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The Environmental Kuznets Curve at Different Levels of Economic Development: A Counterfactual Quantile Regression Analysis for CO_2 Emissions

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Abstract

This paper applies the quantile fixed effects technique in exploring the CO_2 environmental Kuznets curve within two groups of economic development (OECD and Non-OECD countries) and six geographical regions - West, East Europe, Latin America, East Asia, West Asia and Africa. A comparison of the findings resulting from the use of this technique with those of conventional fixed effects method reveals that the latter may depict a flawed summary of the prevailing income-emissions nexus depending on the conditional quantile examined. We also extend the Machado and Mata decomposition method to the Kuznets curve framework to explore the most important explanations for the CO_2 emissions gap between OECD and Non-OECD countries. We find a statistically significant OECD-Non-OECD emissions gap and this contracts as we ascent the emissions distribution. The decomposition further reveals that there are non-income related factors working against the Non-OECD group's greening. We tentatively conclude that deliberate and systematic mitigation of current CO_2 emissions in the Non-OECD group is required.

JEL Classification: Q56, Q58.

Keywords: environmental Kuznets curve, economic growth, sustainable development, quantile fixed effects, decomposition analysis, income-emissions nexus.

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1. Introduction

The late 1950s ushered in a theory in development economics whose roots extended into other fields of economic specialisation. Kuznets (1950) posited that the early stages of a country's developmental process are associated with increasing income inequality. However, after the attainment of a certain level of development,[4] progress is then associated with declining inequality. Following the works of Shafik and Bandyopadhyay (1992) and Grossman and Krueger (1991, 1995), an environmental economics refinement of Kuznets' theory led to the formulation of the Environmental Kuznets Curve (EKC) hypothesis. This hypothesises an inverted U-shaped relationship between per-capita emissions and GDP, with the former and latter measured on the ordinate and abscissa planes of a graph respectively. Empirical investigations of the theory typically employ per-capita estimates of income and emissions as indicators of economic progress and environmental depletion respectively.

The inception of the EKC theory stirred considerable debate about the ensuing policy implications of the income-emissions nexus in the environmental economics literature. As investigations confirming the theory may lead to recommendations that improving environmental quality is an associated product of rising incomes, it is not surprising for advocates to suggest that the only way to achieve good environmental standards is through a decent level of economic development (see for instance, Romero-Avila, 2008). Accordingly, higher income economies can invest more in greening and consumers in these economies are not only able to spend more on environmental protection but they can intensify their demand for a cleaner environment by advocating for stringent environmental regulations. These views led Beckerman (1992) to suggest that "*in the long-run, the surest way to improve your environment is to become rich*." Similarly, Panayotou (1993) stated that an improvement in environmental quality "*is an inevitable result of structural and behavioural changes accompanying economic growth*." A far-fetched implication of these views may be that developing countries are too poor to be green and little in the way of environmental clean-up is conducted in these countries (Perman and Stern, 2003). Thus, a reliance on such prescriptions may lead to a misleading interpretation of the EKC; that economic growth is both the cause and remedy to environmental damage in the long-run, thereby disparaging the relevance of environmental policies in achieving environmental clean-ups.[5]

[4] This paper uses the terms economic development, growth and progress interchangeably. The paper does not distinguish between the three concepts.

[5] Moreover, if the recommendations of the advocates were indeed true, this would therefore imply that environmental protection would be experienced in the high income nations alone. However, according to Dasgupta et al. (2002), the regulation of pollution and enforcement of pollution mitigation policies increase

Considerations of environmental sustainability and the greenhouse effect of CO_2 emissions may lead to considerable scepticism about the aforementioned recommendation of advocates. Global warming and climate change, primarily caused by anthropogenic CO_2 emissions, are arguably the most worrying environmental challenge confronting the world. Meteorological data indicate that average global temperature is on the rise. Thirteen of the world's warmest years on record occurred in the last fifteen years (Australian Government Bureau of Meteorology, 2012). Leaving the current levels of CO_2 emissions and rising trend in temperatures uncontrolled could have serious implications on the ecosystem's carbon sequestration capacity and the economic and social livelihoods of the present and future generation. These problems lead to concerns about how the needs of the future generation's climate and environment could be sustainably catered for if we continued with business as usual emissions without meaningful efforts to mitigate current emissions. Essentially, can we afford to rely on the belief that emissions will automatically peak then eventually decline when the world achieves a certain level of economic development at some (unknown) point in time as the primary means of mitigating emissions? Thus, there is need for a critical evaluation of the CO_2 EKC. This may provide signals on the relevance of relying on the recommendations of advocates or complementing these with appropriately designed instruments for mitigating emissions.

Also, the customary econometric methods used in investigating the CO_2 income-emissions nexus have attracted considerable criticisms (see for instance Stern, 2004). Most empirical studies exploring the income-emissions nexus employ a panel dataset of countries and these studies rely almost exclusively on the use of conventional longitudinal econometric techniques particularly the fixed and random effects methods. A major criticism stems from the methods' focus on estimating the rate of change in the conditional mean of emissions (as a quadratic or cubic function of income). The focus on conditional mean estimations produces constant slope coefficients across heterogeneous countries thereby being incapable of capturing country level heterogeneity in Kuznets curve explorations. Moreover, transferring the stylised reasoning about the epidemiological relationship between outdoor concentrations of local pollutants and adverse human health to the Kuznets curve subject – being that higher concentrations of these pollutants, such as particulate matter and sulphur oxide, are more harmful to humans relative to lower concentration levels (see for instance Pope, 2007; Yaduma et al., 2013) – an analogous reasoning applies to the relationship between concentrations of CO_2 emissions and the greenhouse effect. This therefore implies that the

with income but the greatest increases happen from low to middle income levels and increased regulation is expected to have diminishing returns. Accordingly, environmental regulation is likely to be enjoyed by the low income countries as well and these countries may exhibit the income-emissions relationship posited by the dictates of the EKC.

use of estimation techniques that provide a constant income-emissions relationship, especially for a group of largely heterogeneous countries, may not provide useful information on country specific turning point incomes where the Kuznets curve exists.

Thus, investigating the income-emissions relationship at different regions of the conditional emissions distribution may be more informative about turning point incomes relative to estimations focusing on the conditional mean alone. A quantile form investigation of the relationship at the upper, median and lower tails of the emissions distribution corresponds to examining the relationship for the highest, median and least polluting countries in a panel sample. As the relationship for the mean or median polluting countries may not necessarily be the same for the highest and least polluting countries in a given emissions distribution, this form of investigation provides a means of capturing country level heterogeneity in Kuznets Curve explorations. In other words, the income regressors in an EKC exploration may not only determine the mean but also other parameters of the conditional distribution of emissions (see, for instance, Mills and Waite, 2009; Halkos, 2011). Hence, the reliance of a majority of empirical studies on conditional mean estimations spurs the need for the application of alternative estimation techniques with a greater flexibility of capturing the heterogeneity of countries emissions levels in Kuznets Curve investigations. This paper is particularly interested in capturing this form of distributional heterogeneity whilst exploring the Kuznets Curve theory.

Given this background, this article contributes to the growing empirical literature on the Environmental Kuznets Curve by investigating the validity of the CO_2 income-emissions nexus across different quantiles of the conditional distribution of emissions. We employ the quantile fixed effects method to provide empirical insights into the distributional heterogeneity of this relationship. This method corresponds to a random coefficients setup allowing for heterogeneous income-emissions relationships at different conditional quantiles of the emissions distribution.[6] The technique is capable of identifying various relationships that may be missed by the application of conventional mean regressions thereby providing an opportunity for a more comprehensive examination of the carbon EKC theory. To our knowledge, this paper is the first to comprehensively employ this technique to introduce (distributional) heterogeneity in investigating the CO_2 income-emissions

[6] The two techniques - quantile regression and random coefficients models – are related as they can estimate flexible slope coefficients across quantiles or groups. However, the latter model assumes that parameters are independent and identically distributed (iid) – thus, independent of explanatory variables – while the former does not rely on this assumption (see Fox et al., 2011). Hence, in the Kuznets curve context, a quantile regression model does not require the coefficient of income to be independent of income. The assumption of iid parameters by random coefficients models may be restrictive in some applications.

nexus.[7] We empirically examine the relationship between per-capita measures of CO_2 emissions and GDP for the entire world and different sub-sets of countries – OECD, Non-OECD, West, East Europe, Latin America, East Asia, West Asia and African regions. An exploration of the EKC at different percentiles of the conditional distribution of emissions is necessary due to two main reasons. Foremost, the conditional median estimates – one of the percentiles covered by the conditional quantile method – are more robust to outliers on the dependent variable than the estimates of the conditional mean (Koenker, 2004, 2005). Second, the conditional mean estimation only characterises the mean effect of income on emissions thereby failing to characterise the full distributional impact. The information gained by examining the effect of income on a measure of central tendency – mean or median – of a particular emissions distribution may not necessarily be informative for other quantiles except this effect is not different from those at the other regions (see for instance Huang et al., 2007; Flores et al., 2012). Thus, conditional quantile estimation provides an opportunity for a richer exploration of the CO_2 income-emissions nexus as it allows an assessment of the impact of income across the entire conditional distribution of emissions, thereby, extending beyond the conditional mean.

