Let the Data Speak: Revisiting the Environmental Kuznets Curve in Africa

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Abstract

This paper revisits the Environmental Kuznets Curve hypothesis and applies a flexible semi-parametric panel fixed effects technique to identify a definite shape of the income-pollution relationship for a sample of 49 African countries for the period 1990-2010. Compared with standard panel data techniques which yields different conclusions, the former reveals that the income-pollution nexus is monotonically increasing and decreasing for CO_2 and PM_{10} emissions respectively. Hence, the effect of economic growth differs with each atmospheric pollutants and is not sufficient for improving environmental quality. There is need for policies that emphasizes sustainable economic growth and the use of cleaner energy sources.

Keywords: Environmental Kuznets Curve; Air pollutants; Semi-parametric method; Africa.

JEL Classification: C14; C33; O55; Q5

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1 Introduction

The relationship between economic growth and the environment remains a debatable issue in the field of environment economics. Recent scientific evidence of global warming, resource depletion, air and water pollution have been linked to the harmful effects of human activities on the environment (i. e. the so-called anthropogenic effects). This has raised concerns among researchers and policy makers on how best to make economic growth (hence, income) compatible with environmental quality, that is, the sustainability of economic growth. Since the economy and environment link is complex and highly controversial, much of the analysis focus on the trade-off between income and environmental degradation (pollution) within the framework of the so-called "Environmental Kuznets Curve" (EKC) hypothesis .

According to the EKC hypothesis, the income-pollution relationship follows an inverted U-shaped pattern similar to the inequality-growth proposition of Simon Kuznets. Intuitively, it posits that higher level of income increases environmental pollution in the early stages of development through industrialization. However, pollution reduces with higher levels of income after a certain threshold level as the economy adopts cleaner and environmentally friendly technology in the production process. Thus, the EKC hypothesis emphasizes economic growth as a pre-condition for the attainment of improved environmental quality or reduced environmental degradation. This viewpoint is aptly summarized by Beckerman (1992) that "*although economic growth usually leads to environmental deterioration in the early stages of the process, in the end, the best and probably the only way to attain a decent environment in most countries is to grow rich*". Such a proposition makes identifying the shape of the relationship significant for designing an appropriate joint economic and environmental policy, as the impact of economic growth on the environment may be positive or negative (Azomahou et al., 2006). For instance, the existence of a positive monotonic relationship would suggest further deterioration of the environmental quality with higher levels of income, and this trajectory can only be reversed when income stagnates. On the contrary, if the relationship exhibits a non-monotonic (i. e. nonlinear) curve, then environmental pollution will be reversed at higher incomes levels, thus making economic growth compatible with environmental quality.

Since the seminal work of Grossman and Krueger (1991), an extant literature have emerged to identify the EKC hypothesis of an inverted U-shaped environment-income relationship. To date, empirical studies have produced mixed and inconclusive evidence depending on the choice of countries, measures of environmental pollutants and econometric techniques employed. Dinda (2004), Galeotti (2007), and more recently, Kaika and Zervas (2013a,b) provide an excellent survey of the literature . Even in the context of African countries, the evidence on the EKC hypothesis is far from a consensus. For instance, Orubu and Omotor (2011) find evidence of an inverted U-shaped relationship for particulate matter (PM_{10}) emissions. However, in the case of organic water pollutants, their evidence suggested a positive relationship. Osabuohien et al. (2014) find evidence of the EKC hypothesis for both CO_2 and PM_{10} emissions. Ogundipe et al. (2014) controls for income heterogeneity in African countries, and find no evidence for the EKC hypothesis for Africa (all countries combined), low-income and upper middle-income countries except for lower middle-income countries in Africa. Yaduma et al. (2015) finds a monotonically increasing income and CO_2 emissions relationship for Africa based on quantile regression.

Since the underlying forces which determine the shape of the EKC relationship are assumed to be captured by a reduced form models, most studies usually employ parametric model specifications of quadratic or cubic polynomial functions to capture non-linearities and to gauge the threshold points. These models assume *ex ante* specific functional forms in validating the EKC hypothesis. Such an ad hoc approach is considered restrictive and incapable of accounting for the complexity in the EKC relationship. Moreover, when the model assumptions are inconsistent with the true data generating process, then a functional misspecification bias will result in wrong policy prescriptions. On the other hand, studies utilizing longitudinal data with standard panel data techniques often neglects the importance of heterogeneity across countries or regions due to economic, social, political, structural and biophysical differences which may have varying effects on environmental quality (Dinda, 2004). These techniques assume parameter homogeneity which implies that the income-pollution trajectory will be the same for all countries. This assumption have been rejected as being inadequate with suggestions for a more flexible approach that is robust to functional form specification and parameter heterogeneity (Vollebergh et al., 2005).

