

1 An investigation of the role of population age structure and carbon dioxide emissions in

2 Africa

3 Abstract

4 The study investigates the effects of population age structure, that is, the number of people
5 who could potentially be economically active (15-65 years) on carbon dioxide emissions in
6 Africa at different income levels. The study seeks to determine whether the economically
7 active population of the African countries play significant roles in the rising carbon dioxide
8 (CO₂) emissions on the continent or not. We employed fixed effects, random effects and
9 generalized least squares (GLS) estimators, and measures the quantitative impacts from an
10 augmented STIRPAT model constructed assuming that population structure, manufacturing
11 sector, the services sector, final consumption expenditure (annual growth) are the predictors
12 of CO₂ emissions (environmental impacts). The findings suggest mixed results of positive
13 and negative impacts of population age structure: The quantitative impacts indicate that the
14 average impact of population age structure on CO₂ emissions, when the population age
15 structure change across time and between countries in LICA and UICA increases by 1 per
16 cent, reduces CO₂ emissions by about 0.67 per cent and 1.08 per cent respectively, holding all
17 other predictors constant. Whereas the estimated results indicate that the average impact of
18 population-age-structure on CO₂ emissions, when the population structure change across time
19 and between countries in LMICA increases by 1 per cent, increases CO₂ emissions by about
20 0.52 percent, holding all other predictors constant. The implication is that in lower-middle-
21 income-countries in Africa the active-population-age groups (15-65 years) play a significant
22 role in carbon-dioxide-emissions load in the continent, whereas in low-income-countries and
23 upper-income-countries in Africa the reverse is the case.

24
25 **Keywords: Population age structure, carbon-dioxide-emissions, manufacturing-sector,**
26 **services-sector and consumption.**

27 1 Introduction

28 One of the main developments of the economically active population (15-65 years) of
29 African countries is its impact on the environment. As population age structure pressure and
30 demands

31 increase to meet the essentials of life, such as food, water, shelter and transportation, the
32 conjecture is that population age structure is largely responsible for increasing agricultural
33 practices and energy demand, and both of these trends have accelerated since 1960, according

34 to the World Bank Development Indicator (2013), fuelling the debate on the interactions
35 between population age structure and environmental problems in Africa.

36 Concerns over the issue of the population-environment nexus can be traced to the early
37 debate on the relationship between population and natural resource scarcity. Malthus (1798)
38 argues that the means of subsistence determine population growth, and that population
39 changes when the means of subsistence change. In contrast, Boserup (1965, 1976, 1981,
40 1985) contends that the means of subsistence do not determine population growth, population
41 density and population age structure rather the reverse, with population determining
42 agricultural growth. In other words, a society with sustained increase in active population age
43 structure is a prerequisite for technological innovation and substitution, and technological
44 breakthroughs increase agricultural yield, leading to surpluses and the efficient distribution of
45 food, enabling the natural habitat to support a larger population at the same level of well-
46 being.

47 Furthermore, the Boserupian tradition argued strongly that an increasing active population
48 age structure stands a better chance of economic development, and that a more economically
49 active populous society can provide technological solutions to environmental threats more
50 effectively than a small society whose economically active population is stagnant (Simon,
51 1980, 1981a, 1981b). The implication is the net impact of population age structure on the
52 environment is either null or, in fact, positive.

53 The aspects of the linkages between population and environmental impacts overlooked by
54 previous studies are that: empirical works on the relationship between the impact of
55 population age structure (economically active population) in the economies of African
56 countries at different income levels and carbon dioxide emissions are scant. The purpose of

57 this study is to assess the net impact of the economically active population on carbon dioxide
58 emissions across African countries and see how this impact varies per capita income.

59 This research paper is organized as five sections and the structure of this empirical research
60 takes the following form. Section 2 presents the literature review. Section 3 presents the
61 Methodology, data sources, the models and summary statistics. Section 4 presents data
62 analysis and interpretations. Section 5 offers the concluding remarks, suggestions and
63 contributions of the study.