For an additional expository analysis whilst investigating the income-emissions relationship, it is worth exploring further the most important reasons accounting for differences in carbon emissions distribution from one economic group of countries to another. Following the labour economics literature, these explanations are reached using decomposition techniques. This literature has extensively employed the Oaxaca (1973) and Blinder (1973) decomposition method to decompose gaps in wage distributions between males and females, white and black workers or skilled and unskilled employment amongst other uses (see for example DiNardo et al., 1996; Hertz et al., 2008; Fortin et al., 2010). Its extension to the EKC framework provides an opportunity to decompose the gap in CO_2 emissions distribution between the two economic groups considered (OECD and Non-OECD) into two key factors contributing to the gap; differences in characteristics between the two groups and differences in returns to characteristics between the two samples. This allows us to disentangle whether cross-group differences in CO_2 emissions are associated with group-specific economic development or from differences in the distribution of common characteristics or covariates in one group as compared to the other. However, the method as originally proposed by Oaxaca and Blinder (OB) decomposes the mean gap of the outcome variable only, thereby raising distributional concerns as with the conventional panel methods previously alluded to. This has spurred improvements to the OB method, the most notable being an extension

[7] However, it is worth noting that Huang et al. (2007) employed the same method to investigate the original Kuznets relationship between income inequality and economic development. Also, Flores et al. (2012) used the technique in exploring the EKC for nitrogen and sulphur emissions at the US state level.

to various quantiles of the distribution of the outcome variable (Fortin et al., 2010). This improvement moves in tandem with the quantile estimations of the CO_2 income-emissions nexus to be explored in this paper. To separate the effects of differences in OECD and Non-OECD covariate distributions from differences in returns to covariates for each quantile of the distribution of the emissions gap, we employ the Machado and Mata (2005) quantile extension of the OB decomposition technique. As at the time of writing, this paper is the first to systematically employ the quantile decomposition technique to investigate the income-emissions relationship.

The rest of the paper is organised as follows: section two surveys empirical evidence on the subject; section three presents the methods and data to be employed for the study's estimations; section four analyses the main results of the estimations; and the final section summarises the study's findings and proffers policy recommendations.

2. Survey of Literature

The pioneering work of Grossman and Krueger (1991) provides a theoretical framework for an inverted U-shaped relationship between economic development and environmental quality. These analysts investigated the impact of rising incomes – primarily resulting from increased trade flows from the North American Free Trade Area – on environmental quality. Using cross-sectional data on pollution and per-capita incomes for a group of developed and developing countries, their study found that sulphur dioxide and dark matter (smoke) concentrations increased and then decreased with low and high levels of per-capita incomes respectively; thereby confirming the EKC. This study paved way for the emergence of the EKC (strong) advocates' recommendation that environmental clean-up is an inevitable and eventual process of growth (see Beckerman, 1992). The purported notion that economic progress automatically leads to greening has led to a plethora of studies investigating the theme, thus, making the EKC a subject of long standing debate in the environmental economics field. In fact, the hypothesis is one of the most investigated themes in the field of applied environmental economics (see for instance Galeotti et al., 2009). Analysts of the subject can be generally classified as optimists or sceptics; the former consisting of those taking the hypothesis to suggest that economic growth is untimely good for the environment and the latter consisting of those pointing to methodological flaws in deriving the EKC or advocating caution in interpreting the causes and implications of the hypothesis (Nahman and Antrobus, 2005).

Grossman and Krueger (1991) argue that there are three basic mediums in which progress impacts on the environment; scale, technique and composition effects. The scale effect implies the rudimentary reasoning that an increased scale of economic activity leads to greater pollution, ceteris-paribus. Hence, pollution rises with growth. The technique effect connotes the idea that progress may be associated with improvements in production techniques and adaptation of greener technologies; thereby implying an environmental enhancement effect of growth. Development may pave way for a change in the composition of economic production – moving from intensive, heavy machinery driven and (thereby) heavy polluting industries to services and light manufacturing industries. Closely linked to this is the perception that increasing incomes does not only enhance consumers' effective demand for a greener environment but this demand is augmented by advocating for stricter environmental regulations. However, as most firms are clearly driven by profits, the enforcement of tighter environmental regulations in high-income economies may lead to the migration of heavy polluting industries from high-income to low-income economies, to take advantage of laxer environmental regulations in the latter economies. This form of industry migration is termed Pollution Havens Hypothesis (see for instance Dinda, 2004; Hill and Magnani, 2002). Consequently, the composition effect produces an ambiguous effect on environmental quality depending on whether the country assessed is high-income (developed) or low-income (developing). From the pollution havens perspective, the general expectation is that it should lead to environmental improvements and depletion in the former and latter economies, respectively.[8] It is worth noting that the role of this industry-type migration as a major indicator of environmental degradation or greening still remains largely uncertain in the environmental economics literature (see for instance, Grossman and Krueger, 1996; Cole, 2003).

Grossman and Krueger's (1991) explanations spurred a proliferation of empirical studies on the subject; to confirm or refute the Kuznets Curve proposition. Analysts applied a variety of methods in their investigation with a great deal of available studies examining a group of countries employing cross-sectional and panel techniques, particularly the fixed effects method. However, the basic assumption behind pooling time-series data of different countries into one panel is that environmental quality-economic development trajectory would be the same for all countries; thereby inferring homogeneous slopes across the entire sample. This assumption neglects the heterogeneity arising from cross-country variations; due to different economic, social, political,

[8] In addition to the movement of these industries, there are technical transfers, particularly of advanced and cleaner production technologies, from the developed to developing countries. Consequently, the overall effect of pollution havens on the environmental quality of the developing countries is not a simple one-way relationship. Obviously, this also depends on whether the depletion effect of pollution havens outweighs the enhancement effect of technical transfers.

structural and biophysical differences which may have varying effects on environmental quality (Dinda, 2004).

Surveying the extant literature on the EKC for CO_2, Dijkgraaf and Vollebergh (2005) examined the hypothesis in a panel of 24 OECD countries. Applying the fixed effects technique to a data-set on CO_2 emissions, per-capita income, population and energy consumption spanning from 1960 to 1997, this study confirmed the inverted U-shaped income-emissions relationship but raised doubts on its findings after conducting a test of slope homogeneity across countries in the sample. The null of slope homogeneity largely assumed by the conventional panel fixed effects method was strongly rejected. Consequently, the authors questioned the practice of pooling various countries together in Kuznets Curve investigations. Additionally, they challenged the existence of an overall CO_2 EKC as a result of the flawed homogeneity assumption of traditional panel techniques. Thus, they suggested a further exploration of the CO_2 income-emissions relationship using more flexible panel methods that are capable of capturing the heterogeneity issues usually inherent in longitudinal data analysis.

Following the identified need for a more flexible technique capable of capturing countries' heterogeneity, Musolesi et al. (2010) employed the hierarchical Bayes estimator to show that different CO_2 income-emissions dynamics are associated with different economic and geographical groupings. Using a panel data-set of 109 countries spanning from 1959 to 2001, the study validated the EKC theory in 15 European Union countries, OECD countries and G-7 countries. The hypothesis was also confirmed for the combined sample of countries considered but a monotonically rising relationship was found for the Non-OECD and a group of 40 poorest countries in the analysis. Additionally, the authors conducted a preliminary test for the null of slope homogeneity using Swamy's (1970) chi-square test statistic. This null was strongly rejected. Further, the study found that the EU but not the US, was most responsible for the EKC in the G-7 countries and the full sample. In sum, they noted that the full sample analysis conceals some interesting and critical income-emissions dynamics.

Various studies employed other panel econometric techniques in their exploration of the EKC (see for instance Romero-Avila, 2008; Galeotti et al., 2009). However, as earlier noted, a great deal of these studies examines the income-emissions nexus at the conditional mean of emissions. To our knowledge, the only exception is the recent study by Flores et al. (2012) who applied the conditional quantile fixed effects method to a US state level data-set spanning from 1929 to 1994 to investigate nitrogen oxide (NO_X) and sulphur oxide (SO_2) EKC. This method explains the income-emissions relationship at different percentiles of the conditional distribution of emissions, thereby being able to capture state level heterogeneity in the sample. Their study confirmed the EKC for all quantiles of the conditional distribution of NO_X considered. However, mixed results were found for the SO_2 scenario; both an EKC and a monotonically rising relationship were found. Most importantly, the study found that the traditional mean fixed effects method provides more optimistic turning point income levels than the quantile fixed effects method in the case of NO_X; the latter technique provides turning point incomes that are 19 to 36 percent higher than the former. Based on these authors' analysis, it is therefore not surprising that the largely employed traditional fixed effects technique influences the suggestion that progress is a panacea to pollution. To our knowledge, no study thus far has employed the quantile fixed effects technique in investigating the CO_2 income-emissions nexus. Our paper aims to fill this methodological gap.

3. Econometric Framework

3.1. Quantile Fixed Effects Model

Following the traditional EKC reduced form framework, this paper models per-capita CO_2 emissions as a cubic polynomial function of per-capita income as follows:

$$lnems_{it} = \alpha_i + \gamma_t + \beta_1 \ln inc_{it} + \beta_2 lninc_{it}^2 + \beta_3 lninc_{it}^3 + \varepsilon_{it}. \qquad \text{(i)}[9]$$

Equation (i) represents a conventional longitudinal fixed effects relationship where *lnems* is the log of per-capita CO_2 emissions; *lninc*, *lninc*^{2} and *lninc*^{3} denote the log of per-capita income and its squared and cubic terms, respectively; the subscripts *i* and *t* denote country and time period respectively; α_i is unobserved time invariant country specific effects; γ_t is time specific effects accounting for time varying omitted variables and stochastic trends common to all countries; ε_{it} is the random error term; β_1, β_2 and β_3 are the slope parameters to be estimated.