Following the need for more flexible techniques, nonparametric and semi-parametric regression models have become popular among researchers for detecting the true shape of the income-pollution relationship (Taskim and Zaim, 2000; Azomahou et al., 2006; Bertinelli and Strobl, 2005; Nguyen Van and Azomahou, 2007; Luzzati and Orsini, 2009; Kim, 2013; Chen and Chen, 2015; Nigatu, 2015; Wang et al., 2016). For instance, Taskim and Zaim (2000) examined the existence of EKC for environmental efficiency using a nonparametric methodology for cross-sectional data on CO_2 emissions. They find a U-shaped relationship between environmental efficiency index and income only for countries with sufficiently high GDP per capita income (more than \$5000). Bertinelli and Strobl (2005) used a partially linear model with fixed-effects estimators for a panel of countries and finds a positive relationship at low incomes which flattens out before increasing again for high incomes. Azomahou et al. (2006) finds evidence of an upward sloping, monotonous income and CO_2

emissions relationship with structural stability for a panel of 100 countries. Chen and Chen (2015) examined the EKC hypothesis for industrial CO_2 emissions for 31 Chinese provinces and finds the existence of an inverted U-shaped curve. Nigatu (2015) find that as income rises the level of particulate matter (PM_{10}) pollution rises and falls for low-income and middle income countries. Wang et al. (2016) using the semi-parametric panel fixed effects estimator of Baltagi and Li (2002), finds evidence supporting an inverted U-shaped curve for the relationship between economic growth and sulfur-oxides (SO_2) emissions for China. These methods have the advantage of not requiring correct functional form specification especially when the exact nature of the relationship is unknown. Instead, it allows the data generating process to determine the true shape of the relationship by finding a smooth representation of the data dynamics. Hence, these methods are robust to arbitrary forms of functional form specification, non-linearities and parameter heterogeneity.

Given the following background and the lack of consensus on the income-pollution relationship in African countries with parametric estimation techniques, this paper revisits the EKC hypothesis based on the recent re-orientation of the literature towards non- and semi-parametric methods. Specifically, it aims to determine the possibility of a definite shape for the income-pollution relationship for Africa. For this purpose, the paper uses data from a sample of 49 African countries for the period 1990-2010, and focuses on two atmospheric air pollutants namely, carbon -dioxide (CO_2) and ambient particulate matter (PM_{10}) emissions. In addition, the analysis is conducted using the Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model which has become the reference analytical framework for evaluating the anthropogenic forces behind environmental change. Also, the shape of the income-pollution relationship is gauge using Baltagi and Li (2002)'s proposed semi-parametric panel fixed effects technique which does not require *ex ante* specific functional form of the relationship.

Going forward, the balance of the paper is as follows: Section 2 describes the STIRPAT framework and methodology. Section 3 describes the dataset. Section 4 presents the empirical results of the estimations; and lastly, Section 5 gives the concluding remarks

2 Theoretical framework and methodology

The paper uses the IPAT framework to investigate the income-pollution relationship. Ehrlich and Holdren (1971) first proposed the IPAT model ($I = PAT$) to describe the changes in environmental impacts induced by human activities (i.e. so-called anthropogenic effects). The framework assesses the environmental impact of population, affluence, and technology on the environment. The intuition is that environmental impacts (I) are a multiplicative function of population size (P), affluence described per capita of economic activity (A), and the level of technology per unit of consumption and production (T):

$$I = P \cdot A \cdot T \tag{1}$$

The model is simple as it describes the anthropogenic driving forces behind environmental damages as a mathematical relationship. However, the IPAT model is a mathematical identity and is rigid in terms of the proportionality restrictions between the variables. Following this shortcoming, Dietz and Rosa (1997) developed a stochastic version of the IPAT, designated as STIRPAT, which provides a flexible quantitative framework to investigate environmental impacts. The model specification is

$$I_i = aP_i^b A_i^c T_i^d \varepsilon_i \tag{2}$$

where I, P, A, and T remains as described above; a, b, c and d are parameters of the model; ; ε represents the idiosyncratic error term, and the subscript i denotes observational units (e.g. countries) in a cross-section data. Taking the natural logarithm of Eq. (2) provides a convenient linear specification as follows:

