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Do the Impacts of Bad Governance Influence Carbon Dioxide Emissions in African Countries at Different Income Levels?

Abdulrasaki Saka[1*]

[1]*Department of Economics, Middlesex University, The Burroughs, London NW4 4BT, United Kingdom.*

Author's contribution

The sole author designed, analyzed and interpreted and prepared the manuscript.

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ABSTRACT

Few studies actually investigated the impacts of bad governance (corruption) on carbon dioxide emissions in Africa at different income levels with population age structure and other driver-triggers playing moderating roles. This study uses a unique observation collected from the World Bank (2013) of 51 African sovereign countries to ask directly, what is the net impact of corruption on CO_2 emissions, and to assess the relevance of a range of potential reasons for why the net impacts of corruption on CO_2 emissions across African countries and see how this impacts varies per capita income, for the period 1960-2012. The study employs a panel dataset and used generalised least squares estimator to determine the net impacts of corruption on CO_2 emissions (environmental impacts). The findings suggest that the average effect of corruption perception index over CO_2 emissions, when the corruption perception index changes across time and between countries increases by 1%, CO_2 emissions decreases by about 0.73%, 1.95% for low-income-countries-in-Africa and upper-income-countries-in-Africa respectively, when all other predictors are constant. The negative impacts created by the practice of corruption were found to be an important consideration for future researchers and as a vital factor in the determination of the driving forces of environmental impacts neglected by previous study.

**Corresponding author: E-mail: abdulrasakisaka2@gmail.com;*

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1. INTRODUCTION

Despite a dearth of strong empirical evidence about corruption and environmental impacts relationship with overwhelming driving forces, strong empirical findings and conclusions about the relative importance of the drivers of environmental impacts still appear inconclusive. However, the modelling techniques or methods appear overlapping as consensus is hard to find. The scientists' community is largely divided over the most potent techniques and driving forces of impacts to employ in investigating population-environment nexus. Furthermore, the following econometric methods (augmented Stochastic Impacts by Regression on Population, Affluence and Technology - STIRPAT model) have also been employed in assessing the causal association between the practice of corruption and environment, though few researchers have utilized [1,2,3] models in comparison to the number making use of the STIRPAT model. [4] sum the merit of the STIRPAT model over other methods: in a sentence "the major advantage of the stochastic model is that it places work on driving forces squarely in the methodological tradition of quantitative social science, and invites the application of a powerful repertoire of well-developed tools". By contrast, the preliminary applications and their findings suggest that the STIRPAT approach to investigating the anthropogenic impacts of the driving forces on the environment is a useful way to foreground the debate about the drivers stronger.

The study is organised as follows: Section 2 presents brief evidence on the relationship between the practice of corruption and carbon dioxide emissions. Section 3 presents the methodology. In section 4 we present the data analysis and reports. Section 5 gives the concluding remarks.

2. REVIEW OF LITERATURE

This section provides an overview of the relevant literature regarding the relationship between the practices of corruption, the active population age structure (15-65 years), economic structures, final consumption expenditure and carbon dioxide emission loads among African countries at different income levels, motivating the comparative nature of our study with previous studies. This, therefore, increases our understanding of the anthropogenic driver-triggers of the carbon dioxide emissions concentration.

[1] investigates the linkages between carbon dioxide emissions and good governance, that is, political stability, government effectiveness, regulatory quality, rule of law and low levels of corruption in a cross-section of 99 third world countries for years 1998, 2000, 2002, 2003, 2004, 2005, 2006 and 2007. The findings suggest that political stability and the rule of law reduce the CO_2 emissions. [2] asserts that the peculiar characteristics of the climate change problem pose serious barrier to our ability to address environmental problems. The study suggests that climate change involves the convergence of a set of global problems which is called a *perfect moral storm*. The key point here is that other difficult ethical questions surrounding environmental change might be answered, but action can be hampered due to the storm that makes us vulnerable to moral corruption. [5] investigate deforestation and forest-induced carbon dioxide emissions in tropical countries, and how governance and trade openness influence the forest-income relationship. The estimated results show evidence of an Environmental Kuznets Curve (EKC) determined by corruption and openness of the economy. In addition, further evidence indicates that a more democratic country has a turning point in total CO_2 emissions than countries that are less democratic. However, the findings indicate that whether EKC shifts downward or upward is country-specific. [3] used data for 94 countries which covered the period 1987-2000, and drew a distinction between the direct effect of corruption on pollution and the indirect impact which operates through corruption's effect on per capita income and the resultant effect of income on pollution. The findings indicate that corruption has an increase direct effect on CO_2 emissions. Thus, the overall effect of corruption on both carbon dioxide and sulphur dioxide emissions reduces impact for the different income groups except in high income countries. The study by [6] also examines a cross-country analysis of the impacts of corruption and growth on the environment. The findings support the study of [3], in the sense that the results show a two-way effect of corruption on emissions or direct and indirect impacts. The