64 **2 Literature review**

65 **2.1 Population age structure (15-65 years) and CO₂ emissions: Evidence of relationship**

66 The Malthusian perspective suggests that the age structure of a population affects the rate of
67 contribution of CO₂ emissions. York, et al. (2003a) used the refined STIRPAT (Stochastic
68 Impacts by Regression on Population, Affluence and Technology) model developed from
69 IPAT (Commoner 1971; Ehrlich and Holdren 1971) and ImPACT (Waggoner and Ausubel
70 2002), analytical tools for unpacking the drivers of environmental impacts to examine the
71 linkages between population age structure and CO₂ emissions. The work argued that despite
72 a scientific consensus that humans have dramatically changed the global environment, there
73 is limited knowledge of the specific drivers of impacts due to lack of refined analytical tools.
74 The study discussed the interaction between IPACT, ImPACT and STIRPAT frameworks,
75 their similarities in terms of conceptual underpinnings, pros and cons and their divergent
76 uses. The reformulated STIRPAT model is further refined and developed into the concept of
77 ecological elasticity (see York, et al. 2003b). An estimate of ecological elasticities of
78 population, affluence and other factors for cross-national carbon dioxide emissions from
79 fossil fuel combustion and for the energy footprint, a composite measure which is composed
80 of effects from fossil fuel combustion, fuel wood, hydropower and nuclear power was

81 computed for the period 1996 to 2002. It employed the percentage of population aged 15-65
82 or the non-dependent population as the key predictor of CO_2 emissions. The estimated results
83 indicate that the age structure has a proportional impact or unitary elasticity on carbon
84 dioxide emissions and energy footprint. In addition, an economic development proxy (per
85 capita GDP) monotonically increases carbon dioxide emissions and energy footprint. The
86 study found that the effect on climate of developed countries in temperate region was greater
87 than that of the tropical region. The argument of modernization theorists also found empirical
88 support since urbanization and industrialization are associated with a significant high positive
89 impact. Overall, the study contributed to the literature in terms of methodology as the
90 STIRPAT model augmented with ecological elasticity permits a more precise specification of
91 the sensitivity of environmental problems to their drivers. In addition, the basic science of
92 environmental change is informed of the variables most important for control of
93 environmental change. Similarly, York, et al. (2003b) found that age structure is an indicator
94 which is very useful in examining anthropogenic carbon dioxide emission impacts, over the
95 period 1997-2002. The research assesses various environmental impacts theories: human
96 ecology, economic modernization, democracy and the state perspective, the world system
97 perspective and political economy, and adopts and modifies a framework that relies on
98 ecological principles. The study (York, et al. 2003b) lends support to the strong opinion
99 expressed in previous works; for example, see the argument in York, et al. (2003a) in favour
100 of a reformulation of the environmental change theoretical framework to promote the basic
101 science of identifying the most pressing factors which could be altered for policy formulation.
102 The research used a revised stochastic formulation framework and the most comprehensive
103 measure of environmental impacts or ecological footprint to investigate the determinants of
104 environmental impacts on societies. Overall, the estimated results support the observed
105 theory of human ecology, partially support the political economy perspective, and do not find

evidence for the modernization theory. The basic factor conditions such as population, economic production, geographical factors and urbanization determine the vast majority of cross-national variation in environmental impacts. Taken together, the estimated findings suggest that population; economic development and institutional change are the key predictors of environmental change. Liddle & Lung (2010) revisited the STIRPAT framework, and used the model to identify three environmental impacts determined by the population structure. Their key contribution is that they disaggregated population into age structures (20-34, 35-49 and 50-64), and found divergent anthropogenic impacts across age groups. The dependent population or retirees was found to have a negative environmental impact. The study showed that population impacts are different in absolute terms. It also found a positive linkage between urbanization and carbon dioxide emissions.

As we adopt population age structure approach, we contribute to this literature by avoiding the exact specification of previous models, and used active population age structure (15-65 years), manufacturing sector, service sector, final consumption expenditure as determinants of carbon dioxide emissions in Africa at different income levels. Our model is therefore consistent with the critique we noted in the previous studies as they do not take into account any preferences for most African countries.

3 Methodology

3.1 Data sources

All our data were collected from the World Bank (2013) statistical data Bank. The study constructs an unbalanced time series cross-section (TSCS) data set of 51 countries in Africa for the period 1960-2012. The size of the sample changes according to the model specification. The excluded countries are mostly Islands whose data are not available from the World Bank between the period under investigation, and Southern Sudan who became independent 5 years ago. The African continent consists of a 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 Soberania, Reunion and Lampedusa and Lampione), all located on the African continental plate (see National Geographic, 2011; De Waal, 2010; Freshfield, 1869; Rennell, 1830; von Strahlenberg, 1730; Theiler, 1982). However, by international convention, they are considered European (De Waal, 2010). In addition, the Island of Socotra is on the continent of the African plate, but part of Yemen territory (Freshfield, 1869; National Geographic, 2011; Theiler, 1982). This study considered only the sovereign states on the continent due to data availability. Of the 54 sovereign states in Africa, the research investigates 51 countries which yield a good coverage of 94.44% of the independent countries on the continent. We collected online all the data used in this research from the World Bank Africa Development Indicators. We are now positioned to investigate our anthropogenic environmental impacts by mapping the driving forces into our modified STIRPAT frameworks. The response variable and the predictors are described as follows.

