less powerful nations of the world, who have benefited the least from industrialization". The continent of Africa is seen as an extension of the "pattern of targeted dumping on communities of colour" (Alston and Brown 1993, p. 185). However, the governments of developing countries: Africa, Asia and Latin America are resisting the WMC and IWT which they sometimes describe as *toxic terrorism and economic extortion.* In addition, the African Union labelled this *a crime against Africa and African people*. Vir (1989, p.1) points out that toxic and radioactive waste are shipped from the industrialized nations and dumped on Africa soil. The study called this trade relationship *a silent trade*. Furthermore, Vir (1989) states that due to the increasingly strict environmental and safety laws in US and Europe, the cost of disposal of hazardous toxic waste increased to *$2,500 per ton*, and waste merchants, that is, WMC and IWT have turned to less developing countries and easily accessible African countries. According to Vir (1989, p.1), "this year, several countries in West Africa received offers from the US and Europe". In response to this development, Nigerian government denounced waste dumping in Africa, and was seriously concerned because its neighbour- the Benin Republic agreed to accept radioactive waste from France. The Nigerian government declared that: "no government, no matter the financial inducement has the right to mortgage the destiny of future generations of African children" (Vir, 1989, pp.1-2). Ironically, a week after the government statement, toxic waste of foreign origin was discovered in Nigeria, imported by an Italian business in collaboration with the Iruekpen Construction Company, Nigeria. The Japanese Atomic Energy Research Agency investigated the incident and confirmed that the drums deposited on the Nigerian soil contained highly radioactive material. However, the reports of the World Nuclear Association (2013) minimise these concerns; it is argued that the quantity of radioactive waste is small in comparison to the waste produced by fossil fuel electricity generation. The NEA (1989, p.1) describes the highly radioactive wastes as a by-product which require permanent separation from man's environment where the spent nuclear fuel "arising from reactor operations is chemically reprocessed". The radioactive waste includes highly concentrated liquid solutions of nuclear fission products, solidified through a process called *vitrification*.

Stebbins (2010) deals with the potential health risk of hazardous waste disposal practices, for today's generation and future generations. He argues that industrialized nations are increasing the disposal of unwanted nuclear waste in developing countries. The study states that the US produced the largest quantities of hazardous waste every year, and that about 1, 200 priority *hazardous waste sites* threaten the environment. The study supports previous findings that opposition to disposal facilities at home led to increasing disposal of toxic waste by shipping it to developing countries. Clapp (1994) focuses on the involvement of Africa, non-governmental organisations (NGOs) and the International Toxic Waste Trade (ITWT) attempt to halt trade in toxic waste between industrialised and developing countries. The findings suggest that the collaborative efforts between African governments and NGOs yielded positive impacts as they influenced the outcome of *several international trade conventions*. However, despite strict international laws to keep nuclear waste and radioactivity out of Africa, Clapp (1994, p.218) points out that the waste traders were "able to circumvent existing rules and continue their trade with the continent". The persistent trade in waste led to a further strict ban enforced by the joint action of both Organization for Economic Cooperation and Development (OECD) and non-OECD countries, yet the trade continues and persists with the involvement of key top government officials of developing countries. A growing body of evidence further suggest that industrialised nations in Europe continue to dump toxic waste along the coast of African countries (Maishinski 2010). The following Table documents waste trade statistics between industrialized nations and Africa countries.

Table 1: Waste trade statistics:
Attempted and successful imports of hazardous waste to Africa

Year	1980-87	1988	1989	1990	1991	1992	1993
Hazardous wastes (tons)	10	34	15	9	0	9	0
Year	1994	1995	1996	1997	1998	1999	2000
Hazardous wastes (tons)	21	4		1	0	0	1

Source: A Greenpeace inventory (see Bernstorff and Stais 2001a, p.17).

Table 2: Carbon dioxide emissions (kt) in Africa according to income levels

Income groups	1960	2010
HICA	22.002	4,679.092
UICA	107,377.1	714,734.97
LMICA	27,843.531	386,171.77
LICA	10,729.642	64,935.236
Africa	145,972.275	1,170,521.068

Source: Author's calculation based on World Bank Development Indicators 2013 data set.
*CO_2 E (kt) is carbon dioxide emissions in kilotons.
*HICA is higher income countries in Africa
*UICA is Upper income countries in Africa
*LMICA is low middle income countries in Africa
*LICA is low income countries in Africa

III. METHODOLOGY

3.1 Data sources, descriptions and analysis
• STIRPAT model
Beginning with the challenge of ImPACT identity, an attempt to investigate potential

action and policy levers to alter environmental impacts was carried out by Waggoner and Ausubel (2002), by reformulating IPAT identity into ImPACT identity. The study decomposed T into consumption per unit of GDP (C) and impact per unit of consumption (T), implying that I = PACT. For example, an investigation of carbon dioxide emissions employing the IPAT framework would show that total emissions (I) are the product of population (P), affluence, i.e. per capita GDP (A), and carbon dioxide emission per unit of GDP (T), whereas the ImPACT framework states that total carbon dioxide emissions are equal to the product of P, A, energy consumption per unit of GDP (C), and carbon dioxide emissions per unit of consumption (T). The main objective of the ImPACT framework is to determine the variables that can be altered to minimize environmental impacts and the principal factors that influence each variable.