results suggest that corruption directly impacts by raising pollution at given income levels, and indirectly by decreasing per capita income. But the direct impacts dominate the indirect impacts, and the overall findings show that the outcome variable (pollution) is monotonically increasing in corruption. The results further suggest that the interaction between pollution and corruption is particularly strong at low income levels, suggesting that less developing countries can considerably improve economic and environmental performance by reducing the practice of corruption. In [7], the research employed the theoretical approaches of Inglehart's theory of post-materialism, Dunlap and Mertig's globalization explanation and the prosperity hypothesis perspectives to try to explain individual and cross-national differences in environmental attitudes. The study is based on a multilevel analysis [8] 'is used whenever data is grouped (or nested) in more than one category such states, countries, etc') to the International Social Survey Programme (ISSP) sample data from the period of 1993 to 2000. The findings support the prosperity hypothesis (the relationship between environmentalism and economic prosperity). In addition, the evidence indicates that an individual with a better quality of life shows higher levels of environmental concern than their compatriots. Similarly, richer countries also show more concern about environmental quality than poor countries. The findings further suggest that concern regarding environmental quality is closely associated with post-materialistic attitudes and other socio-demographic factors. As in the studies of [9], the researcher argues that it is possible to combine economic growth, protecting natural resources and ensuring social justice as complementary objectives only if the poor can be assisted to live healthier lives on their own terms. [10] works analyse the relationship to ultimate targets, performance under conditions of uncertainty, volatility of carbon prices, the inefficiencies of taxation and regulation, potential for corruption and accounting finagling, and ease of implementation of carbon tax. He advocates price-type approaches such as carbon taxes to curb the practice of corruption in the mitigation of global warming. The study by [11] assesses the decision makers' recognition that the conventional path of achieving economic growth at the expense of the environment had to change by targeting the practice of corruption that hinders the mitigation of environmental impacts. The [12] argued that the practice of corruption circumvents environmental quality policies. It states that vast sums of money are being invested to thwart climate change. Furthermore, the [12] study maintains that:

> if money that's meant to halt global warming and guard against extreme weather is lost to corruption, we are all in serious trouble. That is why we are asking people to help us monitor climate finance in their countries, and working around the world to develop practical safeguards against corruption in climate governance.

These literature reviewed deepen our understanding of the fact that the practice of corruption is convoluted in different context. On the one hand, it relationship with carbon dioxide emissions may leads to environmental impacts by circumventing environmental quality policies. On the other hand, reducing the practice of corruption may also lighten the burden of the economy.

3. METHODOLOGY

3.1 Data Sources and Coverage

The data used for this study are data set collected by the World Bank 2013. It concentrates on 51 countries out of the 54 sovereign countries in Africa for which fully harmonised data are available. We constructed an unbalanced data set of 51 African countries for the period 1960-2012, with a sample of 2764 observations. However, the actual sample size depends on the specification of the models. The research excluded Equatorial Guinea (she is the only high income country in Africa- HICA, and cannot be applied in a panel data analysis), data are unavailable for CO_2 in the case of São Tomé and Príncipe, and South Sudan got her independent at 2011, and data are not available for most of our variables. Out of the 54 Africa countries, our samples of 51 countries are fairly large enough and satisfactory for our investigation. Among the 51 Africa countries, 26 are low income countries in Africa (LICA), 15 are lower middle income countries in Africa (LMICA), 10 are upper income countries in Africa (UICA) and 1 is a high income country in Africa (HICA) (these grouping are in line with the [13] classification). The information on carbon dioxide emissions collected includes emission from total fossil fuel consumption and cement manufacture. The study actually used per capita carbon dioxide emissions defined as the aggregate emissions from total fossil fuel consumption and cement manufacture deflated by population size.

The population growth rate is also gathered from the World Bank. The affluence (final consumption expenditure (annual % growth)) data is gathered from the same source. The technology was disaggregated into economic structures: manufacturing sector value added as a per cent of GDP and services sector value added as a per cent of GDP, permitting comparisons across the different countries and over time [14].

3.1.1 Response variable

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, HFCs (hydrofluorocarbons), PFCs (Perfluorocarbons) and SF_6 (Sulphur hexafluoride) (thousand metric tons of CO_2 equivalent) [9] 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 CO_2 produced during consumption of solid, liquid and gas fuels, and gas flaring. We gathered this information from the [15], which was originally provided by the Carbon Dioxide Information Analysis Centre, Environmental Sciences Division, Oak Ridge National Laboratory, Tennessee, USA.

This study considered the key indicators of environmental impact. [4] argue that key indicators are a reduced set of core indicators that serve a wider purpose, and they inform the general public and provide key signals to decision makers. The study addresses carbon dioxide emissions because they constitute about 80% of all greenhouse gas emissions. Table 1 below shows the atmospheric greenhouse gases (except water vapour) adjusted for heat retention characteristics, relative to CO_2. The carbon dioxide emission constitutes an important greenhouse gas (GHG) emission which causes *climate change*. Per capita CO_2 emission as an indicator of environmental impact is the individual quantity of emissions generated per person by a country in a year, and this is expressed in metric tons. The data only consider certain forms of human activity generated from the burning of fossil fuels, "gases released and flared in petroleum and natural gas extraction and refining" and other industrial processes, gases released from stored fuels and cement manufacturing, emission from land use, land-use change and forestry [16].

3.1.2 Predictor variables

The population dimension estimates are collected from the following World Bank 2013 catalogue sources: World Development Indicators: United Nations Population Division, World Population Prospects, United Nations Statistical Division, Population and Vital Statistics Report (various years), Census reports and other statistical publications from national statistical offices; Eurostat: Demographic Statistics; Secretariat of the Pacific Community: Statistics and Demography Programme; and US Census Bureau: International Database and United Nations World Urbanization Prospects.