3.1.1 Carbon dioxide emissions (environmental impacts)

For our outcome variable, we used the World Bank data analysis in 2013 for per capita carbon dioxide emissions, and related emissions in Africa, comprising agricultural methane emissions, agricultural nitrous oxide emissions, carbon dioxide emissions from residential buildings and commercial public services, energy related methane, methane emissions, nitrous oxide emissions, nitrous oxide emissions in industrial and energy processes, other greenhouse gas emissions, hydrofluorocarbons (HFCs), (Perfluorocarbons (PFCs) and Sulphur hexafluoride (SF₆).

(thousand metric tons of CO₂ equivalent) and PM10 (Atmospheric particulate matter with a mean aerodynamic diameter of 10 µm) country level (micrograms per cubic metre). Of these emissions, we examine only carbon dioxide emissions stemming from the burning of fossil fuels and manufacture of cement, which include CO₂ produced during consumption of solid, liquid and gas fuels, and gas flaring. We gathered this information from the World Bank Development Indicator (2013), which was originally provided by the Carbon Dioxide Information Analysis Centre, Environmental Sciences Division, Oak Ridge National Laboratory, Tennessee, USA.

3.2 The predictor variables

3.2.1 Population age structure

The population structure describes the composition of age structure of the total population of a country into age brackets of working age groups and dependent age groups: 1-15 years (school age), 15-65 years (working age) and 65 + (retirees-dependent population). The population structure is the number of people who could potentially be economically active.

3.2.2 Technology: Manufacturing and services sector

This study does not enter into the controversy surrounding technology but represents technology with two structural indicators: manufacturing as a percentage of GDP (Gross Domestic Product) and services as a percentage of GDP (this is consistent with many studies of ecology and modernisation). This also finds support with recent studies (see Shi 2003). Manufacturing as a percentage of GDP is the manufacturing sector of value added expressed as a percentage of GDP. The services are the value added expressed as a percentage of GDP.

3.2.3 Consumption

We derived “data on final consumption expenditure (annual % growth) (FCEG)” from the World Bank Development Indicator (2013) data files, and the catalogue sources of World Development Indicators consist of World Bank national accounts data and OECD National Accounts data files. The FCEG is the average annual growth of final consumption expenditure based on constant local currency. Aggregates are based on constant 2005 US dollars. Final consumption expenditure (formerly total consumption) is the sum of household final consumption expenditure (formerly private consumption).

3.3 Models

The 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 seven key elements: population (P); final consumption expenditure (FCEG) (annual growth); consumption per capita GDP (A); technology (T): decomposed into economic structures (manufacturing (M) and services (S) sectors) 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 (see York, Rosa, & Dietz 2003). 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.

3.3.1 Endogeneity bias

Many scholarly outputs in the global community of STIRPAT users have employed the STIRPAT model because it allows for unobserved and omitted variables which are constant over time but which may be correlated with some of the explanatory variables, for example,

the initial level of technological efficiency and the possibility of using several lags of the instruments to control for endogeneity bias. The STIRPAT permits *GMM estimation* of dynamic models. In addition, it also allows the use of *fixed effects or random effects, generalised least square/feasible generalised least square (GLS/FGLS), panel corrected standard error (PCSE) estimation* techniques, thereby paving way for the analysis of the impact on growth of the driving forces that change over time (Sianesi & Reenen, 2002; Temple, 1999). Baltagi (2008), Hsiao (2003), and Wooldridge (2010), state that in a general panel data analysis, we have:

$$y_{it} = \alpha_i^* + \beta_i x_{it} + e_{it} \quad i = 1, \dots, N, \quad (3.1.0)$$

$$t = 1, \dots, T,$$

where x is a scalar exogenous variable, and e_{it} is the error term with mean zero and constant variance σ_x^2 . The parameters α_i^* and β_i may be different for different cross-sectional units, although they stay constant over time. Following this assumption, a variety of sampling distributions may occur. According to Baltagi (2008) and Hsiao (2003), such sampling distributions can seriously mislead the least-squares regression of y_{it} on x_{it} when all NT are used to estimate the model:

$$y_{it} = \alpha^* + \beta x_{it} + e_{it} \quad i = 1, \dots, N, \quad (3.1.1)$$

$$t = 1, \dots, T,$$

With respect to equations (3.1.0) and (3.1.1), Hsiao (2003, p.9) considers the situation that the data are generated as in either of the two cases below:

Case 1: Heterogeneous intercept ($\alpha_i^* \neq \alpha_j^*$), homogeneous slope ($\beta_i = \beta_j$). The study maintains that in these cases, pooled regression ignoring heterogeneous intercepts should not

222 be used, since the direction of the bias of the pooled slope estimates is different from that
223 identified a priori; ‘it can go either way’.