$$lnI_i = a + b\ lnP_i + c\ lnA_i + d\ lnT_i + \varepsilon_i \tag{3}$$

As a refinement to the STIRPAT model, York et al. (2003) argues that the quadratic terms of the components P, A, and T along with additional environmental impact factors can be incorporated into the model provided it is consistent with the multiplicative specification. Thus, Eq. (3) can be extended with the incorporation of a quadratic term for the affluence (A) variable in line with the EKC hypothesis to capture possible existence of an inverted U-shaped relationship. This inverted U-shaped relationship can be explained by three basic mechanisms, namely, the scale, composition, and technique effects. The scale effect suggests the idea that environmental quality deteriorates with expansion in economic activities, and generally economic growth. In the early stages of development as the economy transits from primary to industrial production, more inputs of natural resources are exploited to increase the scale of production, and output. This generates wastes and emissions as by-products which contribute to the environmental pollution. However, economic growth generates structural change and technological progress, which in turn, creates the composition and technique effects. The composition effect is linked with the production shift from pollution-intensive industries to services-based ones which are less polluting. On the other hand, the technique effect is associated with the adoption of cleaner and environmentally-friendly production technology that that faces out dirtier techniques and reduces pollution per unit of output. Closely linked with this production perspectives is the consumption viewpoints which suggest that higher levels of income for consumers intensifies their demand for cleaner and greener environment as well as the institution of stricter environmental regulations. Overall, the EKC suggest that the negative scale effect will be offset by the combined positive composition and technique effects which should reduce pollution over time (see Dinda, 2004; Kaika and Zervas, 2013a).

Consequently, the extended version of the STIRPAT model with all variables transformed to their natural logarithmic form and estimated coefficients interpreted as elasticities is specified as follows:

$$E_{it} = \beta_1 gdpc_{it} + \beta_2 gdpc_{it}^2 + \beta_3 pop_{it} + \beta_4 enit_{it} + \alpha_i + \tau_t + \varepsilon_{it} \tag{4}$$

where E is a measure of environmental quality of country i at time t; *pop* denotes the population size; *gdpc* is GDP per capita; *enit* denotes technology which is proxied by energy intensity to capture technology damaging effect on the environment. α_i represents country-specific effect that is constant with time, and a time-specific effect τ_t to account for time-varying omitted variables and stochastic shocks that are common to all countries. Depending on the sign and statistical significance of the slope parameters of the *gdpc* variable, an important information as to the form of the income-pollution relationship is discernible: (i) if $\beta_1 > 0$ ($\beta_1 < 0$, respectively) and $\beta_2 = 0$, then the relationship is monotonically increasing (decreasing); and (ii) if $\beta_1 > 0$ and $\beta_2 < 0$, then an inverted U-shaped curve is observed for the relationship with the turning point given as $E^* = \frac{-\beta_1}{2\beta_2}$.

Within this framework, standard panel data techniques can be use to estimate Eq.(4). However, a major drawback of the above parametric model analysis is that it assumes *ex ante* specific functional form and does not account for parameter heterogeneity across countries in the sample. Moreover, higher polynomial regression, and more generally parametric regression models, have been shown to have undesirable "nonlocal effects" (Magee, 1998). As Yatchew (1998) points out, most economic theory does not identify a specific functional form for the relationship between a dependent variable and its covariates in a regression. Thus, to avoid possible functional form misspecification in the above parametric framework, we take an alternative approach using a semi-parametric regression framework which relaxes the functional form assumptions and allows the data generating process to determine the true shape of the income-pollution relationship. Given that the true relationship is *a priori* unknown, we specify a semi-parametric partially linear panel model with fixed effects as follows:

$$E_{it} = m(gdpc_{it}) + \beta_3 pop_{it} + \beta_4 enit_{it} + \alpha_i + \tau_t + \varepsilon_{it} \tag{5}$$

where $m(\cdot)$ is an unknown smooth function with only income, $gdpc$, entering the regression nonparametrically while other control variables are specified parametrically. This model accommodates the inclusion of more control variables without concerns for the curse of dimensionality problem associated with fully nonparametric models. The presence of the unobserved heterogeneity α_i can be removed through first-differencing:

$$\begin{aligned} E_{it} - E_{it-1} = [m(gdpc_{it}) - m(gdpc_{it-1})] + \beta_3(pop_{it} - pop_{it-1}) \\ + + \beta_4(enit_{it} - enit_{it-1}) + \varepsilon_{it} - \varepsilon_{it-1} \end{aligned} \tag{6}$$