3.1.2.1 Population size

The population size refers to the total population or total number of people in geographically

Table 1. The Important greenhouse gases (except water vapor)

ACEPPB	PIB	NLA	MMA	TPPBC	PCT
Carbondioxide (CO_2)	288,000	68,520	11,880 (2)	368,400	99.438%
Methane (CH_4)	848	577	320	1,745	0.471%
Nitrous Oxide (N_2O)	285	12	15	312	0.084%
Misc. gases (CFC's)	25	0	2	27	0.007%
Total	289,158	69,109	12,217	370,484	100%

Where: ACEPPB is all concentration expressed in parts per billion (ppb), PIB is the pre-industrial baseline NLA is the natural additions, MMA is the man made additions, TPPBC is the Total (ppb) concentration PCT is the percentage of total
Source: U.S. Department of Energy, (October, 2000)

sovereign states. The total population is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship as citizens of the country where they live. However, all refugees not permanently settled in the country of asylum are generally considered part of the population of the country of origin. Population size is the total number of human beings occupying a specified sovereign country in Africa [15].

3.1.2.2 Technology

The information on technology is derived from the [15] national accounts data and OECD National Accounts data files. This study does not enter into the controversy surrounding technology but represents technology with two structural indicators: manufacturing as a percentage of Gross domestic product-GDP and services as a percentage of GDP (this is consistent with many studies of ecology and modernisation). This also finds support with recent studies. 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. The services' correspond to International Standard Industrial Classification (ISIC) divisions 50-99, and comprise value added in the wholesale and retail trade (including hotels and restaurants), transport, and government, financial, professional, and personal services such as education, health care, and real estate services. In addition, it also includes imputed bank service charges, import duties, and any statistical discrepancies noted by national compilers as well as discrepancies arising from rescaling. The value added is defined as the net output of a sector after summing up all outputs and subtracting intermediate inputs. The measurement calculates value added without making deductions for depreciation of fabricated assets or depletion and degradation of natural resources. According to the [15], the industrial origin of value added is determined by the ISIC. In addition, for Vehicle Assembly Building (VAB) countries, gross value added at factor cost is used as the denominator.

3.1.2.3 Final consumption expenditure (annual % growth) (FCEG)

We derived data on final consumption expenditure (annual % growth) (FCEG) from the [15] 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). This estimate includes any statistical discrepancy in the use of resources relative to the supply of resources.

3.1.2.4 Corruption (C)

Our data source for corruption as an indicator of bad governance was gathered from Transparency International which applied Transparency International's Corruption Perception Index (TI-CPI), an aggregate indicator that ranks countries in terms of the degree to which corruption is perceived to exist among public officials. The argument in favour of an aggregated index of individual sources is that a combination of sources measuring the same phenomenon is more reliable than each source taken separately. The TI used the following data sources to calculate the Corruption Perception Index (CPI); that is, the CPI is calculated by employing data from 13 different surveys or assessments produced by the following 10 independent organizations: Africa Development Bank, country policy and institutional assessments; Asia Development Bank, country performance assessment ratings; Bertelsmann Foundation, Bertelsmann transformation index; Economist Intelligence Unit, country risk service and country forecast; Freedom House, nations in transit; Global Insights, formerly World Markets Research Centre, country risk ratings; Institute for Management Development, World competitiveness report; Political and Economic Risk Consultancy, Hong Kong, Asian Intelligence; World Economic Forum, global competiveness report; and World Bank, country policy and institutional assessments. The CPI method was developed by Johann Lambsdorff, from the University of Passau, for Transparency International.

3.1.2.5 Data quality

The quality of the data on all the variables used represents the most accurate and global development data available. The Africa Development Indicators provided by the World Bank data bank are an invaluable reference instrument for analysts and policy makers on African matters [15].

3.2 Model Specification

Building on the works of [17, 18], we starts with the assumption that in the data collected the relationship between environmental impacts (I) and exogenous variables (x): including population age structure (Pt), manufacturing sector value added as a per cent of GDP (M), services sector value added as a per cent of GDP (S), final consumption expenditure of government (FCEG) and corruption (C) is of the form:

$$y_i = \beta^{/} x_i + e_i, \qquad (3.1.0)$$

Where y is I, i is the country, $\beta^{/}$ is the parameter, x is the explanatory variable and e the error term.

That is, $I_i = f(Pt_i, FCEG_i, M_i, S_i, C),\ (3.1.1)$

In a panel data setting, equation becomes:

$$I_{it} = f(Pt_{it}, FCEG_{it}, M_{it}, S_{it}, C), \quad (3.1.2)$$

Where t is the time or year.

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:

$$Y_{it} = a + \beta X_{it} + e_{it} \qquad (3.1.3)$$

Where the outcome variable (Y) and explanatory variable (X) have both i and t subscripts for $i = 1,...,N$ sections and $t = 1,...,T$ 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 $(3.1.3)$ above, the coefficients *a* and *β* do not have any subscripts, implying both a and β will be identical for all units and for all years. We can introduce heterogeneity into equation $(3.1.3)$ 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, LICA, LMICA, UICA and HICA, and differences are expected in their behaviour. This is consistent with [14] 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” [17]. Therefore, our new model becomes:

$$Y_{it} = a_i + \beta X_{it} + e_{it} \qquad (3.1.4)$$

where Y is the dependent variable, X is the explanatory variable, β is the parameter, ‘a’ is the constant, and e 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 *β* 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” [19]. Extensive studies have also revealed that simple linear panel data models can be estimated using three different methods:

a) with a common constant (CCM) as in equation $(3.1.3)$ above;
b) permitting for fixed effects (FE); and
c) permitting for random effects (RE).

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/s of the study.