224 Case 2: Heterogeneous intercepts and slopes ($\alpha_i^* \neq \alpha_j^*, \beta_i \neq \beta_j$). Hsiao (2003) and Wooldridge
225 (2010) state that a straightforward pooling of all NT observations, assuming identical
226 parameters for all cross-sectional units, would lead to nonsensical results because it would
227 represent an average of coefficients that differ greatly across individuals.

228 Baltagi (2008), Hsiao (2003), and Wooldridge (2010) also consider the classic analysis of
229 covariance procedures. In this case, the studies took into account the assumption that the
230 parameters characterizing all temporal cross-sectional sample observations are identical, and
231 examined a number of specifications which permits differences in behaviour across
232 individuals as well as over time. For example, “a single-equation model with observations of
233 y depending on a vector of characteristic X” can be stated as follows:

234 a. When slope coefficients are constant, and the intercept varies over individuals, we
235 have:

$$236 \quad y_{it} = \alpha_i^* + \sum_{k=1}^K \beta_k x_{kit} + e_{it}, \quad i = 1, \dots, N, \quad (3.1.2)$$

$$237 \quad t = 1, \dots, T,$$

238

239 b. When slope coefficients are constant, and the intercept varies over individuals and
240 time, we have:

$$241 \quad y_{it} = \alpha_i^* + \sum_{k=1}^K \beta_k x_{kit} + e_{it}, \quad i = 1, \dots, N, \quad (3.1.3)$$

$$242 \quad t = 1, \dots, T,$$

243 c. When all coefficients vary over individuals, we have:

$$244 \quad y_{it} = \alpha_i^* + \sum_{k=1}^K \beta_{ki} x_{kit} + e_{it}, \quad i = 1, \dots, N, \quad (3.1.4)$$

$$245 \quad t = 1, \dots, T,$$

246 d. When all coefficients vary over time and individuals, we have:

$$247 \quad y_{it} = \alpha_{it}^* + \sum_k \beta_{kit} x_{kit} + e_{it}, \quad i = 1, \dots, N, \quad (3.1.5)$$

$$248 \quad t = 1, \dots, T,$$

249 In each of the above cases, the model is classified further, based on whether the coefficients
250 are assumed to be random or fixed as in Baltagi (2008) and Hsiao (2003). Nerlove (2005);
251 Hsiao (2003, p.14) points out that models with constant slopes and variable intercepts such as
252 (3.1.2) and (3.1.3) are “most widely used when analysing panel data because they provide
253 simple yet reasonably general alternatives to the assumption that the parameters take values
254 common to all agents at all times”.

255 Furthermore, the analysis of covariance basically tests two aspects of the estimated regression
256 coefficients: the homogeneity of regression slope coefficients and the homogeneity of
257 regression intercept coefficients. The procedures for testing these two cases are as follows:

- 258 ▪ Test whether or not slopes and intercepts simultaneously are homogeneous among
259 different individuals at different times.
- 260 ▪ Test whether or not the regression slopes collectively are the same.
- 261 ▪ Test whether or not the regression intercept are the same.

262

3.3.2 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 (see York, Rosa, & Dietz 2003a; 2003b) 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 (1994). The STIRPAT equation is:

$$I_i = a P t_i^\alpha A_i^\beta T_i^\varphi e_i \quad (3.1.6)$$

Equation (3.1.6) can be linearized by taking logarithms on both sides of the equality.

$$\ln(I_i) = \ln(a) + \alpha \ln(P t_i) + \beta \ln(A_i) + \varphi \ln(T_i) + \ln(e_i) \quad i = 1, \dots, n \quad (3.1.7)$$

Where:

the constant $\ln(a)$ scales the model,

284 α , β and φ are the exponents of the population age structure (economically active segment of
 285 the population- (15-65 years)) (Pt), affluence (A) and technology (T), e is the error term; the
 286 subscript i shows that all the explanatory variables and the error term (e) vary across
 287 observational units. The exponents can be interpreted as elasticities in equation (3.1.7). The
 288 STIRPAT model contains the IPAT as a special case, namely: $a = \alpha = \beta = \varphi = e = 1$
 289

290 The ImPACT identity: $\ln(a) = \alpha = \beta = \varphi = \ln(e) = 1$. This can also be derived from equation
 291 (3.1.7) by setting $\ln(a) = \alpha = \beta = \varphi = \ln(e) = 1$, that signify $a = e$ (Euler number) and the
 292 $e = e$ (Euler number).