To consistently estimate Eq.(6), Baltagi and Li(2002) proposed to approximate $[m(gdpc_{it}) - m(gdpc_{it-1})]$ by the series differences $p^k(gdpc_{it}, gdpc_{it-1}) = [p^k(gdpc_{it}) - p^k(gdpc_{it-1})]$ where $p^k(gdpc)$ are the first k terms of a sequence of functions $(p_1(gdpc), p_2(gdpc), \dots)$. In practice, a typical example of p^k series could be a spline, which corresponds to piecewise polynomials with pieces defined by a sequence of smooth knots which when joined smoothly reduces Eq.(6) down to

$$\begin{aligned} E_{it} - E_{it-1} = [p^k(gdpc_{it}) - p^k(gdpc_{it-1})]\vartheta + \beta_3(pop_{it} - pop_{it-1}) \\ + + \beta_4(enit_{it} - enit_{it-1}) + \varepsilon_{it} - \varepsilon_{it-1} \end{aligned} \tag{7}$$

which can be consistently estimated by ordinary least squares. Once parameters $\hat{\beta}$'s and $\hat{\vartheta}$ have been estimated, the values of the unit-specific intercepts $\hat{\alpha}_i$ can be calculated in order to recover the error component residual

$$\hat{u}_{it} = E_{it} - \hat{\beta}_3 pop_{it} - \hat{\beta}_4 enit_{it} - \hat{\alpha}_i = m(gdpc_{it}) + \varepsilon_{it} \tag{8}$$

The curve $m(\cdot)$ can be easily estimated by regressing $\hat{u}_{it}$ on $gdpc_{it}$ using flexible estimation methods such as kernel or spline regression. Here, we use the B-spline regression model of order $k = 4$.

Table 1: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
CO_2 emissions					
co2pc	1008	−1.165	1.432	−4.481	2.328
pop	1008	15.730	1.543	11.156	18.887
enit	1008	7.922	0.841	5.189	10.279
gdpc	1008	6.616	1.101	4.243	9.675
PM_{10} emissions					
pm10	987	4.019	0.705	1.768	5.759
pop	987	15.856	1.366	12.841	18.887
enit	987	7.909	0.839	5.189	10.279
gdpc	987	6.541	1.033	4.243	9.675

3 Data

We investigate the definite shape of the income-pollution relationship for a sample of 49 African countries over the period 1990–2010 (see Table A1 in Appendix for country listing). Population is measured as total population, affluence which captures economic prosperity is measured as real GDP per capita (constant 2005 US dollars). Technology is measured using energy intensity. Energy intensity is often expressed as total energy use per dollar GDP. Here, energy intensity is expressed as total primary energy consumption per dollar GDP (Btu per year 2005 PPP US dollars). Environmental degradation is captured using two atmospheric air pollutants, namely, CO_2 emissions and ambient particulate matter (PM_{10}). CO_2 emissions (metric tons per capita) include burning of fossil fuels and cement manufacturing, but excludes emissions from land use such as deforestation. PM_{10} captures fine suspended particles less than 10μm in diameter, and is capable of penetrating deeply into the respiratory tract, causing significant health damage to humans and animals. This consist of chemically stable substances such as dust, soot, ash, smoke, and liquid droplets from fuel consumption, industrial and construction activities. The data on per capita carbon emissions, and ambient particulate matter, population size, and GDP Per capita is sourced from the World Bank's *World Development Indicators* online database while energy intensity is obtained from the International Energy Statistics of the U.S. Energy Information Administration (EIA)[1]. Table 1 presents the summary statistics with all variables transformed to their natural logarithm form.

[1] Available at http://www.eia.gov/cfapps/ipdbproject/IEDIndex3.cfm

Table 2: Parameter estimates of income-CO_2 emissions nexus

	OLS	FE	RE	SEMI-PAR
	(1)	(2)	(3)	(4)
gdpc	1.156^{***}	-0.242	0.031	
	(0.183)	(0.563)	(0.523)	
gdpcsq	-0.007	0.085	0.068	
	(0.013)	(0.035)	(0.034)	
pop	0.074^{***}	-0.025	0.026	0.599^{**}
	(0.011)	(0.177)	(0.069)	(0.286)
enit	0.520^{***}	0.229^{***}	0.294^{***}	-0.031
	(0.028)	(0.082)	(0.071)	(0.082)
Constant	-13.793^{***}	-4.789^{*}	-7.148^{***}	
	(0.645)	(2.849)	(2.385)	
N	1008	1008	1008	960
R^2	0.86	0.49	0.49	0.11

Note: Country and time dummies are included in all models. OLS, FE and RE are standard panel data techniques of ordinary least squares, fixed and random effects models respectively; while SEMI-PAR denotes the semi-parametric panel fixed effects models. Robust standard errors in parenthesis. ***, **, * indicates 1%, 5% and 10% significance level.