The STIRPAT model has its root in the refinement of IPAT and ImPACT identities by Dietz and Rosa (1994a). The STIRPAT equation is:

$$I_i = aPD_i^{\mathrm{a}} A_i^{\mathrm{b}} T_i^{\mathrm{j}} e_i \qquad (1)$$

Equation (3.1.0) can be linearized by taking logarithms on both sides of the equality.

$$\ell n(I_i) = a + \mathrm{a}\ \ell n(PD_i) + \mathrm{b}\,\ell n(A_i) + \mathrm{j}\ \ell n(T_i) + e_i$$

$$i = 1, .., n \qquad (2)$$

Where:

the constant “a” scales the model,

α, β and φ are the exponents of the population density (PD), affluence (A) and technology (T), e is the error term; the subscript i shows that all the explanatory variables and the error term (e) vary across observational units. The exponents can be interpreted as elasticities in equation (2). The STIRPAT model contains the IPAT as a special case, namely: $a = \mathrm{a} = \mathrm{b} = \mathrm{j} = e = 1$.

The Impact identity: $a = \mathrm{a} = \mathrm{b} = \mathrm{j} = e = 1$. This can also be derived from equation (1) by setting a = α = β = φ = e = 1.

In the case of the STIRPAT framework, any of the elasticity coefficients can be greater than 1, or less than 1, or may be equal to 1.

In a panel data analysis, the model (2) above becomes:

$$\ell n(I_{it}) = a + \mathrm{a}\ \ell n(PD_{it}) + \mathrm{b}\,\ell n(A_{it}) + \mathrm{j}\ \ell n(T_{it}) + e_i \qquad (3)$$

Where t is the time period or the year, and the model (3) is known as a panel data with a common constant.

The STIRPAT model is employed as a starting point because it allows for an additive regression model in which all the variables can be conducted in logarithmic form, facilitating estimation and hypothesis testing (York et al., 2003a), the limitations of both IPAT and ImPACT. In addition, the York *et al.* (2003a) study used the STIRPAT model refined by Dietz and Rosa (1994a), and combined T with the error term, rather than estimating it separately to conform to the IPAT framework, which York *et al.* (2003a) T to balance I, P and A. The modifications yield:

- **Fixed effects, random effects and GLS/ FGLS estimators**

According to Asteriou and Hall (2011), the strength of longitudinal data is in the efficient analytical method which permits the inclusion of data for N cross-sections, in our case, African countries. The panel data put together a matrix set composed of a time series for each cross-sectional member in the dataset, and make a variety of estimation methods available. The superiority of the longitudinal data method over other methods lies in the number of observations available which increase by including developments over time.

The linear panel data model is formulated from a sample that consists of N cross-sectional units, in our case, different African countries, according to income levels observed in different years, specifically between 1960 and 2012. For example, we can consider a general linear panel model with one independent variable, given by:

$$Y_{it} = a + b X_{it} + U_{it} \qquad (4)$$

where the outcome variable (Y) and explanatory variable (X) have both i and t subscripts for i = 1, 2, . . . N sections and t = 1, 2, . . ., T years. If a full set of data both across countries (African countries in our case) and across time (years) have been obtained, we call this type of data set balanced; otherwise, we refer to it as unbalanced. It is important to note that in equation (3) above, the coefficients a and b do not have any subscripts, implying both a and b will be identical for all units and for all years. We can introduce heterogeneity into equation (3) by making a change across the countries (N cross-sectional units), i.e. by relaxing the rule that the constant should be the same for all cross-sections, for example, in our sample observation of different subgroups of countries in Africa, low income countries in Africa (LICA), lower middle income countries in Africa (LMICA), upper income countries in Africa (UICA) and high income countries in Africa (HICA), and differences are expected in their behaviour. This is consistent with Shi (2003) who points out that the basic STIRPAT model in its current state and form is likely to incur heterogeneity bias, arising from the distorting effect of unmeasured country-specific variables. The panel data derive from their theoretical ability to permit the isolation effects of specific actions, treatments or more general policies, based on the assumption that "economic data are generated from controlled experiments in which outcomes are random variables with a probability distribution that is a smooth function of the various variables describing the conditions of the experiment" (Hsiao, 2003, p.8). Therefore, our new model becomes:

$$Y_{it} = a_i + b X_{it} + U_{it} \qquad (5)$$

where Y is the dependent variable, X is the explanatory variable, β is the parameter, 'a' is the constant, and U is the error term. i = 1, . . . , N and t = 1, . . . , T.

Here, a_i is now different for each country in the sample. An important question is whether the b coefficient should also change across different countries, but "this would require a separate analysis for each one of the N-cross-sectional units and the pooling assumption is the basis of panel data estimation" (Asteriou and Hall, 2011, p.417). Extensive studies have also revealed that simple linear panel data models can be estimated using three different methods: with a common constant as in equation (2 and 3) above; permitting for fixed effects; and permitting for random effects.

These different methods are very suggestive, and reinforce the point that in panel data estimation, tests may be carried out to determine the most appropriate method/s to use, given the nature of data analysis and objective of the study.

• The common constant method

The common constant method (TCCM), better known as the pooled OLS method (TPOM), of estimation presents results based on the assumption that there are no differences among the data matrices of the cross-sectional dimension (N). That is to say, the model estimates a common constant "a" for all cross-sections (common constant for all countries in each group). This further means that TCCM indicates there are no differences between the estimated cross-sections, and it is useful under the hypothesis that the data set is a priori homogeneous, according to Asteriou and Hall (2011). The study maintained that TCCM is quite restrictive, and cases of more interest involve the inclusion of fixed and random effects in the method of estimation. For example, if we are to estimate the 51 sampled countries in Africa using pooled OLS regression, we pool all 51 observations together and run the OLS regression model, neglecting the cross-section and time series nature of data. The major problem with this model is that it does not distinguish between the various countries we have. The major problem with such a model is that it does not allow for unexplained differences across countries. In other words, by pooling all observations, or only grouping countries according to income levels, we assume away the heterogeneity or individuality of the various countries in the sample. Normally, there will be substantial differences across countries which cannot be linked simply to the variables in the study. However, because the common constant method assumed away the individuality of the various 51 African countries in our sample population, it is, therefore, not suitable for our empirical analysis, and to the fixed effects method we now turn.