3.2.1 The fixed effects method (FEM)

The basic objective of FEM as a model or the Least Squares Dummy Variable (LSDV) model is that it allows for heterogeneity or individuality among our 51 African 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. [1] corroborate this perspective, and argue that FEM is different from Common Constant Method (CCM), 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 states 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:

$$Y_{it} = a_i + \beta_1 X_{1,it} + \beta_2 X_{2,it} + ... + \beta_k X_{k,it} + e_{it} \quad (3.1.5)$$

In matrix notation, we have:

$$Y = D\alpha + X\beta^{/} + e \quad (3.1.6)$$

3.2.2 Analysis of covariance

In model (3.1.2), assuming that parameters are constant over time but can vary across individuals, [17] postulates a separate regression for each individual:

$$y_{it} = a_i^{*} + \beta_i^{/} X_{it} + e_{it} \qquad \begin{array}{l} i = 1,...,N \\ t = 1,...,T \end{array} \quad (3.1.7)$$

Three types of restriction are imposed on (3.1.4). These are:

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

$$y_{it} = a_i^{*} + \beta^{/} X_{it} + e_{it} \quad (3.1.8)$$

With reference to our observed data, our model is of the form:

$$\begin{aligned} &\ell n(\mathrm{I}_{it}) = a_i + \alpha \ell n(Pt_{it}) + \beta \ell n(FCEG_{it}) \\ &+\theta \ell n(M_{it}) + \psi \ell n(S_{it}) + \mu(C_{it}) + e_{it} \end{aligned} \quad (3.1.18a)$$

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

$$y_{it} = \alpha^{*} + \beta_i^{/} X_{it} + U_{it} \quad (3.1.9)$$

Then, our model for the observed data becomes:

$$\begin{aligned} &\ell n(\mathrm{I}_{it}) = a + \alpha \ell n(Pt_{it}) + \beta \ell n(FCEG_{it}) \\ &+\theta \ell n(M_{it}) + \psi \ell n(S_{it}) + \mu(C_{it}) + e_{it} \end{aligned} \quad (3.1.10)$$

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

$$y_{it} = a^{*} + \beta_i^{/} X_{it} + e_{it} \quad (3.1.11)$$

$$Y = \begin{bmatrix} Y_1 \\ Y_2 \\ " \\ Y_N \end{bmatrix}_{NT\,\mathrm{X}1}, D = \begin{bmatrix} iT & 0 & " & 0 \\ 0 & iT & " & 0 \\ " & " & " & " \\ 0 & 0 & " & iT \end{bmatrix}_{NT\,\mathrm{X}\,N} \quad (3.1.12)$$

$$\mathrm{X} = \begin{bmatrix} x_{11} & x_{12} & " & x_{1k} \\ x_{21} & x_{22} & & x_{2k} \\ " & " & & \\ x_{N1} & x_{N2} & & x_{nk} \end{bmatrix}_{NT\,\mathrm{X}\,K} \quad (3.1.13)$$

and:

$$\alpha = \begin{bmatrix} a_1 \\ a_2 \\ " \\ a_N \end{bmatrix}_{N\,\mathrm{X}1}, \beta' = \begin{bmatrix} \beta_1 \\ \beta_2 \\ " \\ \beta_K \end{bmatrix}_{K\,\mathrm{X}1} \quad (3.1.14)$$

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” [19]. [19,17] maintain that 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 researchers 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.

3.2.3 Tests of fixed effects

Usually, many studies applied tests to check whether FE is captured in the model or not. We employed the F-test to check FE against the simple common constant OLS method. The commonly used F-Statistic is:

$$F=\left\{\left[\left(R^2_{FE}-R^2_{CC}\right)/\left(N-1\right)\right]/\left[\left(1-R^2\right)\left(NT-N-K\right)\right]\right\} \sim F\left(N-1, NT-N-K\right) \quad (3.1.15)$$

where R^2_{FE} is the coefficient of determination of the FE model,

R^2_{CC} is the coefficient of determination of the common constant model.

If F-Statistic > F-critical, reject the null hypothesis.

3.2.4 The random effects method (REM)

The REM is another alternative method of estimating a model. [19,17,18] support the fact 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:

$$a_i = a + \varepsilon_i \quad (3.1.16)$$

where ε_i is a zero mean standard random variable. Therefore, our random effects model becomes:

$$Y_{it} = a_i + \beta_1 X_{1it} + \beta_2 X_{2it} + \ldots\ldots + \beta_k X_{kit} + e_{it} \quad (3.1.17)$$

$$Y_{it} = (a+\varepsilon_i) + \beta_1 X_{1it} + \beta_2 X_{2it} + \ldots\ldots + \beta_k X_{kit} + e_{it} \quad (3.1.18)$$

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

$$Y_{it} = a + \beta_1 X_{1it} + \beta_2 X_{2it} + \ldots\ldots + \beta_k X_{kit} + (\varepsilon_i + e_{it}) \quad (3.1.19)$$

That is,

$$\ell n(I_{it}) = (a+\varepsilon_i) + \alpha \ell n(Pt_{it}) + \beta \ell n(FCEG_{it}) + \theta \ell n(M_{it}) + \psi \ell n(S_{it}) + \mu(C_{it}) + e_{it} \quad (3.1.20)$$

$$\ell n(I_{it}) = a + \alpha \ell n(Pt_{it}) + \beta \ell n(FCEG_{it}) + \theta \ell n(M_{it}) + \psi \ell n(S_{it}) + \mu(C_{it}) + \varepsilon_i + e_{it} \quad (3.1.21)$$

Where there are T observations on outcome y for country i (in our study), the error term $(\varepsilon_i + e_{it})$ consists of two components: ε 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. $v_{it} = \varepsilon + e$ is the component error.

[1] 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" [19]. In addition, [18] suggest the use of the error components model in panel data analysis.