4 Empirical Results

In revisiting the EKC analysis for Africa, Eq. (4) is estimated using three standard panel data techniques of OLS, fixed (FE) and random (RE) effects models while Eq. (5) is estimated with Baltagi and Li (2002) semi-parametric panel fixed effects models (SEMI-PAR) as the exact income-environment relationship is not known and can differ across countries or regions. Table 2 presents the empirical estimates in each columns for each estimation technique respectively. The population variable is statistically significant and has a positive coefficient estimates (i.e. 0.074 and 0.599) for the OLS and SEMI-PAR estimations respectively. This implies that higher population exacerbates pressure on the environmental quality. However, the significance is lost when estimated with FE and RE techniques. For energy intensity, the estimated coefficients are positive and statistically significant only for the OLS and FE estimations. This implies that higher consumption of fossil fuels in the production process will increase carbon emissions which in turn, will put further pressure on environmental quality. However, for RE and SEMI-PAR estimations, the coefficient estimates for energy intensity variable is positive (0.294) and negative (-0.031)

respectively and are not significant. Across all four estimation, the impact and importance of population and energy intensity differs which reiterates the issue of robustness in the literature as different estimation techniques yields different outcomes.

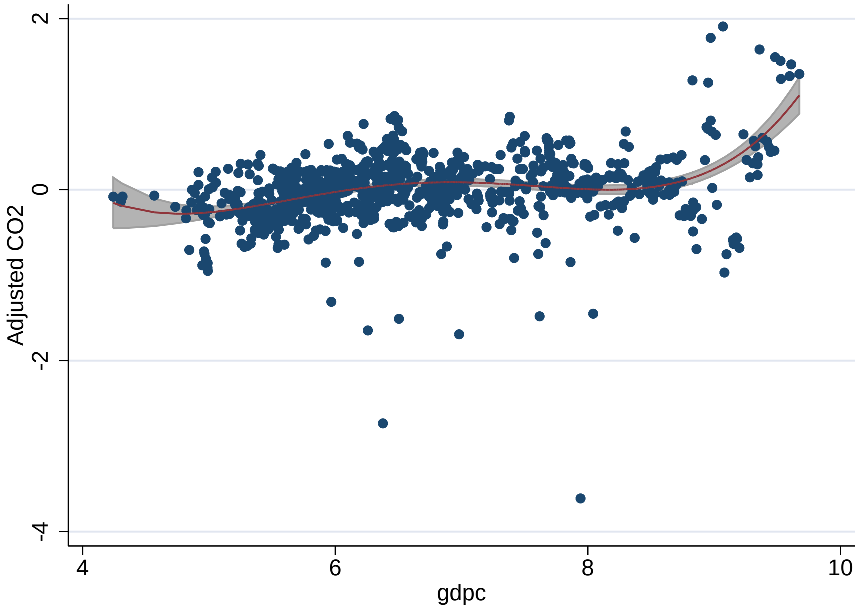

Figure 1: Partial fit of income and CO_2 emissions relationship: Points in graph are estimated partial residuals for CO_2 emissions; maroon curve represents fitted values for adjusted effects of other explanatory variables, and bounded by the 95% confidence bands.

Considering the income variable and its quadratic term, the OLS estimation result indicates that income is positive and statistically significant whereas its quadratic term although negative is not significant. On this basis, the result indicate that the income-CO_2 emissions nexus in Africa follows a positive relationship. In other words, higher income with economic growth will increase carbon emissions which in turn worsens environmental quality. On the other hand, both income and its quadratic term are not significant in both FE and RE estimations, as such there is no evidence to support the EKC hypothesis in Africa. Unlike these parametric models which yields a unique coefficient estimate, non- and semi-parametric models provides a partial regression plots that describes the true shape of the relationship between a dependent variable and the regressor of interest while holding other regressors at a fixed point such as their means. Figure 1 presents the partial fit for the income-CO_2 emissions relationship. The fitted curve shows a relatively flat but positive relationship which supports the OLS estimation in Column 1. Further, this indicates that there is no evidence supporting the validity of the EKC hypothesis for African countries. Thus, for most African countries that are still at the intermediate stage of development with the agriculture sector being dominant and a less sophisticated industrial sector, economic growth will typically have a scale effect on the environment. This highly anticipated as

Africa's contribution to greenhouse gases emissions has been increasing although it is the least when compared with emissions from industrialized countries.

Table 3: Parameter estimates of income-PM_{10} emissions nexus

	OLS (1)	FE (2)	RE (3)	SEMI-PAR (4)
gdpc	2.783^{***}	-0.383	-0.694	
	(0.202)	(0.526)	(0.615)	
gdpcsq	-0.217^{***}	0.017	0.030	
	(0.014)	(0.034)	(0.040)	
pop	0.071^{***}	-1.421^{***}	-0.998^{***}	-1.371^{***}
	(0.014)	(0.099)	(0.096)	(0.081)
enit	-0.054^{**}	-0.045	-0.032	0.020
	(0.023)	(0.069)	(0.071)	(0.013)
Constant	-5.380^{***}	28.647^{***}	23.328^{***}	
	(0.741)	(2.758)	(2.770)	
N	987	987	987	940
R^2	0.31	0.73	0.70	0.19

Note: Country and time dummies are included in all models. OLS, FE and RE are standard panel data techniques of ordinary least squares, fixed and rand effects models respectively; while SEMI-PAR denotes the semi-parametric panel fixed effects models. Robust standard errors in parenthesis. ***, **, * indicates 1%, 5% and 10% significance level.