As mentioned earlier, the model above estimates a homogeneous income-emissions relationship for all countries in the sample, thus, not being able to capture the existing

[9] It is worth noting that the traditional framework does not control for other possible determinants of emissions; for instance population density, energy use, income distribution within the country and trade openness amongst other factors. This is not to imply that this framework belittles the role of these factors. The choice of income (in its level, quadratic and cubic polynomials) is based on three main reasons: First, the EKC hypothesis is mostly concerned with the shape of the relationship between income and emissions but not obtaining best predictions for emissions in subsequent years; Secondly, data limitations restrict the analysis to income and emissions. In this respect, the use of panel techniques that sweep cross country effects away enables us to control implicitly for any invariant determinants; Thirdly, the framework allows comparability with similar studies (see Azomahou et al., 2006, for more details).

heterogeneity amongst countries to be investigated. To bridge this gap, this paper employs a quantile fixed effects version of equation (i). The quantile transformation of this equation is:

$$Qlnems_{it}(\tau|lninc_{it}, \alpha_i, \gamma_t) = \alpha_i(\tau) + \gamma_t(\tau) + \beta_1 \ln inc_{it}(\tau) + \beta_2 \ln inc_{it}^2(\tau) + \beta_3 lninc_{it}^3(\tau) + \varepsilon_{it}, \text{ (ii)}$$

where Q denotes quantile regression, τ denotes selected quantiles (0.1, 0.25, 0.5, 0.75 and 0.9) and all other variables are as previously defined. Since both the time series and cross-section dimensions of our sample are (arguably) large, this paper assumes heterogeneous distributional shifts; that is, $\alpha_i(\tau)$ and $\gamma_t(\tau)$ vary between quantiles (see Koenker 2004). Our dataset employs a globally representative sample and the richness of this data enables the estimation of country and time fixed effects at each quantile with good precision. The quantile fixed effects model in equation (ii) captures the heterogeneity of the countries in the sample by providing different marginal effects based on each observation's position on the conditional distribution of emissions.[10] This technique paves way for a comprehensive understanding of the varying income-emissions relationships in-built in a single EKC system.

To sum, it is worth noting that quantile regression is not the same as applying OLS to different sub-sets of the data obtained by dividing the complete data-set into different percentiles of the response variable. Doing this would amount to an incomplete use of the entire data-set. Quantile regression uses the entire data-set in obtaining estimates for each conditional quantile considered; however, some observations are given more weight than others depending on the conditional quantile considered. For instance, an estimation of the quantile regression function for a low quantile, say $\tau = 0.25$, for examining the effect of income on emissions in the lower tail of the emissions distribution is different from estimating a mean regression when we condition on data on the lower tail of the distribution. Thus, $Qems_{it}(0.25|lninc_{it})$ is not the same as $E(ems_{it}|ems_{it} < c, lninc_{it})$, for some appropriately chosen c meant to capture the lower tail of the distribution. There is no theory that informs the choice or interpretation of the parameter c while τ has a natural interpretation (see Alexander et al., 2008; Wagner, 2004 for more details).

[10] The conventional fixed effects method estimates: $E(ems_{it}|inc_{it}) = \alpha_i + \gamma_t + \beta_1 inc_{it} + \beta_2 inc_{it}^2 + \beta_3 inc_{it}^3$, and the corresponding quantile fixed effects version estimates: $Q_\tau(ems_{it}|\alpha_i, \gamma_t, inc_{it}) = \alpha_i(\tau) + \gamma_t(\tau) + \beta_1 inc_{it}(\tau) + \beta_2 inc_{it}^2(\tau) + \beta_3 inc_{it}^3(\tau)$, where τ is selected quantile. Consequently, the two functions represent different optimisation problems (see for instance Flores et al., 2012). The conventional fixed effects technique minimises the mean squared error given by: $\min_{\beta \epsilon \Re^P} \sum_{i=1}^{N} (ems_{it} - \alpha_i - \gamma_t - \beta_1 inc_{it} - \beta_2 inc_{it}^2 - \beta_3 inc_{it}^3)^2$. Similarly, the quantile fixed effects method minimises an asymmetrically weighted sum of absolute residuals. The solution to the quantile fixed effects version of the minimisation problem is given by: $\min_{\alpha,\gamma,\beta} \sum_{k=1}^{q} \sum_{t=1}^{T} \sum_{i=1}^{N} \rho_{\tau_k}[ems_{it} - \alpha_i(\tau_k) - \gamma_t(\tau_k) - inc_{it}(\tau_k) - inc_{it}^2(\tau_k) - inc_{it}^3(\tau_k)]$, where $\rho_\tau(u) = \mu[\tau - 1(u > 0)]$ is called the check function. This is solved by linear programming techniques (see Koenker, 2004 for more details).

3.2. Decomposition Procedures

To further investigate the OECD-Non-OECD emissions gap, we employ the Machado and Mata (2005) extension of the BO decomposition to a quantile distribution system. This technique decomposes the emissions differential of the OECD vs Non-OECD countries at each quantile into a component attributable to differences in covariates between the OECD and Non-OECD groups and another component attributable to differences in the returns to covariates between the two groups. The former component is generally referred to as endowment or explained effect and the latter coefficient, returns or unexplained effect. The use of the terms 'explained and unexplained effects' stems from the interpretation that the two effects are explained by the covariates and other factors unaccounted for in the model respectively. This interpretation of the returns effect plays an important role in the paper's decomposition analysis in the next section.

The Machado and Mata (2005) decomposition technique is based on the generation of a counterfactual distribution of (log) emissions for Non-OECD countries; the distribution of CO_2 emissions that would have prevailed in the Non-OECD group if it had the same income as the OECD group but retained the returns to its income. Essentially, the counterfactual exercise answers the question, what would happen to the Non-OECD's emissions distribution if its characteristics were as in the OECD group but it maintained the returns to its characteristics? A comparison of the counterfactual and estimated emissions distribution for the Non-OECD group yields the OECD-Non-OECD emissions gap attributable to differences in covariates. The remainder of the gap is attributable to differences in returns to covariates. This method relies on the estimation of a marginal density function of (log) emissions that is consistent with the estimated conditional quantile process defined by:

$$Qlnems_{group}(\tau|X_{group}) = \beta_{group}(\tau)X_{group} \qquad \tau \in (0,1) \qquad \text{(iii)}$$

Where X is a vector of the covariates (*income, income*^{2}*, income*^{3} and the fixed effects), β is a vector of quantile regression coefficients to be estimated and *group* denotes the two economic groupings (OECD and Non-OECD).[11] The Machado and Mata algorithm is outlined as follows:

a. Generate a random sample of size m from a uniform distribution U[0,1] to obtain τ_j for j= 1,2,…,m. These are the quantile regression coefficients to be estimated; $\beta_{group}(\tau_j)$.
b. Use the OECD covariates to generate fitted values $ems^*_{Non\text{-}OECD}(\tau) = X_{OECD}\beta_{Non\text{-}OECD}(\tau_j)$.[12] For each τ_j this generates N Non-OECD fitted values, where N is the number of observations in the OECD sample.

[11] As in the left hand side variable, emissions, the income variables are measured in logs as well.

We denote $f(lnems_{group})$ as an estimator of the marginal density of log emissions based on the observed sample and $f^*(lnems_{group})$ an estimator of the marginal density of emissions based on the generated sample. The counterfactual densities are denoted $f^*(lnems_{Non\text{-}OECD};X_{OECD})$ for the density that would prevail in Non-OECD countries if these countries' covariates were distributed as in OECD countries but retained the returns to their own covariates.[13] The raw differential in emissions distributions between OECD and Non-OECD groups compares the counterfactual with the observed densities of emissions in the two groups. Hence, the overall gap from $f(ems_{OECD})$ to $f(ems_{Non\text{-}OECD})$ at each quantile is decomposed as follows:

$$f(lnems_{OECD}) - f(lnems_{Non-OECD}) = [f^*(lnems_{Non-OECD}; X_{OECD}) - f(lnems_{Non-OECD})] + [f(lnems_{OECD}) - f^*(lnems_{Non-OECD}; X_{OECD})], \qquad \text{(iv)}$$

where *ln* denotes natural logs and all other variables are as previously defined.[14] The first term (in brackets) on the right-hand side of equation (iv) measures the contribution of differences in endowments to the raw differential at the τth percentile; the explained effect. The second term measures the contribution attributable to differences in the coefficients to the emissions gap at the τth quantile; the unexplained effect. By providing answers to which of the two effects contributes more to an estimated OECD-Non-OECD emissions gap, this procedure provides more insights into the EKC exploration. This decomposition exercise is not merely appealing for the extra econometric exposition it offers. It identifies the relevance of income and other factors in explaining the emissions differential between the two economic blocs. This could be informative

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12 Conversely, the Non-OECD covariates could be used to generate $ems^*_{OECD}(\tau)=X_{Non\text{-}OECD}\beta_{OECD}(\tau_j)$. Estimation results can be expected to differ. Given our research perspective, we prefer using the OECD sample as the "counterfactual".

13 Again, a similar counterfactual density could be generated for the OECD group if necessary; $f^*(lnems_{OECD};X_{Non\text{-}ECD})$. That is, the OECD distribution of emissions if its covariates were distributed as in the Non-OECD group.

14 Similarly, $f(lnems_{Non-OECD}) - f(lnems_{OECD}) = [f^*(lnems_{OECD}; X_{Non-OECD}) - f(lnems_{OECD})] + [f(lnems_{Non-OECD}) - f^*(lnems_{OECD}; X_{Non-OECD})]$.