293 In the case of the STIRPAT framework, any of the elasticity coefficients can be greater than
 294 1, or less than 1, or may be equal to 1.

295 3.3.3 Fixed effects

296 In a panel data analysis, the model (3.1.7) above becomes:

$$297 \ln(I_{it}) = \ln(a) + \alpha \ln(P_{it}) + \beta \ln(A_{it}) + \varphi \ln(T_{it}) + \ln(e_{it}) \quad (3.1.8)$$

298 where t is the time period or the year.

299 The STIRPAT model is employed as a starting point because it allows for an additive
 300 regression model in which all the variables can be conducted in logarithmic form, facilitating
 301 estimation and hypothesis testing (York et al., 2003a), the limitations of both IPAT and
 302 ImPACT. In addition, the York et al. (2003a) study used the STIRPAT model refined by
 303 Dietz and Rosa (1994), and combined T with the error term, rather than estimating it
 304 separately to conform to the IPAT framework. Shi (2003) disaggregates T into economic

305 structures- manufacturing sector and services sector) to balance I, P and A. The modifications
 306 yield:

$$307 \quad \ell n(I_{it}) = \ell n(a) + \alpha \ell n(Pt_{it}) + \beta \ell n(A_{it}) + \theta \ell n(M_{it}) + \psi \ell n(S_{it}) + \ell n(e_{it}) \quad (3.1.9)$$

308 Shi (2003) also estimated model similar to (3.1.9), however, we cannot estimate model
 309 (3.1.9) for the following reason: biases arise in pooled least-squares estimates because of
 310 heterogeneous intercepts. In this case, “pooled regression ignoring heterogeneous intercepts
 311 should never be used. In addition, the direction of the bias of the pooled slope estimates
 312 cannot be identified a priori; it can go either way “(Hsiao 2003, pp. 9).

313

$$314 \quad \ell n(I_{it}) = \ell n(a_i) + \alpha \ell n(Pt_{it}) + \beta \ell n(A_{it}) + \theta \ell n(M_{it}) + \psi \ell n(S_{it}) + \ell n(e_{it}) \quad (3.1.10)$$

315 In addition, model (3.1.9) cannot be estimated directly as was the case with Shi (2003)
 316 because affluence (A_{it}) is the Gross Domestic Product Per Capita (GDP), (M_{it}) is the
 317 manufacturing sector, a component of GDP and (S_{it}) is the services sector, another different
 318 component of GDP. If we estimates model (3.1.10) the way Shi (2003) did, the implications
 319 is that both variables (A_{it}) and (M_{it}) are closely connected and affect or depend on each
 320 other, and so is the case with both (A_{it}) and (S_{it}). In either case, the problem of collinearity (a
 321 linear association between two independent variables) or correlated explanatory variables will
 322 arise deepening considerable redundancy. However, we solved this problem by employing
 323 final consumption expenditure of government ($FCEG_{it}$) which directly affect the standard of
 324 living of Africans, each year final consumption government expenditure in African countries
 325 remains the engine of economy drivers in the continent as a proxy for (A_{it}). Our modified
 326 models now take the form:

$$\ln(I_{it}) = \ln(a_i) + \alpha \ln(Pt_{it}) + \beta \ln(FCEG_{it}) + \theta \ln(M_{it}) + \psi \ln(S_{it}) + \ln(e_{it}) \quad (3.1.11)$$

Where:

M is the manufacturing sector as a major component of GDP (percentage of GDP), and

S is the service sector as a major component of GDP (percentage of GDP),

θ and ψ are the exponents of M and S; and all others are as defined above.

The a priori expectation is that all the elasticity coefficients α , β , θ and ψ are expected to be positive.

3.3.4 Random effects

The rationale behind random effects model is that unlike the fixed effects model, the variation across entities is assumed to be random and uncorrelated with the predictor variables included in the model:

“...the crucial distinction between fixed and random effects is whether the unobserved individual effect embodies elements that are correlated with the regressors in the model, not whether these effects are stochastic or not. If you have reason to believe that differences across entities have some influence on your dependent variable then you should use random effects. An advantage of random effects is that you can include time invariant variables. In the fixed effects model these variables are absorbed by intercept.” (Torres-Reyna, 2007, p. 25).