It is also important to check whether there are any implications when using the random effects model compared with the fixed effect model. [19] 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 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 [19]. In our study of 51 African countries according to income levels, the panel data are unbalanced, though both FE and REM are employed and use the Hausman test to determine which of the methods is more appropriate, but applying the random effects on these countries based on income levels indicates that each group (income level) has a common mean value for the intercept.

3.2.5 The relationship between random effect, Generalised Least Square (GLS), Feasible Generalised Least Square (FGLS) and Panel Corrected Standard Error (PCSE)

The study concentrates its findings and report on the GLS/FGLS models, because 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 GLS estimator, and the FEM is a limited case of the REM, the study reports our results using random effect interpretation since the random effects estimator is the same as the GLS/FGLS estimator. This is consistent with the estimation of a random effect by generalized least squares (GLS), as in the studies by [20]. [21] also used a model for the within-cluster correlation of the error such as equicorrelation, and argued that the feasible GLS estimator is more efficient than OLS, and the efficiency gains of FGLS need not necessarily be great. Robinson (1991) [22] describes REM as best linear unbiased prediction (BLUP), and applied the technique in his work. Moulton is more explicit:

> when explanatory variable data in a regression model are drawn from a population with grouped structured, the regression errors are often correlated within groups. Error component and random coefficient regression models are considered as models of the intraclass correlation. The study used several empirical examples to examine the applicability of random effects and the consequences of inappropriately using OLS estimation in the presence of random group effects [23].

The findings suggest that the assumption of independent errors is usually incorrect, and the adjusted OLS standard errors often have a substantial downward bias, suggesting a considerable danger of spurious regression. The implication is that the GLS/FGLS support previous studies with the techniques of GLS regression with correlated disturbances and regression with panel-corrected standard errors (PCSE).

3.2.6 Models estimated: GLS/FGLS

This study proposed that the above models $(3.1.18a)$ for fixed effects and $(3.1.20)$ for random effects are designed and suitable for investigating the population-environment nexus in Africa. In the last few decades, a common characteristic among most African countries regarding the driving forces of anthropogenic impacts on CO_2 emissions is the increasingly sustained opinion that the practices of bad governance (corruption) and per capita net trade circumvent environmental policies aimed at achieving environmental friendliness. However, the output results for fixed and random effects are not robust; therefore, the GLS/FGLS results are more robust. We reportour results based on GLS/FGLS model which captures all our observed data and is of the form:

$$\begin{aligned}\ell n(\mathrm{I}_{it}) &= a + \alpha \ell n(Pt_{it}) + \beta \ell n(FCEG_{it}) \\ &+ \theta \ell n(M_{it}) + \psi \ell n(S_{it}) + \mu(C_{it}) + \varepsilon_i + e_{it}\end{aligned} \quad (3.1.22)$$

We estimated model $(3.1.22)$ for GLS/FGLS on which our findings are reported.

4. RESULTS

4.1 Results of the Impacts of Corruption and Population Age Structure on CO_2 Emissions

The findings suggest that the average effect of corruption perception index over CO_2 emissions, when the corruption perception index changes across time and between countries increases by 1%, CO_2 emissions decreases by about 73%, when all other predictors are constant. The average effect of population age structure over CO_2 emissions, when the population age structure changes across time and between countries increases by 1%, CO_2 emissions increases by about 1.33%%, for LICA, holding all other predictors constant. The CPI and population size are statistically significant at 1% and 5% significance levels, respectively (see Table 2).

The findings indicate that the average effect of corruption perception index over CO_2 emissions, when the corruption perception index changes across time and between countries increases by 1%, CO_2 emissions decreases by about 1.95% for UICA, when all other predictors are constant. The average effect of population age structure over CO_2 emissions, when the population age structure changes across time and between countries increases by 1%, CO_2 emissions abates by about 4.03% 1.35% 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 1.05% for UICA, whereas CO_2 emissions decreases by about 1.63% for LMICA, when all other predictors 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, decreases CO_2 emissions by about 0.64% for UICA, whereas CO_2 emissions increases by about 2.21%, when all other predictors are constant. A 1 % increase in final consumption expenditure when the final consumption expenditure changes across time and between countries, increases CO_2 emissions by about 0.07% for LMICA, when all other predictors are constant. Our findings are consistent with the ecological modernization theory which argues that the efforts of government regulation are the factors that drive environmental impacts [24, 25, 26, 27, 11]. The estimated results for LICA indicate that population age structure and corruption perception index is statistically significant at 1% and 5% significance levels, respectively. In the case of LMICA, the population age structure, manufacturing sector, and services sector are all statistically significant at 1%, 10% and 1% significance levels, respectively. For UICA, the population age structure, manufacturing sector, the services sector and corruption perception index are statistically significant at 1%, 1%, 10% and 10% significant levels, respectively (see Table 2).

We regressed CO_2 emissions on all the explanatory variables, employed fixed effects (FE) and random effects (RE) models, carried out a diagnostic test on both the FE and RE, and the results were not robust, hence, the study found GLS/FGLS more robust than FE and RE. For the elasticity coefficients that are not statistically significant, we suspected this might be due to the limited data available. For example, in our investigation, data on the corruption perception index were only available for the period 1998 to 2012 compared to the data for other driving forces: 1960 to 2012 for population dimensions, and 1960 to 2010 for per capita carbon dioxide emission, for the same study. Therefore, availability of data for the same period might change the results, and might provide us useful information regarding the impact of the practice of corruption on environmental impacts.

However, on the basis of the available data utilized and investigated, the findings are not consistent with the position of the Transparency International that the practice of corruption circumvents the impacts of environmental control, in this case for LICA, LMICA and UICA. The findings do not support previous studies [1,3,2], however, the works of [12,28,29] argue that the practice of corruption undermines efforts to ameliorate environmental problems. In view of the limited data available, we suggest further research on the emission-corruption relationship.