• The fixed effects method (FEM)

The basic objective of FEM as a model or the LSDV model is that it allows for heterogeneity or individuality among our 51 countries by having its own intercept value. The term fixed effect is due to the intercept not varying over time, being time invariant, even though the intercept may differ across countries (see Hsiao 2003). Asteriou and Hall (2011) corroborate this perspective and argue that FEM is different from TCCM, in the sense that FEM treats the intercept as group (section)-specific. In this case, the model permits for different intercepts for each group or section. The study further maintains that FEM is also called the least squares dummy variable (LDSV) estimator because it permits different intercepts for each group; it includes a dummy variable for each group. We now consider a general fixed effects model, as follows:

$$Y_{it} = a_i + \beta_1 X_1 it + \beta_2 X_{2it} + \dots\dots\dots + \beta_k X_{kit} + U_{it} \qquad (6)$$

In matrix notation, we have:

$$Y = D\alpha + X\beta' + U \qquad (7)$$

In model (6), assuming that parameters are constant over time but can vary across individuals, Hsiao (2003) postulates a separate regression for each individual:

$$y_{it} = \alpha_i^* + \beta_i^/ X_{it} + U_{it}$$
$$i = 1, . . , N$$
$$t = 1, . . , T \qquad (8)$$

Three types of restriction are imposed on (8).

These are:

$H_{1:}$ Regression slope coefficients are identical, and intercepts are not. That is:

$$y_{it} = \alpha_i^* + \beta^/ X_{it} + U_{it} \qquad (9)$$

$H_{2:}$ Regression intercepts are the same, and slope coefficients are not. That is:

$$y_{it} = \alpha^* + \beta_i^/ X_{it} + U_{it} \qquad (10)$$

$H_{3:}$ Both slope and intercepts coefficients are the same. That is:

$$y_{it} = \alpha^* + \beta^/ X_{it} + U_{it} \qquad (11)$$

$$Y = \begin{bmatrix} Y_1 \\ Y_2 \\ " \\ Y_N \end{bmatrix}_{NT\times 1}, D = \begin{bmatrix} iT & 0 & " & 0 \\ 0 & iT & " & 0 \\ " & " & " & " \\ 0 & 0 & " & iT \end{bmatrix}_{NT\times N} \qquad (12)$$

$$X = \begin{bmatrix} x_{11} & x_{12} & " & x_{1k} \\ x_{21} & x_{22} & & x_{2k} \\ " & " & & \\ x_{N1} & x_{N2} & & x_{nk} \end{bmatrix}_{NT\times K} \qquad (13)$$

and:

$$\alpha = \begin{bmatrix} a_1 \\ a_2 \\ \text{"} \\ a_N \end{bmatrix}_{N \times 1}, \beta' = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \text{"} \\ \beta_K \end{bmatrix}_{K \times 1} \quad (14)$$

where "the dummy variable is the one that allow us to take different group-specific estimates for each of the constants for each different section" (Asteriou and Hall, 2011, p.418). However, the validity of the FEM is based on the following properties: a) that the estimated results capture all effects that are specific to each individual and do not vary over time. In this case, the fixed effects (FE) would capture geographical factors, natural endowments, and any other of the many basic factors that vary between countries but not over time. This implies that no extra variables which do not change over time (for example, country size) would be added to the model, as this variable will be perfectly co-linear with the FE; and b) sometimes, it may involve a large number of dummy intercepts as some panels may have many thousands of individual members (for example, large survey panels) and in this situation, the FE model would use up N degrees of freedom. This argument is probably correct because the computation may be difficult to calculate many thousands of different intercepts, but the researcher would transform the model by differencing all the variables or by taking deviations from the mean for each variable, which has the impact of removing the dummy intercepts and avoids the problem of estimating so many parameters. However, differencing the model might distort the parameter values, and can remove any long run effects. The FE model can also be extended to include a set of time dummies, called the two-way FE model, and has the merit of taking full account of any effects that change but are common across the whole panel.

In order to achieve our objective of the role of international trade as a determinant of carbon dioxide emissions in Africa, our estimated fixed effects model is takes the form:

$$1n(I_{it}) = a_i + \alpha 1n(PD_{it}) + \beta 1n(A_{it}) + \varphi 1n(T_{it}) + \delta 1n(NTA_{it}) + e_i \quad (15)$$

Where NTA is the net trade (proxy for international trade)

In addition, the York *et al.* (2003a) study used the STIRPAT model refined by Dietz and Rosa (1994), and combined T with the error term, rather than estimating it separately to conform to the IPAT framework. In contrast, Shi (2003) disaggregates T into economic structures-manufacturing sector (M) and services sector (S) to balance I, P and A. The modifications yield:

$$1n(I_{it}) = a_i + \alpha 1n(PD_{it}) + \beta 1n(A_{it}) + \theta 1n(M_{it}) + \psi 1n(S_{it}) + \delta 1n(NTA_{it}) + e_{it} \quad (16)$$