Employing the original OB method, the emissions gap corresponding to equation (iv) is: $\overline{lnems}_{OECD} - \overline{lnems}_{Non-OECD} = \hat{\beta}'_{OECD}(\bar{X}_{OECD} - \bar{X}_{Non-OECD}) + \bar{X}'_{Non-OECD}(\hat{\beta}_{OECD} - \hat{\beta}_{Non-OECD})$, where the first and second terms on the left hand side of the equation are the mean outcomes of the OECD and Non-OECD per-capita emissions respectively; the right hand side of the equation denotes the emissions gap, $\bar{X}_{OECD}$ and $\bar{X}_{Non-OECD}$, are vectors of explanatory variables evaluated at their means for the OECD and Non-OECD groups respectively; $\hat{\beta}_{OECD}$ and $\hat{\beta}_{Non-OECD}$ are the conforming vectors of estimated coefficients for OECD and Non-OECD groups. Thus, the first and second terms of the right hand side of the equation are the explained and unexplained components of the emissions gap respectively [see Oaxaca (1973) and Blinder (1973) for more details].

in suggesting key factors to be targeted in minimising the differential thereby contributing to the formulation of appropriate mitigation policies.[15]

Table 1: Economic and Geographical Groupings and Countries Covered

Geographic/Economic Group	Countries Covered
OECD*	Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Japan, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, South Korea, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States.
West	Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States.
East Europe	Albania, Armenia, Azerbaijan, Belarus, Bosnia, Bulgaria, Croatia, Czech Republic, Estonia, Georgia, Hungary, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Macedonia, Moldova, Poland, Romania, Russian Federation, Slovakia, Slovenia, Tajikistan, Turkmenistan, Ukraine, Uzbekistan.
Latin America	Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, El Salvador, Guatemala, Haiti, Honduras, Jamaica, México, Nicaragua, Panamá, Paraguay, Peru, Trinidad and Tobago, Uruguay, Venezuela.
East Asia	Afghanistan, Bangladesh, Cambodia, China, Hong Kong, India, Indonesia, Japan, Laos, Malaysia, Mongolia, Nepal, North Korea, Pakistan, Philippines, Singapore, South Korea, Sri Lanka, Thailand, Vietnam.
West Asia	Bahrain, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia, Syria, Turkey, United Arab Emirates, West Bank and Gaza, Yemen.
Africa	Algeria, Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Cape Verde, Central African Republic, Chad, Comoro Islands, Congo "Brazzaville", Cote D'Ivoire, Djibouti, Egypt, Equatorial Guinea, Eritrea and Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea Bissau, Kenya, Liberia, Libya, Madagascar, Malawi, Mali, Mauritania, Mauritius, Morocco, Mozambique, Namibia, Niger, Nigeria, Rwanda, Sao Tome and Principe, Senegal, Seychelles, Sierra Leone, Somalia, South Africa, Sudan, Swaziland, Tanzania, Togo, Tunisia, Uganda, Zaire (Congo Kinshasa), Zambia, Zimbabwe.

* All countries in the full sample but not in the OECD group make up the Non-OECD group.

[15] We use Blaise Melly's publicly provided Stata code for this decomposition. For more details on this code, see http://www.econ.brown.edu/fac/Blaise_Melly/code_counter.html and http://www.econ.brown.edu/fac/Blaise_Melly/code_rqdeco.html.

3.3 Data Description and Summary Statistics

Following the vast EKC literature, this paper proxies economic development and environmental damage with per-capita GDP and per-capita CO_2 emissions respectively. We employ data on annual per-capita GDP measured in 1990 International Geary-Khamis dollars obtained from the Maddison Dataset at www.ggdc.net/MADDISON/oriindex.htm. Data on annual CO_2 emissions (in metric tons per-capita) from fossil fuel burning, cement manufacture, and gas flaring are obtained from the World Bank's World Development Indicators (2009). The data-set comprises an unbalanced panel of yearly observations covering 154 countries, with the time period spanning from 1960 to 2007. This is a globally representative sample and the data set is large in both time-series and cross-sectional dimensions. Also, the large number of countries covered increases the diversity of investigated countries and regions in comparison to previous EKC studies. Table 1 provides a list of all the countries in the sample based on their economic and geographical contiguity. Each country is classed into the OECD or Non-OECD bloc, or one of the six geographical regions covered; West, East Europe, Latin America, West Asia, East Asia and Africa.

Table 2 presents summary statistics of the income and emissions variables employed in this study, separated by economic and geographical groupings. The mean per-capita income for the two economic groups and seven regions considered – World, OECD, Non-OECD, West, East Europe, Latin America, East Asia, West Asia and Africa are \$5,169, \$12,531, \$3,223, \$14,588, \$5,340, \$4,329, \$3,771, \$7,594, and \$1,628 respectively. As expected, the Western and African regions have the highest and lowest average per-capita incomes respectively. The minimum and maximum per-capita income observations for the complete sample – \$207 and \$42,916 – are Zaire's (Congo Kinshasa) 2001 and Qatar's 1973 per-capita incomes, respectively. For all groupings, the mean income is considerably higher than its corresponding median observation, with an exception of the OECD, Western and East European groups where the mean and median observations are reasonably identical. The table also provides the maximum, minimum and standard deviation (sd) values of per-capita income for other regions considered.

Table 2: **Data Summary**

Variables	Mean	Median	Min	Max	sd
	Geographical Regions				
	World				
Income	5168.96	2811.633	206.5366	42916.23	5913.922
Emissions	4.435729	1.606196	0.0005567	105.736	7.408073
	OECD				
Income	12531.48	12064.23	1226.389	31357.37	5942.79
Emissions	8.451581	7.89927	0.5016128	22.84792	4.385215
	Non-OECD				
Income	3222.562	1940.666	206.5366	42916.23	4094.912
Emissions	3.364123	0.900827	0 .0005567	105.736	7.677549
	West				
Income	14587.9	14324.2	2955.836	31357.37	5403.46
Emissions	9.097003	8.233196	0.9189601	22.84792	4.246003
	East Europe				
Income	5340.328	4901.829	820.2494	20565.96	2980.06
Emissions	6.751345	6.069122	0.453943	19.89363	4.292865
	Latin America				
Income	4329.301	3672.72	672.4241	20801.3	2678.374
Emissions	2.262891	1.391259	0.0389847	27.86173	3.145726
	East Asia				
Income	3771.399	1534.156	426.0661	31130.11	5401.565
Emissions	2.450627	0.7673387	0.004365	19.10338	3.474071
	West Asia				
Income	7593.584	4732.719	923.1468	42916.23	7277.61
Emissions	12.71124	4.025418	0.0175833	105.736	18.3873
	Africa				
Income	1628.09	1059.674	206.5366	20361.38	1692.942
Emissions	0.9010168	0.2309844	0.0005567	18.57901	1.977811

Conversely, the corresponding mean per-capita CO_2 emissions for the two economic groups and seven regions discussed in the preceding paragraph consecutively are 4.4, 8.5, 3.4, 9.1, 6.8, 2.3, 2.5, 12.7, and 0.9 metric tons per-cubic meter respectively. Contrary to a priori expectation of the OECD and/or Western groups to record the highest mean per-capita emissions, the West Asian region turns-up with the highest per-capita emissions while the African region records the lowest. However, it may be worth noting that the Western region records the highest emissions in absolute but not per-capita terms. As in the case of income, the mean per-capita emissions for the different groups are considerably higher than their corresponding median observations. Again, the only exceptions where these two observations are practically not too different are the OECD, Western and East European groups. For the global sample, the minimum and maximum per-capita emissions observations, 0.0005567 and 105.736 metric tons per-cubic meter, are Somalia's 1991 and Qatar's 1963 emissions respectively. The table also provides the minimum, maximum and standard deviation values of per-capita emissions for the other groups considered.

Table 3: Results of Conditional Quantile and Conditional Mean Estimations
(Bootstrapped Standard Errors in Parenthesis)

Dep Variable: lnemissions

Variables	Quantiles (τ)					Mean
	0.1	0.25	0.5	0.75	0.9	
WORLD						
lnincome	-7.0239* (2.6733)	-5.8682** (2.4768)	-11.1366* (2.0548)	-13.3500* (1.6375)	-15.9845* (1.8473)	-10.3512* (1.4834)
lnincomesq	1.1420* (0.3247)	0.9800* (0.2982)	1.6084* (0.2428)	1.8537* (0.1964)	2.1333* (0.2207)	1.5235* (0.1850)
lnincomecb	-0.0538* (0.0131)	-0.0463* (0.0118)	-0.0709* (0.0095)	-0.0796* (0.0078)	-0.0893* (0.0087)	-0.0678* (0.0076)
intercept	7.4750 (7.1641)	6.1927 (6.6662)	21.2604* (5.7781)	28.1431* (4.5198)	36.3214* (5.1009)	18.4953* (3.9168)
Turning Point	$15,334	$18,253	$17,532	$19,127	$19,627	$17,603
OECD						
lnincome	-9.8058** (4.9292)	-13.8399* (5.3143)	-18.0604* (5.1298)	-11.0752* (2.9860)	-10.5815* (4.0188)	-16.1587* (3.3245)
lnincomesq	1.4278** (0.5608)	1.9512* (0.6097)	2.4417* (0.5728)	1.6241* (0.3448)	1.5648* (0.4537)	2.2166* (0.37890)
lnincomecb	-0.0614* (0.0212)	-0.0834* (0.0233)	-0.1026* (0.0213)	-0.0709* (0.0133)	-0.0687* (0.0171)	-0.0935* (0.0144)
intercept	19.1826 (14.3835)	29.3655*** (15.3587)	41.8538* (15.2331)	22.2085* (8.6152)	21.0042*** (11.8720)	36.2507* (9.6867)
Turning Point	$31,548	$25,197	$21,990	$24,836	$24,440	$24,573
NON-OECD						
lnincome	-0.9257 (3.4701)	0.7984 (2.1803)	-0.5908 (2.5657)	-3.7116 (2.2821)	-8.9209* (2.1446)	-5.8955* (1.8319)
lnincomesq	0.3108 (0.4288)	0.0871 (0.2640)	0.2199 (0.3083)	0.5863** (0.2772)	1.1885* (0.2723)	0.9038* (0.2337)
lnincomecb	-0.0164 (0.0176)	-0.0071 (0.0106)	-0.0109 (0.0121)	-0.0250** (0.0111)	-0.0480* (0.0114)	-0.0396* (0.0098)
intercept	-7.4332 (9.2550)	-10.3431*** (5.9517)	-5.1796 (7.0468)	3.9356 (6.1801)	18.8538* (5.5968)	7.8731*** (4.7348)
Turning Point	N/A	N/A	N/A	N/A	N/A	$35,939

Table 3 Contd.