Turning to the alternative measure of environmental pollution, Table 3 presents the empirical results for all four estimation techniques in the case of the income-PM_{10} emissions nexus. The population variable is statistically significant with a positive coefficient estimate for the OLS estimation (i.e. 0.071) in Column 1. Other estimations report a negative coefficient with statistically significance for FE, RE and SEMI-PAR estimations. Energy intensity has a negative coefficient estimates across all three parametric models whereas it is positive for the semi-parametric model. However, statistical significance is only obtained in the OLS estimation. This is understandable as domestic fuel burning for cooking and heating represents the major source of PM_{10} emissions in Africa rather than industrial-related sources (Karagulian et al., 2015). In terms of the income variable and its quadratic term, there is no evidence of the EKC hypothesis for the FE and RE estimation approaches except with OLS estimation in Column 1. This means that as income rise in African countries due to economic growth, PM_{10} emissions will rise and after reaching a turning point of approximately 609 U.S. dollars will reduce and much so with environmental pollution, as people switch from pollution-intensive activities such as cooking with biomass fuel to gas while environmentally-friendly and cleaner technologies replace dirtier production techniques. In order to validate the robustness of this outcome, Figure 2 presents the partial fit of the income-PM_{10} emissions. The fitted curve shows that the relationship is monotonically decreasing as income rises.

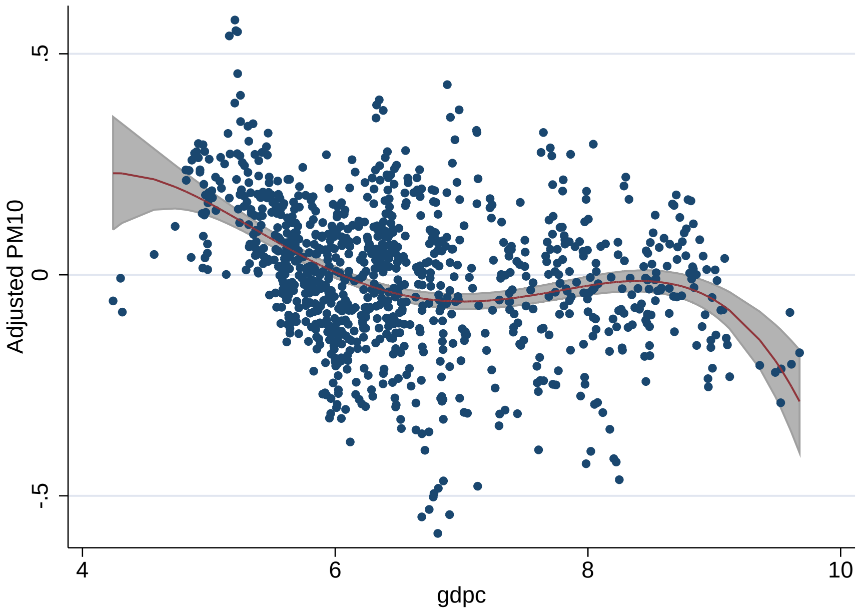

Figure 2: Partial fit of income and PM_{10} emissions relationship: Points in graph are estimated partial residuals for PM_{10} emissions; maroon curve represents fitted values for adjusted effects of other explanatory variables, and bounded by the 95% confidence bands.

From the foregoing, the empirical results show that the nature of the income-pollution relationship is fundamentally an econometric problem, as the validity of the EKC relationship depends on the estimation approach used and its associated model assumptions on functional form specification. For this analysis, standard panel data techniques of fixed (FE) and random (RE) effects models do not offer insight into the existence of an inverted U-shaped EKC curve, a monotonically increasing or decreasing relationship. However, its OLS counterpart shows evidence of a monotonically increasing relationship for CO_2 emissions as well as the inverted U-shaped curve for income-PM_{10} emission relationship. This inconsistency reiterates the econometric caveats in the literature surrounding *ex ante* restrictions on the functional form specification and robustness issues. On the contrary, the semi-parametric analysis provides a more definite shape of the income-pollution relationship with flexibility in functional form specification as a monotonically increasing and decreasing relationship is observed for CO_2 and PM_{10} emissions respectively.