Table 2. The impacts of corruption and population age structure on CO_2 emissions

Baseline Model- Regressed per capita CO2 emissions- ℓn(I) on Population Age Structure- ℓn(PT), 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 corruption ℓn(C).

Dependent Variable: ℓn(I)	**GLS/FGLS**					
Variable	**LICA**		**LMICA**		**UICA**	
ℓn(Pt)	1.335***	(0.263)	-4.030***	(1.055)	-1.35***	(0.226)
ℓn(M)	0.030	(0.181)	-1.631**	(0.521)	1.05***	(0.186)
ℓn(S)	-0.327	(0.192)	2.211***	(0.580)	-0.64**	(0.187)
ℓn(FCEG)	0.011	(0.018)	0.002	(0.087)	-0.10	(0.058)
ℓn (C)	-0.730*	(0.360)	-1.153	(1.542)	-1.95**	(0.627)
Sample		123		44		55
log likelihood		3246.29		102.91		

$^{***}P < 0.001$; $^{**}P < 0.01$; $^{*}P < 0.05$.
**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.*
**We used Cross-sectional time-series FGLS regression for LICA*

5. CONCLUSIONS

This study explored to investigate the unique observation collected from the [15] of 51 African sovereign countries to ask directly, what is the net impact of corruption on CO2 emissions, and to assess the relevance of a range of potential reasons for why the net impacts of corruption on CO2 emissions across African countries and see how this impacts varies per capita income, for the period 1960-2012.

Results are also found that the average effect of corruption perception index over CO_2 emissions, when the corruption perception index changes across time and between countries increases by 1%, CO_2 emissions decreases by about 0.73%, 1.95% for LICA and UICA respectively, when all other predictors are constant.

Finally, the findings show that corruption is a vital control variable that has been typically left out of previous empirical analyses, regarding the relationship between population and CO_2 emissions in African countries [30,31]. The evidences presented on the empirical study indicate that the relationship between corruption perception index [32] and environment are consistently negative, and at variation with the expected results, and previous studies [6,3,7]. Indeed, the relationship still remains inconclusive. Therefore, further research is still needed to integrate the divergent findings in the literature in order to determine at different income levels in African countries the key predictors of the environmental impacts.

COMPETING INTERESTS

Author has declared that no competing interests exist.

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APPENDIXES

Appendix A

Table 4.1. The impacts of corruption and Population age structure on CO_2 emissions

Baseline Model- Regress per capita Co_2 emissions- ℓn(I) on Population Age Structure- ℓn(PT), 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 corruption ℓn(C).

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

Variable	LICA		LMICA		UICA	
Intercept	7.364	(6.266)	-57.458**	(15.066)	-5.178	(3.689)
ℓn(Pt)	-5.480**	(1.685)	12.872**	(3.579)	-5.286	(1.340)
ℓn(M)			0.609	(0.413)	0.230	(0.229)
ℓn(S)	0.554***	(0.065)	-0.341	(0.316)	0.967	(0.197)
ℓn(FCEG)	0.061	(0.015)	-0.023	(0.041)	-0.024	(0.015)
ℓn (C)	0.206	(0.264)	-0.180	(0.634)	0.621	(0.339)
R-sq: within		0.44		0.33		0.64
Between		0.006		0.004		0.65
Overall		0.0001		0.04		0.69
Sigma_u		1.01		1.48		1.18
Sigma_e		0.133		0.17		0.07
rho		0.98		0.98		0.99

****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.*

Appendix B

Table 4.2. The impacts of corruption and Population age structure on CO_2 emissions

Baseline Model- Regress per capita Co_2 emissions- ℓn(I) on Population Age Structure- ℓn(PT), 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 corruption ℓn(C).

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

Variable	LICA		LMICA		UICA	
Intercept	-2.723	(6.189)	-50.987***	(14.343)	-14.644**	(4.251)
ℓn(Pt)	-2.291	(1.626)	10.941**	(3.383)	1.525	(0.862)
ℓn(M)			0.485	(0.375)	0.205	(0.303)
ℓn(S)	0.441***	(0.063)	-0.178	(0.295)	0.204	(0.305)
ℓn(FCEG)	0.013	(0.016)	-0.026	(0.041)	-0.085	(0.056)
ℓn (C)	0.301	(0.279)	-0.130	(0.640)	0.208	(0.866)
R-sq: within		0.42		0.32		0.34
Between		0.0003		0.000		0.79
Overall		0.0054		0.019		0.83
Sigma_u		0.68		1.35		0
Sigma-e		0.13		0.17		0.07
rho		0.96		0.98		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.*

Appendix C

Table 4.3. 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.*

Appendix D

Table 4.4: Definitions of variables

Variables	Definition	Unit of Measurement
Carbon dioxide (CO_2) emissions (I)	Metric ton of carbon per capita	US $ 2005 Constant prices
Population Dimensions (P)	Population density Population size Population structure Population growth	Number
Population growth (PG)	Annual growth rate of a Country's population	Per cent
Population density (PD)	Population per square meter	Number
Population size (PS)	Annual total population of a Country	Number
Population Structure (PT)	Population of working-age (Population age 18-65 years)	Number
GDP per capita	Gross domestic product deflated by population	US Dollar per capita per year in constant2005 prices.
Manufacturing as per cent of GDP (M)	Manufacturing sector value added expressed as percentage of GDP	Per cent