The random effects equation start with one explanatory variable is:

$$y_{it} = a + \beta x_{it} + e_{it} + \varepsilon_{it} \quad (3.1.12)$$

Where

350 e_{it} is the between-entity error;

351 ε_{it} is the within-entity error; and

352 All others are as defined above.

353 Random effects equation with two or more explanatory variables is of the form:

354
$$y_{it} = a + \beta_1 x_{1,it} + \beta_2 x_{2,it} + \dots + \beta_k x_{k,it} + e_{it} + \varepsilon_{it} \quad (3.1.13)$$

355 Where

356 e_{it} is the between-entity error;

357 ε_{it} is the within-entity error; and

358 All others are as defined above.

359 On the basis of the data collected for our investigation, the relationship between
360 environmental impacts (I) and exogenous variables (x) is of the form:

361
$$\ln(I_{it}) = \ln(a) + \alpha \ln(Pt_{it}) + \beta \ln(FCED_{it}) + \theta \ln(M_{it}) + \psi \ln(S_{it}) + \ln(e_{it}) + \ln(\varepsilon_{it}) \quad (3.1.14)$$

362 The Random effects assume that the entity's error term is not correlated with the predictors
363 which allows for time-invariant variables to play a role as explanatory variables. In random
364 affects you need to specify those individual characteristics that may or may not influence the
365 predictor variables. The problem with this is that some variables may not be available
366 therefore leading to omitted variable bias in the model (Torres-Reyna, 2007, p. 26).

367

368 **The relationship between Random Effects, Generalized Least Square (GLS), Feasible**
369 **Generalized Least Square (FGLS) and Panel Corrected Standard Error (PCSE)**

370 We report our results using random effect interpretation since random effects estimator is the
371 same as the GLS estimator. This is consistent with the estimator of a random effect by GLS
372 as in the studies of Park (2005-2009). Ullah & Giles (2001) also used a model for the within-
373 cluster correlation of the error, such as equicorrelation, and argued that the feasible GLS
374 estimator is more efficient than OLS, and the efficiency gains of FGLS need not necessary be

375 great. Robinson (1991) describes random effects as best linear unbiased prediction (BLUP),
376 and applied the technique in his works. The works of Moulton (1986, p.1) is more explicit:
377 “when explanatory variable data in a regression model are drawn from a population with
378 grouped structured, the regression errors are often correlated as models of the intraclass
379 correlation. The study used several empirical examples to examine the applicability of
380 random effects and the consequences of inappropriately using OLS estimation in the presence
381 of random group effects”. The findings suggest that the assumption of independent errors is
382 usually incorrect and the adjusted OLS standard errors often have a substantial downward
383 bias suggesting a considerable danger of spurious regression. The implication is that the
384 GLS/FGLS support previous studies with the techniques of GLS regression with corrected
385 disturbances and regression with panel-corrected errors (PCSE).

386 We estimated model (3.1.14) for GLS and the results are shown in Table 4.0 below: The
387 approach of this study is slightly different from the York et al. (2003a, 2003b) works, as this
388 study considered T as an important variable that should be disaggregated into manufacturing
389 sector and services sector and estimated, instead of making the blanket assumption that T
390 could be treated as part of the error term as in York et al. (2003a; 2003b). Thus, we identify
391 two important components of technology that need to be empirically tested to achieve part of
392 the objective of the impact of human activities on emissions. The identified disaggregated
393 technologies are: manufacturing sector as a major component of GDP (percentage of GDP)
394 and services sector as a component of GDP (percentage of GDP) (Shi, 2003). This is
395 consistent with the economic modernization perspective and neoclassical economic growth
396 theory which maintained that structural factors play crucial role in mitigating environmental
397 impacts. Both theories argued that “the shift occurring away from manufacturing economies
398 and toward service economies is commonly identified as a potential solution to
399 environmental problems, because service economies are presumed to be less dependent on

natural resources than an industrial economy” (York et al., 2003b, p.284). More still, the percentage of manufacturing and the percentage of services captured the difference in T. It is expected that economies whose GDP outputs are heavily derived from manufacturing will be energy-intensive and will produce higher emissions. By contrast, economies whose GDP is largely derived from services will be less energy-intensive and will produce lower emissions (Shi, 2003).