Variables	Quantiles (τ)					Mean
	WEST					
	0.1	0.25	0.5	0.75	0.9	
lnincome	-49.7372* (18.3407)	-34.2193*** (19.0715)	-12.1094 (19.5596)	5.0830 (13.7072)	-0.8310 (10.7115)	-30.0443* (11.0665)
lnincomesq	6.0364* (2.0109)	4.3918** (2.0708)	1.9841 (2.1012)	0.0367 (1.4552)	0.6478 (1.1396)	3.9511* (1.1995)
lnincomecb	-0.2382* (0.0734)	-0.1796** (0.0749)	-0.0929 (0.0752)	-0.0194 (0.0515)	-0.0402 (0.0403)	-0.1644* (0.0433)
intercept	134.1021** (55.6693)	85.2296 (58.5279)	18.2759 (60.6719)	-32.1252 (43.0299)	-13.0735 (33.4814)	72.4936** (33.9666)
Turning Point	$17,539	$19,154	N/A	N/A	N/A	$18,237
	EAST EUROPE					
Variables	Quantiles (τ)					Mean
	0.1	0.25	0.5	0.75	0.9	
lnincome	6.7364 (8.7150)	0.7427 (9.4556)	17.5084** (7.2493)	12.8960* (4.7739)	15.8279* (5.6458)	-0.7769 (6.5778)
lnincomesq	-0.6084 (0.9764)	0.0951 (1.1073)	-1.8718** (0.8522)	-1.3590** (0.5682)	-1.7045** (0.6764)	0.3491 (0.7975)
lnincomecb	0.0193 (0.0368)	-0.0079 (0.0433)	0.0692** (0.0333)	0.0501** (0.0224)	0.0633** (0.0268)	-0.0195 (0.0320)
intercept	-25.2881 (26.0158)	-7.6514 (26.9973)	-54.9430* (20.5353)	-40.9444* (13.3106)	-49.0482* (15.6242)	-5.3512 (17.9898)
Turning Point	N/A	N/A	N/A	N/A	N/A	N/A
	LATIN AMERICA					
Variables	Quantiles (τ)					Mean
	0.1	0.25	0.5	0.75	0.9	
lnincome	24.6223 (15.4098)	24.5839** (12.1272)	-1.3467 (15.3070)	-18.0577 (12.1242)	-22.8847** (9.4057)	0.6525 (8.5446)
lnincomesq	-2.7748 (1.8677)	-2.8080*** (1.4427)	0.3412 (1.8574)	2.4065 (1.4954)	2.9065** (1.1563)	0.0927 (1.0374)
lnincomecb	0.1065 (0.0755)	0.1090*** (0.0573)	-0.0187 (0.0749)	-0.1029*** (0.0612)	-0.1195** (0.0471)	-0.0080 (0.0419)
intercept	-73.9574*** (42.3890)	-72.7212** (33.9805)	-0.9969 (41.8693)	43.6654 (32.6186)	58.6773** (25.3607)	-6.7217 (23.3900)
Turning Point	N/A	N/A	N/A	$10,891	$13,358	N/A

Table 3 Contd.

	EAST ASIA					
Variables	Quantiles (τ)					Mean
	0.1	0.25	0.5	0.75	0.9	
lnincome	-4.2758 (5.5423)	-5.4398 (3.7026)	-4.4984 (3.5529)	-8.4915** (3.5791)	-13.6720* (3.5583)	-2.2036 (2.8506)
lnincomesq	0.7408 (0.6741)	0.8976** (0.4461)	0.8188*** (0.4308)	1.2756* (0.4240)	1.8462* (0.4199)	0.5206 (0.3422)
lnincomecb	-0.0339 (0.0271)	-0.0408** (0.0178)	-0.0389** (0.0173)	-0.0566* (0.0167)	-0.0775* (0.0165)	-0.0261*** (0.0136)
intercept	1.2263 (14.8368)	5.4189 (10.1588)	2.7893 (9.6443)	14.5090 (9.9748)	30.0345* (9.9567)	-3.3146 (7.8170)
Turning Point	N/A	N/A	N/A	$22,922	$22,011	N/A
	WEST ASIA					
Variables	Quantiles (τ)					Mean
	0.1	0.25	0.5	0.75	0.9	
lnincome	-10.0156 (13.5672)	-3.9640 (10.2096)	-12.1607** (5.3383)	-9.5314 (7.9640)	-0.1769 (11.1039)	29.4900*** (16.6699)
lnincomesq	1.1346 (1.5465)	0.4313 (1.1544)	1.3514** (0.6191)	1.0535 (0.9389)	-0.0524 (1.3460)	-3.3486*** (1.9074)
lnincomecb	-0.0405 (0.0582)	-0.0132 (0.0433)	-0.0471** (0.0236)	-0.0359 (0.0365)	0.0073 (0.0539)	0.1277*** (0.0720)
intercept	28.1458 (39.2497)	12.1834 (30.1336)	36.9108** (15.4526)	29.3698 (22.2937)	3.4745 (30.2616)	-85.6641*** (48.2779)
Turning Point	N/A	N/A	N/A	N/A	NA	NA
	AFRICA					
Variables	Quantiles (τ)					Mean
	0.1	0.25	0.5	0.75	0.9	
lnincome	15.1533* (2.1850)	12.5700* (3.0021)	11.0233** (4.8699)	2.1953 (7.0959)	-5.1070 (3.7611)	4.9264 (3.2712)
lnincomesq	-2.0051* (0.3080)	-1.6369* (0.4001)	-1.4174** (0.6285)	-0.3141 (0.9216)	0.6393 (0.5080)	-0.6415 (0.4386)
lnincomecb	0.0927* (0.0140)	0.0757* (0.0175)	0.0654** (0.0268)	0.0201 (0.0395)	-0.0213 (0.0227)	0.0336*** (0.0193)
intercept	-40.9902* (5.0138)	-34.8052* (7.4288)	-30.4862** (12.5140)	-7.0430 (18.0216)	11.8111 (9.2379)	-15.3255*** (7.9792)
Turning Point	N/A	N/A	N/A	N/A	N/A	NA

NB: *, ** and *** denote significance at the one, five and ten percent levels respectively.

4. Results and Discussions

4.1. Quantile Fixed Effects Analysis

For the purpose of an elucidatory comparison across econometric procedures, we present results for the quantile fixed effects estimations and the traditional mean fixed effects technique in table 3. In this table, the estimated income coefficients (in level, quadratic and cubic terms) and intercept for each economic and geographical group and the five quantiles considered *(τ = 0.1, 0.25, 0.5, 0.75 and 0.9)* are presented in the first five columns of the quantile section of the table. The last column labelled "Mean" presents the corresponding results for the conditional mean estimation.[16] As a conventional practice, we report bootstrapped and robust standard errors for the conditional quantile and conditional mean estimates in parenthesis, respectively.

The results in table 3 are complemented by the diagrams in figure 1 (see appendix). The figure provides a pictorial representation of the fitted curves of the estimated income-emissions relationship for the five conditional quantiles considered, as well as the conditional mean. The lines labelled quant10, quant25, quant50, quant75, quant90 and mean represent the estimated curves for the 10th, 25th, 50th, 75th, 90th percentiles and the mean, respectively. In these diagrams, the solid curves represent a significant income-emissions relationship – where the three income variables are statistically significant – and the dotted curves represent an insignificant relationship, where one or more of the income variables are statistically insignificant. The figure therefore provides pictorial evidence confirming or refuting the proposition of an inverted U-shaped relationship between per-capita CO_2 emissions and per-capita income. If an inverted income-emissions relationship exists, it also provides pictographic evidence of the turning point level of income for the estimated Kuznets Curve relationship.

For the global sample, an examination of the shape of the estimated curves and the significance of the income coefficients reveals that there is evidence in support of the EKC in all scenarios; the five conditional quantiles and conditional mean. Despite the curves of the income-emissions relationship being almost identical across conditional quantiles and mean albeit lying on different sections of the plane in the diagram, the estimates for the conditional quantile results are relatively different at different quantiles of the conditional distribution of emissions. In a nutshell, the conditional quantile and conditional mean estimations provide a turning point of about $15,300

[16] It is worth noting that the table omits the numerous year and country fixed effects accompanying the income coefficients.

to \$19,600 and \$17,600 respectively (see table 3 and figure 1); these estimates are considerably higher than the global mean per-capita income, \$5,169. The mean estimation therefore provides optimistic turning point levels of income for countries with emissions in the upper tail of the emissions distribution – 0.75 and 0.9 quantiles – and gets this approximation just about right for countries in the median and 0.25 quantiles. However, it estimates a relatively high turning point for countries with emissions in the 10th percentile. Regardless of the global sample providing evidence of the EKC hypothesis for all conditional quantiles considered and conditional mean also, the conditional quantile results provide a more rigorous and informative analysis of the turning points of this ascertained relationship.