Variables	**Definition**	**Unit of Measurement**
Service as per cent of GDP (M)	Service sector value added expressed as percentage of GDP	Per cent
Openness of the economy (O)	Total Export minus total import	Number
The practice of Corruption(C)	Corruption Index	Number
Country Specific (fi)	Dummies	Number
Year Specific (ti)	Dummies	Number
Total sample size	Africa countries	51
Sovereign Africa countries	Countries	54
Number of high income countries in Africa	HICA	1
Number of upper income countries in Africa	UICA	10
Number of lower middle income countries in Africa	LMICA	15
Number of low income countries in Africa	LICA	26
sub-Saharan Africa countries	SACs	48
North African Countries	NACs	6
Total sample size	Africa continent	2764

Appendix E

Table 18.0. Data used for Corruption Perception Index (CPI) for UICA

Year	Country									
	Algeria	**Botswana**	**Angola**	**Gabon**	**Libya**	**Mauritius**	**Namibia**	**Seychelles**	**South A**	**Tunisia**
1995									5.62	
1996									5.68	
1997									4..95	
1998		6.1				5.0	5.3		5.2	5.0
1999		6.1				4.9	5.3		5.0	5.0
2000		6.0	1.7			4.7	5.4		5.0	5.2
2001		6.0				4.5	5.4		4.8	5.3
2002		6.4	1.7			4.5	5.7		4.8	4.8
2003	2.6	5.7	1.8		2.1	4.4	4.7		4.4	4.9
2004	2.7	6.0	2.0	3.3	2.5	4.1	4.1	4.4	4.6	
2005	2.8	5.9	2.0	2.9	2.5	4.2	4.3	4	4.5	4.9
2006	3.1	5.6	2.2	3.0	2.7	5.1	4.1	3.6	4.6	4.6
2007	3.0	5.4	2.2	3.3	2.5	4.7	4.5	4.5	5.1	4.2
2008	3.2	5.8		3.1	2.6	5.5	4.5	4.8	4.9	4.4
2009	2.8	5.6	1.9	2.9	2.5	5.4	4.5	4.8	4.7	4.2
2010	2.9	5.8	1.9	2.8	2.2		4.4	4.8	4.5	4.3
2011	2.9	6.1	2.0	3.0	2.0	5.1	4.4	4.8	4.1	3.8
2012	34	65	22	35	21	57	48	52	43	41

Source: Author's Calculation from Transparency International 1995-2012

Appendix F

Table 18.1. Data used for Corruption Perception Index (CPI) for LMICA

Year	Country														
	Cameroon	**Cape verde**	**Congo. R**	**Cote d'Ivo**	**Djibouti**	**Egypt**	**Ghana**	**Lesotho**	**Mauritania**	**Morocco**	**Nigeria**	**Senegal**	**Sudan**	**Swaziland**	**Zambia**
1995															
1996											.69				
1997											1.76				
1998	1.4			3.1		2.9	3.3			3.7	1.9	3.3			3.5
1999	1.5			2.6		3.4	3.3			4.1	1.6	3.4			3.5
2000	2.0			2.7		3.1	3.5			4.7	1.2	3.5			3.4
2001	2.0			2.4		3.6	3.4				1.0	2.9			2.6
2002	2.2			2.7		3.4	3.9			3.7	1.6	3.1			2.6
2003	1.8		2.2	2.1		3.3	3.3			3.3	1.4	3.2	2.3		2.5
2004	2.1		2.3	2.0		3.2	3.6			3.2	1.6	3.0			2.6
2005	2.2		2.3	1.9		3.4	3.5	3.4		3.2	1.9	3.2	2.1		2.6
2006	2.3		2.2	2.1		3.3	3.3	3.2	3.1	3.2	2.2	3.3	2.2		2.6
2007	2.4	4.9	2.1	2.1	2.9	2.9	3.7	3.3	2.6	3.5	2.2	3.6	1.8		2.6
2008	2.3	5.1	1.9		3.0	2.8	3.9	3.2	2.8	3.5	2.7	3.4	1.6		2.8
2009	2.2	5.1	1.9	2.1	2.8	2.8	3.9	3.3	2.5	3.3	2.5	3.0	1.5	3.6	3.0
2010	2.2	5.1	2.1	2.2	3.22	3.11	4.1	3.5	2.3	3.4	2.4	2.9	1.6	3.2	3.2
2011	2.5	5.5	2.2	2.2	3.0	2.9	3.9	3.5	2.4	3.4	2.4	2.9	1.6	3.1	3.7
2012	26	60	26	29	36	32	45	45	31	37	27	36	13	37	

Source: Author's calculation from Transparency International perception index (1995-2012)
**Central A. is Central Africa Republic*
** CongoD is Congo Democratic Republic*
**G. Bissa is Guinea Bissau*