In addition, both the OLS and semi-parametric results show that differences in the income-pollution relationship depends on the indicator for environmental pollutants. For atmospheric air pollutants, evidence suggest that the EKC relationship is associated with environmental pollutants with short-term and local impacts, rather than with global, indirect and long-term impact on human health and overall environmental quality (Arrow et al., 1995; Dinda, 2004). Local pollutants such as ambient particulate matter have recognizable negative effects on the local communities and a comparatively low abatement cost, whereas global pollutants such as CO_2 emission have a long-term effects with a high abatement cost. Thus, most empirical studies involving CO_2 emission typically indicate a positive relationship rather than the inverted U-shaped curve since economic growth is associated with increased energy use (Dinda, 2004; Kaika and Zervas, 2013a,b). Following from the semi-parametric analysis, the evidence show that higher income levels with economic growth in Africa will lead to increased energy demand, and in turn, increased CO_2 emissions, as African countries are supposedly in their intermediate stages of development. In other words, African countries are still on the upward section of the EKC relationship for CO_2 emission which is characterized by the scale effect of economic activities on the environment. Meanwhile, economic growth with increased income levels is compatible with a reduction in PM_{10} emission, and an improvement in environmental quality . As shown in Karagulian et al. (2015), domestic fuel burning which includes wood, coal and gas fuel for cooking and heating represents the highest contributor to ambient particular matter in Africa. This is followed by natural sources of soil dust and sea salt, traffic emissions from various vehicle types while a relatively smaller fraction is from industrial-related emissions such as oil combustion, coal burning in power plants. Therefore, as income rises due to economic growth, ambient particulate matter emissions from this sources should decline with the use of environmentally cleaner alternatives.

5 Conclusion

This paper revisits the Environmental Kuznets Curve (EKC) hypothesis with the aim of determining a definite shape of the income-pollution relationship for a sample of 49 African countries for the period 1990-2010. Recent orientation of the literature has led to the use of non- and semi-parametric methods which are robust to functional form misspecification and potential parameter heterogeneity as it allows the data dynamics to determine the true shape of the relationship contrary to widely used parametric methods which assumes *ex ante* specified functional forms. Using the STIRPAT model as its analytical framework and the semi-parametric panel fixed effects estimator of Baltagi and Li (2002) which mitigates against functional form misspecification, the true relationship between income and two atmospheric air pollutants, namely carbon dioxide (CO_2) and suspended particulate matter (PM_{10}) emissions is investigated.

The empirical evidence is summarized as follows. First, the parametric OLS estimation suggest a monotonically increasing relationship between income and CO_2 emissions whereas an inverted U-shaped relationship is obtained for the income-PM_{10} emission relationship. Meanwhile, no form of relationship is observed with panel fixed and random effects estimations. Thus, different parametric specifications could lead to different empirical conclusion and ultimately a wrong policy prescription. Second, the semi-parametric counterpart clearly shows that the income-CO_2 emissions relationship is monotonically increasing while a monotonically decreasing relationship is observed for the income-PM_{10} relationship. Thus, while economic growth is beneficial for the reduction of suspended particulate matter, on the other hand, it leads to an increase in CO_2 emissions in the region. Consequently, economic growth might not be a sufficient condition for improving environmental quality especially in the case of CO_2 emissions. Hence, there is need for an integrated policy design with instruments that makes promoting economic progress compatible with a green environment with emphasis on the use of cleaner energy sources.

References

Arrow, K., Bolin, B., Constanza, R., Dasgupta, P., Folke, C., Holling, C. S., Levin, B.-O., Maler, S., Perrings, K.-G., and Pimentel, D. (1995). Economic growth, carrying capacity, and the environment. *Ecological Economics*, 15:91–95.

Azomahou, T., Laisney, F., and Nguyen Van, P. (2006). Economic development and CO2 emissions: A nonparametric panel approach. *Journal of Public Economics*, 90(6-7):1347–1363.

Baltagi, B. H. and Li, D. (2002). Series estimation of partially linear panel data models with fixed effects. *Annals of Economics and Finance*, 3:103–116.

Beckerman, W. (1992). Economic growth and the environment: whose growth? whose environment? *World Development*, 20:481–496.

Bertinelli, L. and Strobl, E. (2005). The Environmental Kuznets Curve semi-parametrically revisited. *Economics Letters*, 88(3):350–357.

Chen, L. and Chen, S. (2015). The Estimation of Environmental Kuznets Curve in China: Nonparametric Panel Approach. *Computational Economics*, 46(3):405–420.

Dietz, T. and Rosa, E. A. (1997). Effects of population and affluence on CO_2 emissions. *Proceedings of the National Academy of Sciences*, 94:175–179.