Similarly, the OECD results show a significant EKC relationship for all conditional quantiles and mean. However, the relatively late curvature of the plotted coefficients for this group indicates that these countries had to attain very high income levels before growth culminated into environmental improvements; assuming these turning points were not also influenced by policies aimed at mitigating carbon emissions. The conditional quantile and conditional mean techniques provide turning point incomes of about \$22,000 to \$31,000 and \$24,600 respectively. These turning points are at least approximately two times higher than the mean income for this group, \$12,500.

The conditional quantile regression results for the Non-OECD sample turn up an insignificant positive monotonic income-emissions relationship. The only exception is the result for the 0.9 quantile which shows a significant relationship with prospects of an eventual decline.[17] In contrast, the conditional mean results depict a significant EKC relationship with a turning point income of \$35,900. There is a large disparity between this turning point income and the mean income of this group, \$3,223. Such a disparity raises considerable doubts on how the countries in this group would attain this turning point income given that virtually all of them have per-capita incomes significantly less than that depicted by the turning point. More importantly, the two different income-emissions relationships portrayed by the conditional quantile and conditional mean techniques shows that the latter may provide erroneous summaries of the prevailing relationship. The former is more rigorous in its examination of the income-emissions nexus thereby providing a clearer picture of the prevailing relationship at various quantiles of the conditional distribution of emissions.

Next, for the Western region, the conditional quantile technique estimates a significant income-emissions relationship for the 10th and 25th percentiles only. The conditional mean approach depicts a significant relationship as well. The entire family of curves for the Western region

[17] As the income variable (in level) for the 0.75 quantile is marginally insignificant at the 10 percent level, this therefore makes the estimated relationship insignificant.

indicates evidence of an inverted U-shaped income-emissions relationship, albeit some being insignificant. These curves are almost identical across the different conditional quantiles and mean. The diverging inferences on statistical significance show that while the conditional mean technique provides significant evidence in favour of the EKC hypothesis for all the countries in the region, the conditional quantile method is more elaborative and informative by indicating that the estimated relationship may not be significant for observations with emissions in the median and upper tail conditional distribution. Concentrating on the turning points provided by the significant curves, it is therefore suffice to say that the results for the conditional quantile and conditional mean estimations provide turning points of about \$17,500 to \$19,200 and \$18,200, respectively. These turning points are higher than the mean income for this region, \$14,588. However, this disparity in turning point and mean income is not as remarkable as in the global and OECD samples.

The overall result for the East European region shows a monotonically rising income-emissions relationship. The conditional mean estimation depicts this relationship as insignificant. However, as presented by the conditional quantile estimations, the relationship is significant for the median and upper tail quantiles – 75th and 95th percentiles. This result therefore belabours the likelihood of the former technique giving less information on the distribution of emissions than the latter method.

The Latin American region provides an interesting case where various forms of income-emissions relationship are obtained between different conditional quantiles and the conditional mean. The 0.10 and 0.25 quantiles show a monotonically rising income-emissions relationship, with the former relationship being insignificant. Also, the median and conditional mean results show a monotonic (but insignificant) income-emissions relationship with prospects of an eventual decline. On the other hand, the 0.75 and 0.90 quantiles show an inverted U-shaped relationship. However, this evidenced EKC relationship is significant for the 90th percentile only, with the relationship being marginally insignificant for the 75th percentile.[18] Again, these findings reiterate the additional informational gains associated with the application of the conditional quantile over the conditional mean technique; the latter method may conceal more information than it reveals. Inasmuch as this informational gain justifies the sole use of the conditional quantile method as an analytical tool, there is also need for the use of the technique to at least complement the conditional mean method

[18] Precisely, the income and incomesq variables are marginally insignificant at the 10 percent level for the 75th percentile. Also, theoretically, quantile curves are not expected to cross each other. However, it is not unusual to have crossing curves in an empirical application of the quantile regression method but the crossings should not be too many (Koenker, 2005). In the Latin American sample, it is quite inconceivable to avoid these crossings especially in the presence of both the monotonic and inverted U-shaped relationships found in this sample.

for a more in-depth expository analysis of the income-emissions nexus. The conditional quantile results for the 75th and 90th percentiles provide within sample turning points of about $10,900 and $13,400 respectively. These turning points are higher than the mean income for this region, $4,329. In addition to the interesting finding of mixed EKC relationships provided by different percentiles within the conditional quantile method on one hand and the conditional mean technique on the other, these results have far reaching implications. Most importantly, the results confirm Dasgupta et al.'s (2002) argument that environmental clean-ups are possible in developing countries and that peak levels of environmental damage in these countries will be lower than in developed countries (Stern, 2004). Consequently, the inverted U-shaped income-emissions relationship may not exist in developed countries only, but in developing countries as well. There are some developing countries adopting equally stringent environmental control standards as the developed countries. Thus, the argument of no regulatory capacity in developing countries as proposed by the advocates of the EKC theory may be flawed. Therefore, this casts doubts on advocates' proposition that the achievement of economic development is the only solution to environmental damage. As a result, policies aimed at shifting energy use from dirty to cleaner sources whilst promoting the mitigation of carbon emissions should move in tandem with those promoting economic development instead of relying on the latter policies alone for achieving environmental clean-ups.

For the East Asian region, the 0.75 and 0.90 quantiles show a significant EKC relationship (see table 3 and figure 1). The curves for the other quantiles and the mean show a rising income-emissions relationship with prospects of an eventual decline, though this relationship is insignificant. The estimated curves for the 0.75 and 0.90 quantiles intersect those for the median and mean. These curves provide within sample turning point incomes of about $22,900 and $22,000 respectively. However, these turning points are higher than the mean income of the region, $3,711. As in the Latin American scenario, the results for the East Asia region further reiterate Dasgupta et al.'s (2002) argument of developing countries being able to successfully implement pollution mitigation policies, especially the market based instruments. Not surprisingly, Dasgupta et al. (2002) cited one of the countries in this region – China – as a prime example of a developing country being able to implement strict environmental control measures. Again, this finding throws doubt on the suggestion of the EKC advocates that the only way to improve environmental quality is by achieving a decent level of economic development.

The West Asian and African regions show a monotonically increasing income-emissions relationship. With an exception of the conditional mean and median regressions, the monotonic relationship depicted by the West Asian region is generally insignificant. The same applies to the African sample where only results for the median and lower tail are significant.

Following our findings of mixed evidence of the income emissions relationship across the global sample, two economic blocs and six geographical regions analysed on one hand and different quantiles of the conditional distribution of emissions and conditional mean on the other hand, a holistic appraisal of these results suggests that one income-emissions relationship does not fit the entire world. An estimated income-emissions relationship could be monotonic, inverted U-shaped [or (inverted) N-shaped too] depending on the conditional quantile considered and the unique economic, social, structural and environmental characteristics of each economic or geographical grouping. Our scrutiny of the global finding of an inverted U-shaped relationship by both the conditional quantile and conditional mean techniques reveals that while the relationship may hold in a few cases, it cannot be generalised across a wide range of economic and geographical regions facing different levels of economic development. In cases where the relationship is confirmed, the slope of the positive segment of the curve is steeper than the negative segment thereby implying that emissions increases at a faster rate than it declines. Moreover, our results indicate that the conditional mean technique is prone to providing flawed summaries of an underlying income-emissions relationship since it only concentrates on evaluating the effects of the regressors on the mean of emissions. As the conditional quantile method covers the entire distribution of the outcome variable, the technique provides a more rigorous, informative and compelling examination of the income-emissions nexus. The method also provides a basis for capturing countries' heterogeneity while examining the EKC theory by assessing how per-capita income affects emissions based on a country's emissions observations on the emissions distribution.

4.2. Decomposition Analysis

To decompose the OECD-Non-OECD emissions differential into gaps attributable to differences in endowments on one hand and differences due to returns to endowments on the other hand, we follow the Machado and Mata (2005) procedure outlined above.[19] Table 4 presents the results of this estimation. The first, second and third columns in this table present the five percentiles at which the decomposition is evaluated, the raw emissions differential between OECD and Non-OECD countries (at their corresponding percentiles) and the 95 percent bootstrapped

[19] For the purpose of computing bootstrapped standard errors, we bootstrapped the procedure 100 times.

confidence intervals for the estimated raw differentials respectively. The next two columns present estimates of the raw differential attributable to differences in endowments with their corresponding 95 percent confidence intervals respectively; the counterfactual Non-OECD marginal density if all covariates were distributed as in the OECD group versus the estimated Non-OECD marginal density. The final two columns present estimates of the raw differential attributable to differences in returns to endowments with their corresponding 95 confidence interval respectively; the OECD estimated marginal density versus the counterfactual Non-OECD marginal density if all covariates were distributed as in the OECD countries. Further, the table presents standard errors of the estimated raw differentials, endowment and coefficient effects directly below the point estimates in parenthesis. The proportions of emissions differential attributable to the explained and unexplained effects are presented in curly brackets next to the point estimates of these effects.