In addition, model (15) cannot be estimated directly as was the case with Shi (2003) because affluence (A_{it}) is the Gross Domestic Product Per Capita (GDP), (M_{it}) is the manufacturing sector, a component of GDP and (S_{it}) is the services sector, another different component of GDP. If we estimates model (16) the way Shi (2003) did, the implications is that both variables (A_{it}) and (M_{it}) are closely connected and affect or depend on each other, and so is the case with both (A_{it}) and (S_{it}). In either case, the problem of collinearity (a linear association between two independent variables) or correlated explanatory variables will arise deepening considerable redundancy. However, we solved this problem by employing final consumption expenditure of government $(FCEG_{it})$ which directly affect the standard of living of Africans, each year final consumption government expenditure in African countries remains the engine of economy drivers in the continent as a proxy for (A_{it}). Our modified and estimated model now takes the form:

$$\ln(I_{it}) = a_i + \alpha \ln(PD_{it}) + \beta \ln(FCEG_{it}) + \theta \ln(M_{it}) + \psi \ln(S_{it}) + e_{it} \quad (17)$$

Since we are looking for the most appropriate estimator in order to achieve our objective, the random effects we now turn:

• The random effects method (REM)

The REM is another alternative method of estimating a model. Asteriou and Hall (2011); Baltagi (2008); Balestra and Nerlove (1966) state that the difference between FEM and REM is that the latter handles the intercepts for each section (group) not as fixed, but as random parameters. In addition, our sampled countries (51 countries) have a common mean value for the intercept, since we employed random effects, determined by the Hausman test. Thus, the change of intercept for each group comes from:

$$a_i = a + \varepsilon_i \quad (18)$$

Where e_i is a zero mean standard random variable. Therefore, our random effects model becomes:

$$Y_{it} = a_i + \beta_1 X_{1it} + \beta_2 X_{2it} + ... + \beta_k X_{kit} + e_{it} \quad (19)$$

$$Y_{it} = (a + \varepsilon_i) + \beta_1 X_{1it} + \beta_2 X_{2it} + ... + \beta_k X_{kit} + e_{it} \quad (20)$$

e_i is unobserved; it is absorbed into the error term; thus, we now write our model as:

$$Y_{it} = a + \beta_1 X_{1it} + \beta_2 X_{2it} + ... + \beta_k X_{kit} + (\varepsilon_i + e_{it}) \quad (21)$$

Where there are T observations on outcome y for country i (in our study), the error term $(\varepsilon + e)$ consists of two components: e is an 'unobserved heterogeneity' component, and e is an 'idiosyncratic' component. X_{it} is a vector of independent variables measured at time t; ε_i is unobserved in all periods but constant over time; e_{it} is a time-varying idiosyncratic error and $v_{it} = (\varepsilon_{it} + e_{it})$ is the component error. Our random effects model is of the form:

$$\ln(I_{it}) = a_i + \alpha \ln(PD_{it}) + \beta \ln(FCEG_{it}) + \theta \ln(M_{it}) + \psi \ln(S_{it}) + \delta \ln(NTA) + v_{it} \quad (22)$$

Where $v_{it} = (\varepsilon_{it} + e_{it})$

$$\ln(I_{it}) = a_i + \alpha \ln(PD_{it}) + \beta \ln(FCEG_{it}) + \theta \ln(M_{it}) + \psi \ln(S_{it}) + \delta \ln(NTA) + (\varepsilon_{it} + e_{it}) \quad (23)$$

Asteriou and Hall (2011) point out that the drawback of the REM approach is that specific assumptions about the distribution of the random component must be made, and if the unobserved group-specific effects are correlated with the explanatory variables, then our estimates will be biased and inconsistent. On the other hand, the strengths of REM approach are: "it has fewer parameters to estimate than the fixed effects method, and it allows for additional explanatory variables that have equal value for all observations within a group, that is, it allows us to use dummies" (Asteriou and Hall, 2011, p.420). Balestra and Nerlove (1966) suggest the use of the error components model in panel data analysis.

In addition, it is important to check whether there are any implications when using the random effects model compared with the fixed effect model. Asteriou and Hall (2011) maintain that in making a comparison between the two methods, the use of the random effects estimation might be expected to be superior to the fixed effects estimator, the reason being that the REM is the Generalised Least Square (GLS) estimator, and the FEM is a limited case of the REM (as it corresponds to a situation where the variation in individual effects is relatively large). However, the random effects estimator is applied under the assumption that the fixed effects are uncorrelated with the explanatory variables, a condition that creates strict limitations in panel data treatment in practice.

In general, the major difference between the two approaches of testing panel data models is that the FEM assumes that each country differs in its intercept term, whereas the REM assumes that each country differs in its error term.

Generally, in balanced panel data, that is, containing all existing cross-sectional data, the FEM works better. However, in other cases, where the sample consists of limited observations of the existing cross-sectional units, the random effects model might be more appropriate (Hsiao 2003; Asteriou and Hall, 2011). In our study of 51 African countries according to different income levels, the panel data are unbalanced, though both FE and REM are employed and both did not performed better.

On the basis of insufficient observations for Pesaran CD test, we carried out GLS estimation using GLS regression with correlated disturbances and regression with panel-correlated standard errors (PCSE). Since the errors in TSCS are likely to be non-spherical, exhibiting any or all of the: contemporaneous correlation, panel heteroscedasticity, and serial correlation; Kristensen and Wawro (2003, p. 2-3) state that: “ordinary least square (OLS) is not the best linear unbiased estimator (BLUE) and can produced incorrect standard errors when the errors are non-spherical. The GLS, which incorporates information about the errors and thereby makes up the inefficiency OLS is BLUE and will give correct standard errors. However, the GLS assumes that the variance-covariance matrix (Ω), which is used to weight the data, is known when in practice it is not. We estimated GLS model (24) below which is more robust and reported the findings in Section 4.