4 Results

The findings of our empirical investigation are explained as follows. Table 4.0 below shows the relationship between population age structure, other predictors and carbon dioxide emissions. The estimated results suggest that population age structure has negative impacts on emissions in **Low Income Countries in Africa (LICA)** and **Upper Income Countries in Africa (UICA)**, whereas it has positive impacts on emissions in **Low Middle Income Countries in Africa (LMICA)**.

For LICA, the findings suggest that population age structure and manufacturing sector as a percentage of GDP have negative impacts on emissions, whereas services sector value added as a percentage of GDP have positive impacts on emissions. The quantitative impacts indicate that the average impacts of population age structure over CO₂ emissions, when the population age structure change across time and between countries in LICA increases by 1%, CO₂ emissions reduce by about 0.67%, holding all other predictors constant. A 1 point increase in manufacturing sector value added as a percentage of GDP when the manufacturing sector changes across time and between countries, decreases CO₂ emissions by about 0.20%, when all the other predictors are constant. A 1 percentage point increase in services sector value added as a percentage of GDP, when the services sector changes across time and between countries, increases CO₂ emissions by about 0.21%, when all the other predictors are

constant. The estimated results indicate that the population age structure, manufacturing sector and services sector are statistically significant at 10%, 5% and 5% levels of significance, respectively (see Table 4.0 under LICA).

For LMICA, the results show that population age structure and manufacturing sector value added as a percentage of GDP have a positive impact on emissions, whereas the services sector value added as a percentage of GDP has a negative impact. The estimated results indicate that the average impacts of population age structure over CO₂ emissions, when the population structure change across time and between countries in LMICA increases by 1%, CO₂ emissions increase by about 0.52%, 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 CO₂ emissions by about 0.22%, when all the other predictors are constant. A 1 percentage point increase in services sector value added as a percentage of GDP, when the services sector changes across time and between countries, reduces CO₂ emissions by about 0.34%, when all the other predictors are constant. The population age structure, manufacturing sector and services sector apart from the final consumption expenditure are statistically significant at 5%, 10% and 1% levels of significance, respectively (see Table 4.0 under LMICA).

For UICA, the population age structure and final consumption expenditure growth rate have negative impacts on emissions. The services sector value added as a percentage of GDP has positive impacts on emissions. The manufacturing sector value added as a percentage of GDP is not statistically significant. The findings suggest that the average impact of population structure over CO₂ emissions, when the population structure changes across time and between countries in UICA increases by 1%, CO₂ emissions reduce by about 1.53%, holding all other predictors constant. The average impact of final consumption expenditure growth

rate over CO₂ emissions, when the final consumption expenditure growth rate changes across time and between countries in UICA increases by 1%, CO₂ emissions decrease by about 0.07%, when all the other predictors are constant. A 1 percentage point increase in services sector value, added as a percentage of GDP when the services sector changes across time and between countries, increases CO₂ emissions by about 0.24%, when all the other predictors are constant. The population age structure, services sector and final consumption expenditure growth rate are all significant at 1%, 10% and 10% significance levels respectively (see Table 4.0 under UICA).

The fixed effects and random effects estimated results are shown in the appendixes A and B below (see Tables 4.1 and 4.2).

Table 4.0: Basic STIRPAT model: Population age structure- GLS

Baseline Model- Regress per capita CO₂ emissions- $\ln(I)$ on population age structure- $\ln(PT)$, manufacturing sector value added as a percentage of GDP- $\ln(M)$, services sector value added as a percentage of GDP- $\ln(S)$ and final consumption expenditure (annual % growth) $\ln(FCEG)$.

Dependent variable: $\ln(I)$						
Variable		LICA		LMICA		UICA
$\ln(Pt)$	-0.67**	(0.219)	0.52*	(0.239)	-1.538***	(0.120)
$\ln(M)$	-0.20*	(0.085)	0.22**	(0.079)	0.087	(0.086)
$\ln(S)$	0.21*	(0.105)	-.34***	(0.087)	0.236**	(0.087)
$\ln(fceg)$	.001	(0.018)	-0.05	(0.034)	-0.067**	(0.025)
Sample		332		163		178
R-squared		0.91				0.66
Number of groups		21		10		6
average		15.80		16.3		29.66
max		36		27		45
Wald chi2		3400.8		820.8		3720.3
Prob>chi2		0.0000		0.0000		0.0000
Estimated covariances		21		10		21
Est. autocorrel		1		0		1
Est. coefficients		4		4		4
log likelihood						

***P < 0.001; **P < 0.01; *P < 0.05.

*The coefficients are asterisked according to their levels of significance (coefficients not asterisked are not significant), and the standard errors are in parenthesis.