Appendix G

Table 18.2. Corruption perception index (CPI) for LICA

Year	Country																									
	Benin	Burki F.	Burundi	Central A	Chad	Comoros	CongoD	Eritrea	Ethiopia	Gambia	Guinea	Guine B	Kenya	Liberia	Madagascar	Malawi	Mali	Mozambiq	Niger	Rwanda	Sierra L.	Somalia	Tanzania	Togo	Uganda	Zimbabwe
1995																										
1996																										
1997																										
1998													2.5			4.1							1.9		2.6	4.2
1999													2			4.1		3.5					1.9		2.2	4.1
2000		3							3.2				2.1			4.1		2.2					2.5		2.3	3
2001													2			3.2							2.2		1.9	2.9
2002									3.5				1.9		1.7	2.9							2.7		2.1	2.7
2003									2.5	2.5			1.9		2.6	2.8	3	2.7			2.2		2.5		2.2	2.3
2004	3.2				1.7		2	2.6	2.3	2.8			2.1		3.1	2.8	3.2	2.8	2.2		2.3		2.8			2.3
2005	2.9	3.4	2.3		1.7		2.1	2.6		2.7			2.1	2.2	2.8	2.8	2.9		2.4	3.1	2.4	2.1	2.9		2.5	2.6
2006	2.5	3.2	2.4	2.4	2		2	2.9	2.4	2.5	1.9		2.2		3.1	2.7	2.8	2.8	2.3	2.5	2.2		2.9	2.4	2.7	2.4
2007	2.7	2.9	2.5	2	1.8	2.6	1.9	2.8	2.4	2.3	1.9	2.2	2.1	2.1	3.2	2.7	2.7	2.8	2.6	2.8	2.1	1.4	3.2	2.3	2.8	2.1
2008	3.1	3.5	1.9	2	1.6	2.5	1.7	2.6	2.6	1.9	1.6	1.9	2.1	2.4	3.4	2.8	3.1	2.6	2.8	3	1.9	1	3	2.7	2.6	1.8
2009	2.9	3.6	1.8	2	1.6	2.3	1.9	2.6	2.7	2.9	1.8	1.9	2.2	3.1	3	3.3	2.8	2.5	2.9	3.3	2.2	1.1	2.6	2.8	2.5	2.2
2010	2.8	3.1	1.8	2.1	1.7	2.4	2	2.6	2.7	3.2	2	2.1	2.1	3.03	2.6	3.4	2.7	2.7	2.6		2.4	1.1	2.7	2.4	2.5	2.4
2011	3	3	1.9	2.2	2	2.4	2	2.5	3	3.5	2.1	2.2	2.2	3.2	3	3	2.8	2.7	2.5	5	2.5	1	3	2.4	2.4	2.2
2012	36	38	19	26	19	28	21	25	33	34	24	25	27	41	32	37	34	31	33	53	31	8	35	30	29	20

Source: Author's calculation from Transparency International perception index (1995-2012)

- *Burki F. is Burkina Faso*
- *CongoD is Congo Democratic Republic*
- *Guine B is Guinea Bissau*

Appendix H

The Methodology used by the Transparency International (TI)

The TI developed the Corruption Perception Index (CPI) as a composite indicator that measures perceptions of corruption in the public sector among different countries in the world. It puts together various sources of corruption- related data produced by different independent and well known institutions. The different sources are: African Development Bank Governance Ratings (AFDB); Bertelsmann Foundations Sustainable Governance Indicators (BF-SGI); Bertelsmann Foundations Transformation Index (BF-BTI); Economist Intelligence Unit Country Risk Ratings (EIU); Freedom House Nations in Transit (FH); Global Insight Country Risk Ratings (GI); IMD World Competitiveness Yearbook (IMD); Political and Economic Risk Consultancy Asian Intelligence (PERC); Political Risk Services International Country Risk Guide (ICRG); Transparency International Bribe Payers Survey (TI); World Bank-Country Performance and Institutional Assessment (WB); World Economic Forum Executive Opinion Survey (WEF) and World Justice Project Rule of Law Index (WJP).

The TI statistical assessment of the CPI 2012 was done based on: an evaluation of multiple tests. For example, the condition for the consideration of a country's inclusion in the CPI is that it must be evaluated by at least three sources. In addition, a recommendation is made based on the calculation of the standard errors, and is *currently overestimated by the current formula* [33]. It analysis indicates that no source dominates the CPI and all the combined sources contribute to determine the CPI ranking in a balanced way. The TI employed the following methods in its analysis:

a) All the thirteen sources were employed, the old methodology based on rankings that had been used in past releases of the index, and the revised methodology used in the 2012 CPI.
b) The 2012 CPI takes into account the statistical coherence based on the analysis of the covariance structure between the CPI ranking.
c) The TI also considered the interpretation of the difference between two countries by using *Cohen's effect size*.
d) According to [33], it found no absolute difference between normalisation coupled with estimation of missing data.

The old methodology (1995-2011)

The TI employed normalisation method called a *matching percentiles technique*. The approach considered ranking countries on each source. The approach has the advantage of putting together sources that had different distributions.

The New Methodology (2012-2014)

The TI reviewed its old method, and now adds a *simple average of standardised errors*. All the thirteen sources are standardised by subtracting the mean of the data and dividing by the standard deviation (Z-scores) and then rescaled to have a mean 45 and standard deviation 20. The formula used is:

Standardisation = {[X_i – mean (X)]/std (X)} multiply by sign multiply by 20 multiply by 45.

In this new approach, the direction of the source is taken into account at this stage. For example, regarding the sources, the one which has the lower value of the sources, the less the perceived level of corruption, *a negative sign is used*. The TI (2013b) states that this was done for five sources: Economist Intelligence Unit Country Risk Ratings, Freedom House Nations in Transit, Global Insight Country Risk Ratings, Political and Economic Risk Consultancy Asian Intelligence and Transparency International Bribe Payers Survey.

Scores (2012 -2013)

For the years 2012 and 2013, the CPI ranks countries based on how corrupt their public sector is perceived to be. According to TI, 'a country's score indicates the perceived level of public sector corruption on a scale of 0-100, where 0 means that a country is perceived as highly corrupt and 100 means it is perceived as very clean. A county's rank indicates its position relative to other countries included in the index.

Scores (1995-2011)

For the periods 1995 to 2011, the CPI scores in terms of perceptions of the degree of corruption were based on a scale of 0-10, where 0 means highly corrupt and 10 means highly clean.

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