Our augmented Stochastic Regression on Population Density (PD), Final Consumption Government Expenditure (FCEG), Manufacturing Sector value added as a percentage of GDP (M), Services Sector value added as a percentage of GDP (S) and Net Trade (NTA) (STIRPFCEGMSN) models for GLS becomes:

$$\ln(I_{it}) = a + \alpha \ln(PD_{it}) + \beta \ln(FCEG_{it}) + \theta \ln(M_{it}) + \psi \ln(S_{it}) + \delta \ln(NTA) + \varepsilon_i + e_{it} \tag{24}$$

Where:
δ is the parameter for net trade;
ε is the unobserved heterogeneity’ component error term and constant over time;
NTA is the net trade; and
e is an ‘idiosyncratic’ component.

IV. FINDINGS

4.1 Results of the impacts of net trade and population density on CO_2 emissions.

The coefficient for net trade stands out explicitly significant and positive for all the income groupings. The findings show that the average effect of net trade over CO_2, when the net trade changes across time and between countries increases by 1%, CO_2 emissions increases by about 1.68%, 2.45% and 1.01% for LICA, LMICA and UICA respectively, when all other predictors are constant. The average effect of population density over CO_2 emissions, when the population density changes across time and between countries increases by 1%, CO_2 emissions increases by about 0.15% for LICA, whereas CO_2 emissions decreases by about 0.22% and 0.21% for LMICA and UICA respectively, holding all other predictors constant. A 1 percentage point increase in manufacturing sector value added as a percentage of GDP, when the manufacturing sector changes across time and between countries, increases CO_2 emissions by about 0.47% and 1.23% for LMICA and UICA respectively, when all other predictors

Table 3: The impact of net trade and Population density on CO_2 emissions
Baseline Model- Regress per capita Co_2 emissions- ℓn(I) on population density- In(PD), final consumption expenditure growth- ℓn(FCEG), manufacturing sector value added as a percent of GD- ℓn(M), services sector value added as percent of GDP- ℓn(S) and net trade ℓn(nta).

Dependent Variable: ℓn(I) **GLS/FGLS**

Variable		LICA		LMICA		UICA
Intercept	-0.190	(0.914)	0.097	(1.515)		
ℓn(PD)	0.152***	(0.040)	-2.229**	(0.083)	-.211***	(0.034)
ℓn(M)	0.099	(0.084)	0.470**	(0.153)	1.239***	(0.161)
ℓn(S)	-0.194	(0.103)	-.443***	(0.121)	-1.09***	(0.151)
ℓn(FCEG)	-0.001	(0.034)	-0.102	(0.054)	-0.046	(0.052)
ℓn(NTA)	1.687***	(0.197)	2.459***	(0.350)	1.015***	(0.227)
Sample		332		163		178
log likelihood		-174.22		-179.37		

***P < 0.001; **P < 0.01; *P < 0.05.
*The coefficients are asterisk according to their levels of significance (coefficient not asterisk are not significant), and the standard errors are in parenthesis.
*Our dependent variable and all the explanatory variables are in logarithmic forms.
*The GLS/FGLS indicates Generalized Least Squares/ Feasible Generalized Least Squares.

Table 4: The impact of net trade and Population density on CO_2 emissions
Baseline Model- Regress per capita Co_2 emissions- ℓn(I) on population density- In(PD), final consumption expenditure growth- ℓn(FCEG), manufacturing sector value added as a percent of GD- ℓn(M), services sector value added as percent of GDP- ℓn(S) and net trade ℓn(nta).

Dependent Variable: ℓn(I) **Fixed Effects**

Variable		LICA		LMICA		UICA
Intercept	-9.40***	(1.074)	-14.49***	(3.293)	-20.49***	(1.729)
ℓn(PD)	-.970***	(0.091)	-1.419**	(0.221)	-1.29***	(0.207)
ℓn(M)	0.107	(0.135)	-0.069	(0.146)	0.614***	(0.122)
ℓn(S)	0.420**	(0.146)	0.890***	(0.166)	0.542***	(0.147)
ℓn(FCEG)		(0.034)	-0.061	(0.028)	-0.015	(0.024)
ℓn(NTA)	0.026***	(0.019)	1.270***	(0.281)	1.015***	(0.227)
R-sq: within		0.82		0.40		0.59
Between		0.0001		0.22		0.20
overall		0.012		0.008		0.34
Sigma_u		1.55		1.50		2.77
Sigma_e		0.130		0.35		0.30
rho		0.99		0.94		0.98

***P < 0.001; **P < 0.01; *P < 0.05.
*The coefficients are asterisk according to their levels of significance (coefficient not asterisk are not significant), and the standard errors are in parenthesis.
*Our dependent variable and all the explanatory variables are in logarithmic forms.

Table 5: The impact of net trade and Population density on CO_2 emissions
Baseline Model- Regress per capita Co_2 emissions- ℓn(I) on population density- In(PD), final consumption expenditure growth- ℓn(FCEG), manufacturing sector value added as a percent of GD- ℓn(M), services sector value added as percent of GDP- ℓn(S) and net trade ℓn(nta).