In table 4, the OECD-Non-OECD emissions gap is positive and significant at all quantiles investigated. However, the differential contracts as we ascend the emissions distribution. This result confirms the a priori expectation (from the data summary section of the paper) that the OECD countries have polluted more than the Non-OECD countries. Further, the explained and unexplained effects contribute about 50.66 to 52.43 percent and 47.57 to 49.34 percent of the emissions gap respectively. Despite the slight dominance of the former in explaining this gap, its contribution diminishes whilst ascending the specified percentiles. The reverse is the case for the coefficient effect. Essentially, since differences in natural logs are approximately equal to percentage differences (see Baiocchi and Aftab, 2006; Costa-Font et al., 2009), the estimated raw differentials imply that the OECD countries emitted about 66 to 369 percent more than the Non-OECD group. More so, if every other thing remained the same but the Non-OECD sample had the OECD's distribution of income, the former would pollute about 25.66 to 39.77 percent more CO_2 than the latter. Since the results of the unexplained effect also account for a significant proportion of the emissions gap, these results therefore imply that there may be other important non-income related factors explaining the estimated emissions gap – such as technological gap, structural differences or pollution havens – not accounted for in this paper.

Table 4: Quantile Decomposition of Changes in Emissions Distribution between OECD and Non-OECD Countries

Quantiles	Differential	95% Conf. Interval		Contributions					
				Covariates	95% Conf. Interval		Coefficients	95% Conf. Interval	
quant10	3.6859	3.5700	3.8018	39.7735 {52.43%}	0.7274	78.8196	-36.0876 {47.57%}	-75.1240	2.9488
	(0.0591)			(19.9218)			(19.9169)		
quant25	3.3446	3.2546	3.4346	37.3166 {52.35%}	-1.5449	76.1781	-33.9720 {47.65%}	-72.8350	4.8910
	(0.0459)			(19.8277)			(19.8284)		
quant50	2.3407	2.2755	2.4059	34.4338 {51.76%}	-4.0404	72.9079	-32.0931 {48.24%}	-70.5752	6.3891
	(0.0333)			(19.6300)			(19.6341)		
quant75	1.4074	1.3302	1.4846	30.1213 {51.20%}	-8.0670	68.3096	-28.7139 {48.80%}	-66.9079	9.4801
	(0.0394)			(19.4842)			(19.4871)		
quant90	0.6646	0.5707	0.7585	25.6562 {50.66%}	-11.8694	63.1817	-24.9916 {49.34%}	-62.5308	12.5477
	(0.0479)			(19.1460)			(19.1530)		

* Percentages in curly brackets are the contributions of the covariate and coefficient effects to the estimated raw differentials at the corresponding percentile.

Combining the decomposition results with those of the EKC estimations, this implies that even in the face of rising per-capita incomes in the Non-OECD countries, this development has generally not been promising for their environment. In spite of the slight dominance of the covariate over the returns effect in explaining the OECD-Non-OECD emissions gap, an extension of this result to the EKC analysis might imply that income differences between the two groups explains a significant amount of the differences in the shapes of the EKC curves for these economic blocs. However, other unexplained factors are accountable for an equally significant amount of these estimated curves as well. Thus, there is need for policy to target income and other important factors explaining the emissions differential – one of the probable major factors being the use of well-designed mitigation tools – to mitigate carbon emissions. A combination of policies enhancing economic development and pollution mitigation could be more beneficial to achieving cleaner environmental standards relative to policies promoting rising incomes alone.

5. Concluding Remarks

The EKC hypothesis posits that the early stages of economic progress are associated with increasing environmental damage. However, after the attainment of a threshold level of income, progress leads to environmental improvements. Graphically, this denotes an inverted U-shaped relationship between income and environmental degradation; with the former and latter measured on the abscissa and ordinate planes of a graph respectively. Advocates of this theory prescribe that achieving economic development is the solution to environmental pollution. This suggestion may undermine the relevance of environmental policies in mitigating pollution. On the other hand, sceptics accept the possibility of an inverted U-shaped relationship between income and pollution, but suggest caution in interpreting the causes and implications of the hypothesis.

Deviating from conventional methods of EKC investigations, we applied the quantile fixed effects technique in exploring the CO_2 EKC within two groups of economic development (OECD and Non-OECD) and six geographical regions – West, East Europe, Latin America, East Asia, West Asia and Africa. A comparison of the findings obtained from the use of this technique with those of the conventional fixed effects method reveals that the latter is inadequate in capturing distributional heterogeneities within the panel sample under scrutiny and it is likely to depict a flawed summary of the prevailing income-emissions nexus under different distributional structures. In cases where it is successful in capturing the prevailing relationship, it may conceal more information than it reveals.

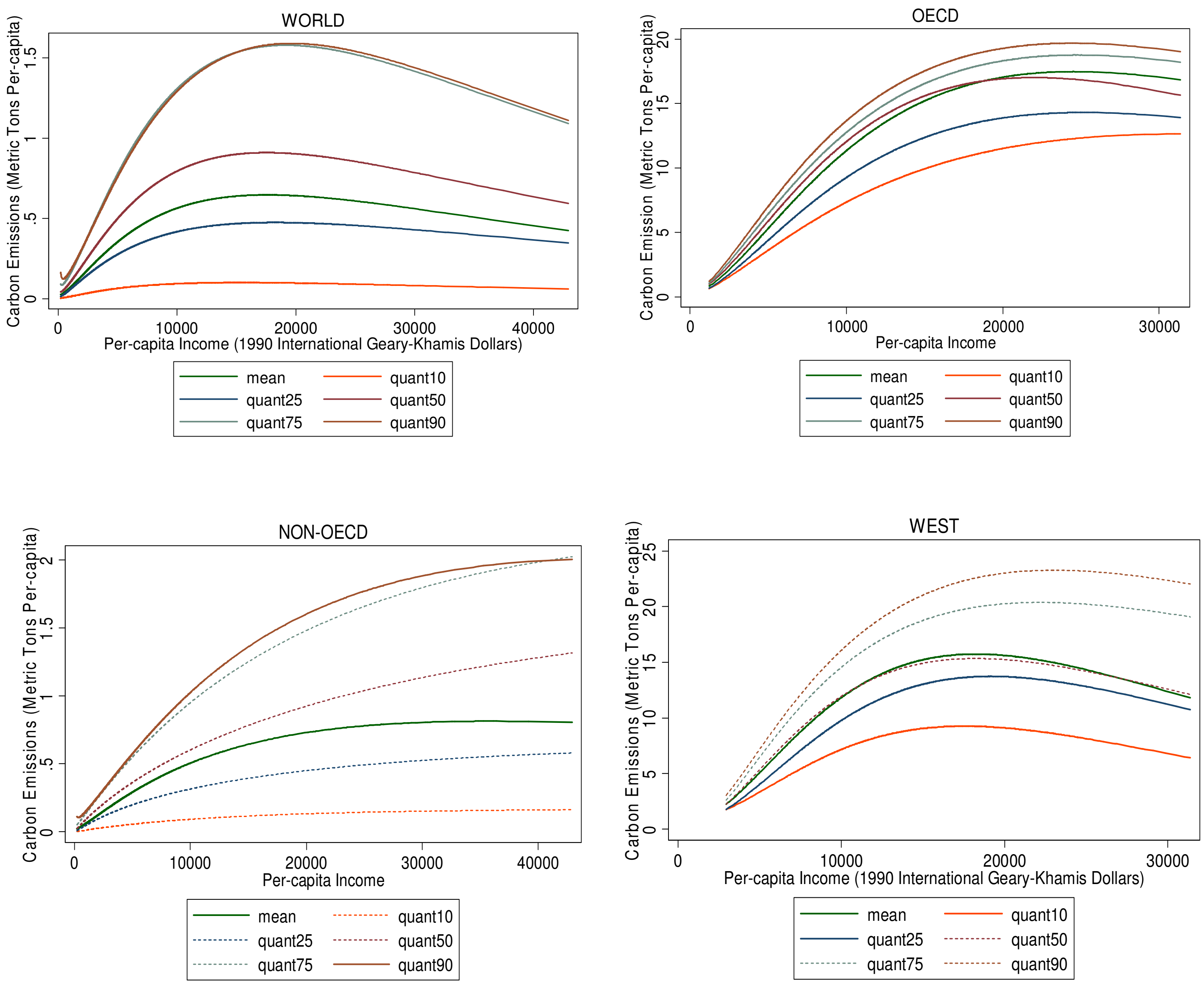
The paper finds the quantile fixed effects method to be more rigorous and informative in its exploration of the income-emissions relationship.