Dinda, S. (2004). Environmental Kuznets Curve hypothesis: A survey. *Ecological Economics*, 49(4):431–455.

Ehrlich, P. and Holdren, J. (1971). Impact of population growth. *Science*, 171:1212–1217.

Galeotti, M. (2007). Economic growth and the quality of the environment: Taking stock. *Environment, Development and Sustainability*, 9(4):427–454.

Grossman, G. and Krueger, A. (1991). Environmental impacts of a North American free trade agreement. NBER Working Paper No. 3914, National Bureau of Economic Research.

Kaika, D. and Zervas, E. (2013a). The Environmental Kuznets Curve (EKC) theory-Part A: Concept, causes and the CO2 emissions case. *Energy Policy*, 62:1392–1402.

Kaika, D. and Zervas, E. (2013b). The environmental Kuznets curve (EKC) theory. Part B: Critical issues. *Energy Policy*, 62:1403–1411.

Karagulian, F., Belis, C. A., Dora, C. F. C., Prüss-Ustün, A. M., Bonjour, S., Adair-Rohani, H., and Amann, M. (2015). Contributions to cities' ambient particulate matter (PM): A systematic review of local source contributions at global level. *Atmospheric Environment*, 120:475–483.

Kim, K. H. (2013). Inference of the environmental Kuznets curve. *Applied Economics Letters*, 20(2):119–122.

Luzzati, T. and Orsini, M. (2009). Investigating the energy-environmental Kuznets curve. *Energy*, 34(3):291–300.

Magee, L. (1998). Nonlocal behaviour in polynomial regressions. *American Statistician*, 52(1):20–22.

Nguyen Van, P. and Azomahou, T. (2007). Nonlinearities and heterogeneity in environmental quality: An empirical analysis of deforestation. *Journal of Development Economics*, 84(1):291–309.

Nigatu, G. (2015). The level of pollution and the economic growth factor: A nonparametric approach to Environmental Kuznets Curve. *Journal of Quantitative Economics*, 13(1):147–159.

Ogundipe, A., Alege, P., and Ogundipe, O. (2014). Income heterogeneity and the Environmental Kuznets Curve in Africa. Munich Personal RePEc Archive Paper No. 55822, Avaliable at http://mpra.ub.uni-muenchen.de/55822/.

Orubu, C. O. and Omotor, D. G. (2011). Environmental quality and economic growth: Searching for environmental Kuznets curves for air and water pollutants in Africa. *Energy Policy*, 39(7):4178–4188.

Osabuohien, E. S., Efobi, U. R., and Gitau, C. M. W. (2014). Beyond the Environmental Kuznets Curve in Africa: Evidence from Panel Cointegration. *Journal of Environmental Policy & Planning*, 16:517–538.

Taskim, F. and Zaim, O. (2000). Searching for a Kuznets curve for environmental efficiency using kernel estimation. *Economics Letters*, 68(2):217–223.

Vollebergh, H. R. J., Dijkgraaf, E., and Melenberg, B. (2005). Environmental Kuznets curve for CO_2: heterogeneity versus homogeneity. CentER Discussion Paper No. 2005-25, Tilburg University.

Wang, Y., Han, R., and Kubota, J. (2016). Is there an Environmental Kuznets Curve for SO2 emissions? A semi-parametric panel data analysis for China. *Renewable and Sustainable Energy Reviews*, 54:1182–1188.

Yaduma, N., Kortelainen, M., and Wossink, A. (2015). The environmental Kuznets curve at different levels of economic development: a counterfactual quantile regression analysis for CO_2 emissions. *Journal of Environmental Economics and Policy*, 4(3):278–303.

Yatchew, A. (1998). Nonparametric regression techniques in economics. *Journal of Economic Literature*, 36:669–721.

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

Appendix

Table A1: List of countries

Algeria	Comoros	Ghana	Mauritius	South Africa
Angola	Congo Dem. Rep.	Guinea	Morocco	Sudan
Benin	Congo Rep.	Guinea Bissau	Mozambique	Swaziland
Botswana	Cote d'Ivoire	Kenya	Namibia	Tanzania
Burundi	Djibouti	Lesotho[a]	Niger	Togo
Burundi	Egypt	Liberia	Nigeria	Tunisia
Cameroon	Equatorial Guinea	Madagascar	Rwanda	Uganda
Cape Verde[b]	Ethiopia	Malawi	Senegal	Zambia
Central Africa Rep.	Gabon	Mali	Seychelles[b]	Zimbabwe
Chad	Gambia	Mauritania	Sierra Leone	

Note: a and b indicates countries with insufficient data on CO_2 and PM_{10} emissions respectively, and were dropped in the estimation for each atmospheric air pollutants.