Dependent Variable: ℓn(I) **Random Effects**

Variable		LICA		LMICA		UICA
Intercept	-7.60***	(1.494)	-11.18***	(2.935)	-11.23***	(0.966)
ℓn(PD)	-.758***	(0.124)	-1.135***	(0.191)	0.065	(0.035)
ℓn(M)	0.103	(0.191)	-0.146	(0.143)	-.176***	(0.172)
ℓn(S)	0.310	(0.211)	0.770***	(0.157)	0.682***	(0.191)
ℓn(FCEG)			-0.066*	(0.029)	-0.003	(0.040)
ℓn(NTA)	0.004***	(0.028)	1.343***	(0.286)	0.462***	(0.430)
R-sq: within		0.81		0.39		0.34
Between		0.0004		0.23		0.68
overall		0.016		0.01		0.66
Sigma_u		0.53		1.006		0
Sigma_e		0.13		0.35		0.30
rho		0.94		0.89		0

***P < 0.001; **P < 0.01; *P < 0.05.
*The coefficients are asterisk according to their levels of significance (coefficient not asterisk are not significant), and the standard errors are in parenthesis.
*Our dependent variable and all the explanatory variables are in logarithmic forms.

are constant. A 1 percentage point increase in services sector value added as a percentage of GDP, when the service sector changes across time and between countries, reduces CO_2 emissions by about 0.44% and 1.09% for LMICA and UICA respectively, when all other predictors are constant. The results for population density and net trade are both statistically significant at 1 % significance levels, for LICA; LMICA indicates that population density, manufacturing sector, the services sector and net trade are statistically significant at 10%, 10%, 1% and 1% significant levels respectively; and UICA suggests that the population density, manufacturing sector, the services sector and net trade are all statistically significant at 1% significance levels. (see Table 3).

The study only reports Table 3 since it is more robust than Tables 4, 5 and 6. In addition, it addresses the problems of serial correlation and heteroscedasticity.

• Managerial Implications

An implication for manager is that increase in CO_2 emissions load in African countries at different income levels operate through openness of the economy, manufacturing sector and population density. The implication is that identifying the main driving forces of environmental impacts in Africa might be of good use to address the environmental challenges on the continent, but it might be of limited use for decision-makers because it is possible that for a given method to be

Table 6: Sample of countries in Africa investigated according to income levels

Serial No	LICA	LMICA	UICA	HICA
1	Benin	Cameroon	Algeria	Equatorial G.
2	Burkina Faso	Cape Verde	Angola	
3	Burundi	Congo Republic	Botswana	
4	Central Africa R.	Cote d'Ivoire	Gabon	
5	Chad	Djibouti	Libya	
6	Comoros	Egypt	Mauritius	
7	Congo Dem. R.	Ghana	Namibia	
8	Eritrea	Lesotho	Seychelles	
9	Ethiopia	Mauritania	South Africa	
10	Gambia	Morocco	Tunisia	
11	Guinea	Nigeria		
12	Guinea Bissau	Senegal		
13	Kenya	Sudan		
14	Liberia	Swaziland		
15	Madagascar	Zambia		
16	Malawi			
17	Mali			
18	Mozambique			
19	Niger			
20	Rwanda			
21	Sierra Leone			
22	Somalia			
23	Tanzania			
24	Togo			
25	Uganda			
26	Zimbabwe			

*Equatorial G. is Equatorial Guinea: The only country in Africa classified as the HICA.
**The study is limited to only sovereign African countries based on different income levels under investigation, further research needs to be extended to other less developing countries.

effective in the continent context, it requires accompanying action that provides strategies to mitigate carbon dioxide emissions to achieve a sustainable environment. In sum, research on the African openness of the economy and carbon dioxide emissions suggests that population density, growth, control of corruption and reduction in the importation of dirty goods are better understood as the variable targets to ameliorate emission impacts. The focus on testing net trade conveys the idea that the basic STIRPAT model becomes meaningful only when investigating environmental impacts, and thus diminishes the traditional knowledge systems explanation of the world environmental impacts with the use of only three basic predictors: population, affluence and technology. Thus, an important task ahead for further research is to contextualize the uses of this method.

• The Policy Implication (s) that Arise From the Study

The methodology employs lead to different policies for addressing environmental concern in Africa than does the initial STIRPAT approach. The later ask us to locate environmental driver-triggers only in population, affluence and technology. By addressing economic structures and net trade, the logic enable us to identify the key drivers of the environmental impacts. We will reduce manufacturing sector (since econometric analyses suggest it is a major contributor to carbon dioxide emissions load in the continent) in favor of services sector and ban dirty goods via importation from the rest of the world. This perspective points to the robustness of the method we used and suggest that decision makers can make use of this new interventions to enhance a low carbon economies in the continent. In terms of policy implication/s, this new approach we used is very likely to mitigate carbon dioxide emissions drastically. The use of this strategy is pressing and urgent in order to pursue a better quality of life and ensure environmental sustainability.

Furthermore, the results show that there is a need for a comprehensive range of policy solutions to stimulate commitment amongst the decision-makers and involves all society stakeholders. As a first step, public enlightenment and campaign of the impacts of environmental disaster must be stressed and the general public well educated. Second, all the seaports, airports and porous borders through which dirty, hazardous, harmful and dangerous commodities and goods find their ways into the continent should be blocked and well police. Third, African governments should ensure all trade activities with the rest of the world are conducted on equal basis and adhere strictly to the international convention prohibiting sales and dumping of dirty goods on the continent. Four, dangerous emissions from exhaust pipes of all form of movable vehicles and burning of fossil fuels must be taxed and prohibited. On the basis of this study, we suggest additional policy measures "in order to foster cognitive, affective and behavioural aspects of engagement" (Lorenzoni, Nicholson-Cole and Whitmarsh 2007; Phelan Link and Tehranifar 2010). Five, indiscriminate burning of bushes, cutting down of trees and destruction of vegetation must be addressed urgently, as these are common practices in most part of Africa. Six, modern method of home wastes management should be adopted in order to reduce common practices of refuse dumps and burning of refuse in the open in cities, towns and villages.