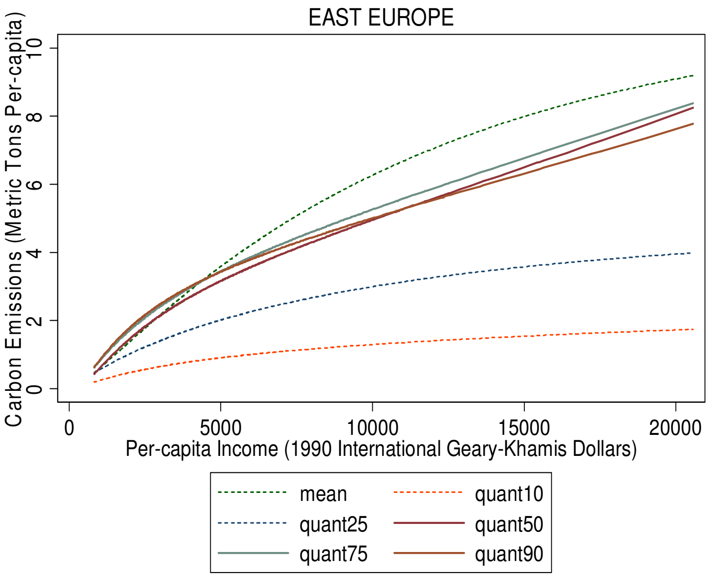
In whole, we confirmed existence of a significant EKC in the global, OECD and western samples. Interestingly, the hypothesis was confirmed in the Latin American and East Asian regions as well thereby reiterating Dasgupta et al.'s (2002) stance that environmental clean-ups are also achievable in developing countries. Thus, turning point incomes may not exist in developed countries alone, but in developing countries as well. Further, our study extended decomposition techniques largely used in labour economics to the EKC framework to provide an additional investigation of the OECD-Non-OECD emissions gap. This decomposition analysis yielded the finding that the OECD group emitted about 60 to 369 percent more CO_2 than its Non-OECD counterpart, depending on the quantile evaluated. Also, if the Non-OECD had the same incomes as the OECD group but every other thing remained the same, the former would pollute about 26 to 40 percent more than the latter. Moreover, we found that there may be other important non-income related factors not captured in this paper militating against the Non-OECD group's greening; such as the shortage of advanced and cleaner production technologies, structural differences and pollution haven amongst others.

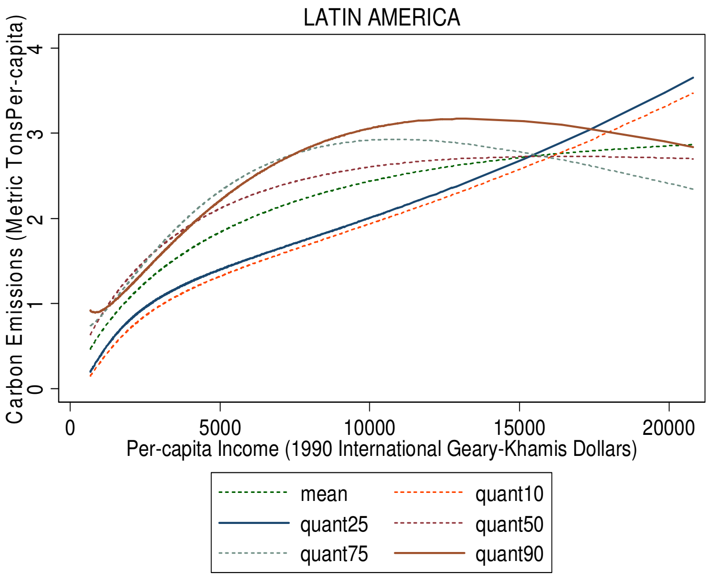
Though the quantile fixed effects procedure employed in this chapter effectively captured distributional heterogeneity of country level emissions in our exploration of the income-emissions nexus, the method is not without flaws. The method may be prone to endogeneity bias especially bi-directional causality. For instance, an increase in economic activity could translate to a rise in carbon emissions via the scale effect. The greenhouse effect of a prolonged increase in emissions could affect regional temperatures. This in turn could lead to an increase or decrease in agricultural productivity, thereby affecting economic output, depending on the region considered. This bi-directional causality may be more pronounced in the case of a local pollutant. A typical example is higher concentrations of particulate emissions brought about by increased economic activity is expected to cause greater damage to human health, ceteris-paribus. This may in turn lead to reduced labour productivity. Thus, future research could extend the quantile fixed effects method to instrumental variable or generalised method of moments techniques to capture country or regional level heterogeneity and control for endogeneity bias in Kuznets curve investigations.

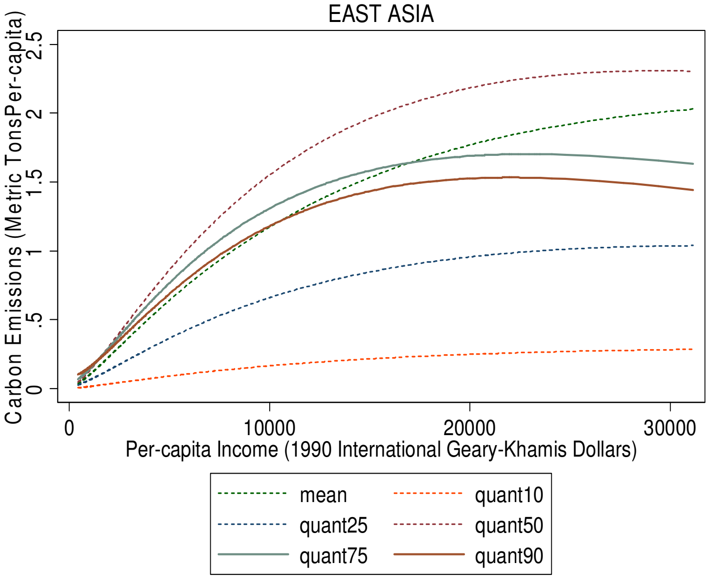
In sum, our exploration of the income-emissions nexus reaches the following clear-cut conclusions; first, no single income-emissions relationship fits all countries of the world; second and most importantly, although our paper finds evidence of the EKC across different levels of economic development, policy makers (especially in developing countries) should ensure that policies in promoting progress move in tandem with those promoting greening; such as policies geared towards a shift to the use of cleaner energy sources. Besides individual country efforts to achieve greening, the clean development mechanism, joint implementation and emissions trading programs of the Kyoto Protocol may provide greater impetus for mitigating CO_2 emissions.

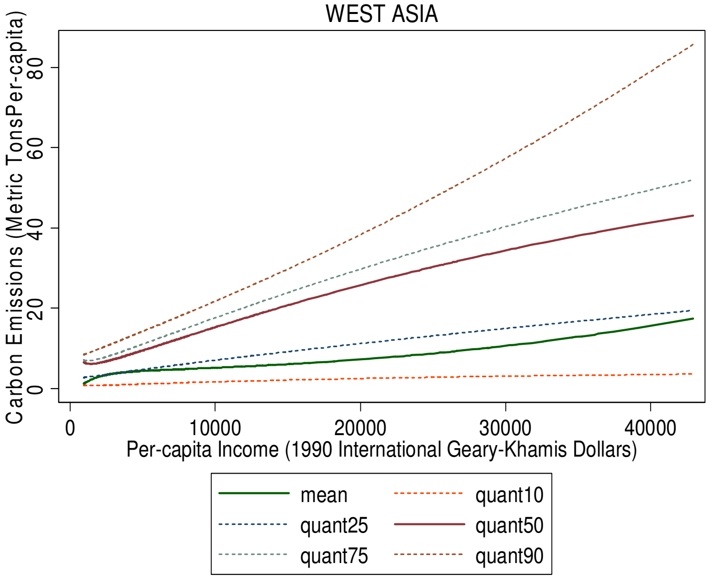
Appendix - Figure 1: Plots of Estimated Income-Emissions Relationships

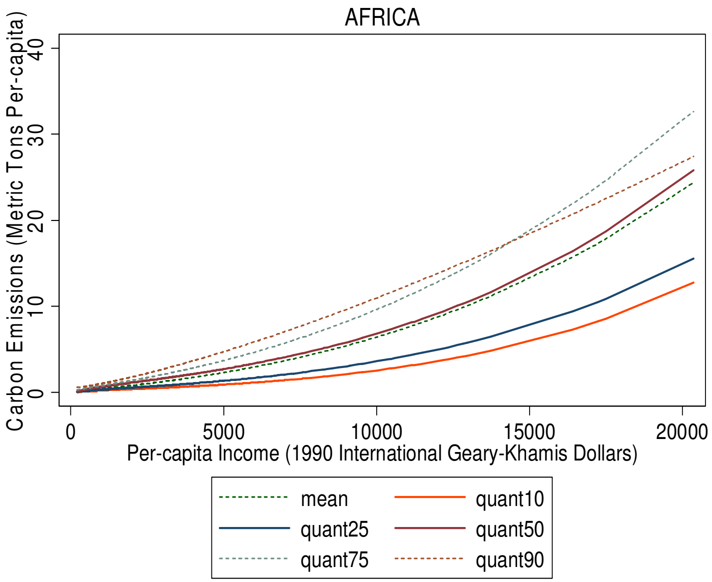



EAST EUROPE
Carbon Emissions (Metric Tons Per-capita)
0
2
4
6
8
10
0
5000
10000
15000
20000
Per-capita Income (1990 International Geary-Khamis Dollars)
mean
quant10
quant25
quant50
quant75
quant90


LATIN AMERICA
Carbon Emissions (Metric TonsPer-capita)
0
1
2
3
4
0
5000
10000
15000
20000
Per-capita Income (1990 International Geary-Khamis Dollars)
mean
quant10
quant25
quant50
quant75
quant90


EAST ASIA
Carbon Emissions (Metric TonsPer-capita)
0
.5
1
1.5
2
2.5
0
10000
20000
30000
Per-capita Income (1990 International Geary-Khamis Dollars)
mean
quant10
quant25
quant50
quant75
quant90


WEST ASIA
Carbon Emissions (Metric TonsPer-capita)
0
20
40
60
80
0
10000
20000
30000
40000
Per-capita Income (1990 International Geary-Khamis Dollars)
mean
quant10
quant25
quant50
quant75
quant90


AFRICA
Carbon Emissions (Metric Tons Per-capita)
0
10
20
30
40
0
5000
10000
15000
20000
Per-capita Income (1990 International Geary-Khamis Dollars)
mean
quant10
quant25
quant50
quant75
quant90

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