*Our dependent variable and all the explanatory variables are in logarithmic forms.

468

469 **5 Conclusions**

470 The evidences presented on the empirical study indicate that the relationship between
471 population age structure and environment impacts is convoluted with mix-results. That is, in
472 the case of the combined low income countries in Africa, and the combined upper income
473 countries in Africa, the findings suggest negative effects on environmental impacts, meaning
474 that as population age structure (economically active population) increases environmental
475 impacts is abated. However, the reverse is the case for low middle income countries in
476 Africa. Indeed, the relationship on both sides of the divides still remains inconclusive.
477 Therefore, further research is still needed to integrate the divergent findings in order to
478 determine at different income levels in African countries the key predictors of the
479 environmental impacts. The research strategy is carried out through empirical investigation,
480 using predominantly methodologies and specific models familiar to us as researchers.

481 We find evidence that the active population age structure has positive carbon dioxide
482 emission loads impacts for LMICA. This evidence supports the previous findings of York et
483 al. (2003b). Expected positive changes in carbon dioxide emissions concentration in LMICA
484 reinforce the works of York et al. (2003a), while an expected positive change in the carbon
485 dioxide emission loads in both the LICA and UICA turned out to be negative.

486 In the light of this study, new ways of investigating the linkages between population-carbon
487 dioxide emissions are being proposed by this study.

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Appendix A

Table 4.1: Basic STIRPAT Model: Population age structure- Fixed Effects

Baseline Model- Regress per capita CO₂ emissions- $\ln(I)$ on population age structure- $\ln(PT)$, manufacturing sector value added as a per cent of GDP- $\ln(M)$, services sector value added as per cent of GDP- $\ln(S)$ and final consumption expenditure (annual % growth)- $\ln(FCEG)$.

Dependent variable: $\ln(I)$			Fixed Effect			
Variable		LICA		LMICA		UICA
Intercept	-1.21	(2.021)	-16.58***	(4.298)	-11.59***	(1.239)
$\ln(Pt)$	-2.33***	(0.551)	6.98***	(1.398)	-0.06	(0.65)
$\ln(M)$	0.10	(0.068)	-0.61***	(0.130)	0.51***	(0.125)
$\ln(S)$	0.29***	(0.076)	0.01	(0.180)	0.06	(0.178)
$\ln(fceg)$	-.006	(0.014)	-0.05	(0.031)	0.01	(0.026)
Sample		332		163		178
R-sq:	within	0.307		0.255		0.497
	between	0.062		0.191		0.467
	overall	0.0008		0.001		0.608
Number of groups		21		10		6
sigma_u		0.873		1.788		0.664
sigma_e		0.232		0.391		0.336
corr(u_i, xb)		-0.541		-0.654		-0.455
average		15.8		16.3		29.7
max		36		27		45
F test	u_i=0:	120.68		60.10		44.12
Prob>F		0.0000		0.0000		0.0000
rho		0.933		0.954		0.795

Appendix B

Table 4.2: Basic STIRPAT Model: Population age structure- Random Effects

Baseline Model- Regress per capita CO₂ emissions- $\ln(I)$ on population age structure- $\ln(PT)$, manufacturing sector value added as a per cent of GDP- $\ln(M)$, services sector value added as per cent of GDP- $\ln(S)$ and final consumption expenditure (annual % growth)- $\ln(FCEG)$.

Dependent variable: $\ln(I)$			Random Effect			
Variable		LICA		LMICA		UICA
Intercept	-1.743	(2.053)	-14.74**	(4.412)	-11.27***	(1.318)
$\ln(Pt)$	-2.05***	(0.554)	5.71***	(1.381)	0.35	(0.451)
$\ln(M)$	0.07	(0.068)	-0.60***	(0.132)	0.32**	(0.119)

ln (S)	0.289***	(0.076)	0.15	(0.175)	0.16	(0.142)
ln (fceg)	-0.006	(0.014)	-.05	(0.032)	0.01	(0.028)
Sample		332		163		178
R-sq:	within	0.306		0.251		0.488
	between	0.060		0.185		0.490
	overall	0.0008		0.003		0.625
Number of groups		21		10		6
sigma_u		0.679		1.179		0.226
sigma_e		0.232		0.391		0.336
corr(u_i, xb)		0(assumed)		0(assumed)		0(assumed)
average		15.8		16.3		29.7
max		36		27		45
Wald chi2		119.00		40.99		158.45
Prob>chi2		0.0000		0.0000		0.0000
rho		0.895		0.900		0.312

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