V. LIMITATIONS OF THE STUDY

The sampled countries are sovereign African countries based on data availability. South Sudan is excluded because it got her independence few years ago and required data are not available. Equatorial Guinea is also excluded because she is the only high income countries in the continent, and our method (panel data analysis) do not permit the use of a single entity (a single country). The study is limited to only sovereign countries in the continent. Partially sovereign countries and countries that are not independent are not considered.

The countries that are excluded are mostly Islands whose data are not available with the World Bank between the periods under investigation. The African continent consist of list of sovereign countries, partially recognized and unrecognized states (Somaliland and

Sahrawi Arab Democratic Republic) and dependent territories, that is, non-sovereign territories (French Southern and Antarctic Lands, Saint Helena, Ascension and Tristan da Cunha, Canary Islands, Ceuta, Madeira, Mayotte, Melilla, Plazas de Soberanda, Reunion and Lampedusa and Lampione), all located on the African continental plate (see National Geographic 2011; De Waal 2010; Theiler 1982; Freshfield 1869; Rennell 1830; Von Strahlenberg 1730). However, by international convention they are considered European (De Waal 2010). In addition, the Island of Socotra is on the continent of African plate, but part of Yemen territory (National Geographic 2011; Theiler 1982; Freshfield 1869). This study considered only the sovereign states in the continent due to data availability. Of the 54 sovereign states in Africa the research investigate 52 countries which yield a good coverage of 96.29% of the independent countries on the continent. We collected online all the data used in this research from the World Bank Africa Development Indicators.

VI. CONCLUSIONS

This study adopts the refined STIRPAT model but is modified to answer our research questions. The logic of the STIRPAT approach is preserved but expanded, treating five key elements: population density (PD); final consumption expenditure (FCEG) (annual growth), technology (T): decomposed into economic structures (manufacturing (M) and services (S) sectors) and net trade (D) as the driving forces influencing carbon dioxide emissions change. Our work considers technology in the STIRPAT model in terms of structure of the economy. Hence, we decomposed technology into manufacturing sector value added as a percentage of GDP (M) and services sector value added as a percentage of GDP (S), and this is consistent with the modernization economy and political economy theories. This contention lends strong support in favour of determining the impacts of both manufacturing and services as contributors to technological impacts which, in turn, determine carbon dioxide emission loads in Africa. In addition, very few studies treated net trade as a driving force of environmental impact in most African countries. We investigate net trade and its impact on the carbon dioxide emissions and found that it is a major contributor to carbon dioxide emission loads in African countries at different income levels.

It is widely believe that African continent has the lowest carbon emissions across the globe when compared with other regions or continents. However, we suggest that in order to maintain low carbon economies in African countries at different income levels, the exchange of goods and services between African countries and the rest of the world should be conducted based on the international trade conventions to avoid a situation where African countries are used as a dumping ground for dirty goods. This is very crucial because the impact of net trade on CO_2 emissions is consistently positive in all the African countries at different income levels.

REFERENCES

Alston, D. and Brown, N. (1993). *Global threats to people of color. Confronting environmental racism: Voices from the grassroots,* 179-194.

Anyinam, C. A. (1991). Transboundary movements of hazardous waste: The case of toxic waste dumping in Africa*. International journal of health services, 21*(4), 759-777.

Asteriou, D. and Hall, S. G. (2011). *Applied econometrics, (second ed.).* Palgrave Macmillan, United Kingdom.

Balestra, P. and Nerlove, M. (1966). Pooling cross section and time series data in the estimation of a dynamic model: The demand for natural gas. *Econometrica: Journal of the econometric society*, 585-612.

Baltagi, B. (2008). *Econometric analysis of panel data (vol. 1).* John Wiley and Sons.

Bernstorff, A. and Stais, K. (2001a). POPS in Africa: Table of Hazardous waste trade 1980-2000, obsolete pesticide stockpiles: A greenpeace inventory, p. 17.

Clapp, J. (1994). Africa, NGOs, and the International Toxic Waste Trade. *Journal of environmental development, 3*, 217-46.

De Waal, T. (2010).*The Caucasus: An introduction*. Oxford University Press. ISBN 0195399765, 9780195399769: 10.

Dietz, T. and Rosa, E.A. (1994a). Rethinking the environmental impacts of population, affluence, and technology. *Human ecology review*, 1, 277-300.

Ehrlich, P. and Holdren, J. (1970). The people's problem. *Saturday review, 4*, 42-43.

Ehrlich, P. and Holdren, J. (1971). Human population and the global environment. *American scientist, 62*, 282-292.

Ehrlich, P.R. and Holdren, J.P. (1971a). Impact of population growth. *Science*, 171, 1212-1217.

Ehrlich, P.R. and Holdren, J.P. (1972b). *Impact of population growth in population, resources and the environment.* Washington, D. C.: U.S. Government Printing Office, 365-77.

Freshfield, D. W. (1869). Journey in the Caucasus. *Proceedings of the Royal geographical Society*, vol. 13-14: Cited as de facto convention by Baron von.

Hsiao, C. (2003). *Analysis of panel data (vol. 34).* Cambridge University Press.

Jorgenson, A. K. (2009). The transnational organization of production, the scale of degradation, and ecoefficiency: A study of carbon dioxide emissions in less-developed countries. *Human ecology review, 16(*1), 64-74.

Kristensen, I.P. and Warwo, G.J. (2003). Lagging the dog? The robustness of panel corrected standard errors in the presence of serial correlation and observation specific effects. In annual meeting of the *Society for Political Methodology*, University of Minnesota.

Li, J. S., Chen, G. Q., Chen, B., Yang, Q., Wei, W. D., Wang, P., Dong, K. Q. and Chen, H.

P., (2017). The impact of trade on fuel-related mercury emissions in Beijing- evidence from three-scale input-output analysis. Renewable and sustain energy reviews, Vo. 75: 742-752. https://doi.org/10.1016/j.rser.2016.11.051.

Liu, Y., Zhou, Y. and Wu, W. (2015). Assessing the impact of population, income and technology on energy consumption and industrial pollutant emissions in China. *Applied Energy,* Vol. 155: 904-917. https://doi.org/10.1016/j.apenergy.2015.06.051.

Liu, X., Mao, G., Ren, J., Yi, R., Li, M., Guo, J. and Zhang, L. (2015). How might China achieve its 2020 emissions target? A scenario analysis of energy consumption and CO_2 emissions using the system dynamics model. *Journal of Clean Production,* Vol. 103: 401-410. https://doi.org/10.1016/j.jclepro.2014.12.080.

Loftus, P. J., Cohen, A. M., Long, J. C. S. and Jenkins, J. D. (2015). A critical review of global decarbonization scenarios: What do they tell us about feasibility? *Wires climate change*, Issue TOC. 6(1): 93-112. DOI: 10.1002/wcc.324.

Lorenzoni, I., Nicholson-Cole, S. and Whitmarsh, L. (2007). Barriers perceived to engaging with climate change among the UK public and their policy implications. *Global environmental change 17:* 445-459.

Maishinski (2010). *EU approves dumping of nuclear waste in Africa.* For Africa by Africa, Thursday, April 8.

National Geographic. (2011). *National geographic Atlas of the World* (9thed.). “Europe” (plate 59); Asia (plate 74). ISBN 978-1-4262-0634-4.

NEA (1989). *NEA issue brief: An analysis of principal nuclear issues, No 3*, January.

Ouyang, X. and Lin, B. (2015). An analysis of the driving forces of energy-related carbon dioxide emissions in China’s industrial sector. *Renewable and sustainable energy reviews*, Vol. 45: 838-849. https:/doi.org/10.1016/jrser.2015.02.030.

Phelan, J. C., Link, B. G. and Tehranifar, P. (2010). Social conditions as fundamental causes of health inequality: Theory, evidence and policy implications. *Journal of health and social behavior, 51(S)*: S28-S40. DOI: 10.1177/00221465510383498.

Rennell, J. (1830). *The geographical system of Herodotus examined and explained. Vol. 1*, Rivington: 244.

Roberts, T., Grimes, P., and Manale, J. (2003). Social roots of global environmental change: a world-systems analysis of carbon dioxide emissions. *Journal of World-Systems Research, 9*, 277-315.

Satterthwaite, D. (2009). The implications of population growth and urbanization for climate change. *Environment and urbanization, 21*, 545-567. Doi: 10.177/0956247809344361.

Shi, A. (2003). The impact of population pressure on global carbon dioxide emissions, 1975-1996: Evidence from pooled cross-country data. *Ecological economics 44,* 29-42.

Stebbins, K. R. (2010). Garbage imperialism: Health implications of dumping hazardous wastes in third world countries. *Medical anthropology, 15*(1), 81-82.

Theiler, W. (1982). *Posidonios Die Fragmente*, Vol. 1. Berlin: De Gruyter: Fragm. 47a.

Vir, A. (1989). Toxic trade with Africa. *Environmental Science and Technology, 23*(1), 23-25.

Von Strahlenberg, P. J. (1730). *Das Nord-und Ostiliche Theil von Europa und Asia (in German):* 106.

Waggoner, P. E. and Ausubel, J. H. (2002). A framework for sustainability science: a renovated IPAT identity. *Proceedings of the National Academy of Science, 99*(12), 7860-7865.

Wooldridge, J. M. (2010). *Econometrics analysis of cross section and panel data.* MIT Press.

World Nuclear Association (2013). *Radioactive waste management*. Retrieved March 15 2014 from http://www.world-nuclear.org/info/Nuclear-Wastes/Raioactive-Waste-Management.

World Bank Development Indicators data set (2013). Statistical Data Bank, Databank.world.org/data/databases.aspx.

Xu, B. and Lin, B. (2015). Factors affecting carbon dioxide emissions in China's transport sector: A dynamic nonparametric additive regression model. *Journal of clean production*, Vol. 101: 311-322. https://doi.org/10.1016/j.jclepro.2015.03.088.

York, R., Rosa, E. A. and Dietz, T. (2003a). STIRPAT, IPAT and ImPACT: analytical tools for unpacking the driving forces of environmental impacts. *Ecological economics 46*, 351-365.

York, R., Rosa, E. A. and Dietz, T. (2003b). Footprint on the earth: The environmental consequences of modernity. *American sociological review 68(2)*, 279-300.

Zhang, S., Wu, Y., Liu, H., Huang, R., Un, P., Zhou, Y., Fu, L. and Hao, J. (2014). Real-world fuel consumption and CO2 (carbon dioxide) emissions by driving conditions for light-duty passenger vehicles in China. *Energy*, Vol. 69: 247-257.

Zhang, N. and Choi, Y. (2013). Environmental energy efficiency of China's regional economies: A non-oriented slacks-based measure analysis. The social science journal, Vol. 50, Iss. 2: 225-234. https://doi.org/10.1016/j.soscij.2013.01.003.

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