Lessons from Quantile Panel Estimation of the Environmental Kuznets Curve*

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Abstract

The environmental Kuznets curve (EKC) hypothesizes that the income-pollution relationship has an inverted U shape: pollution increases with income up to a turning point beyond which it decreases. The empirical literature has concentrated on estimation of this relationship *at the mean* employing longitudinal data, with the typical finding supporting the inverted U shape. Conditional mean estimation, however, can mask heterogeneities present at higher and/or lower quantiles of the emissions' distribution, in addition to being more sensitive to the presence of outliers. We apply methods for conditional-quantile panel fixed effects models to the estimation of the income-pollution relationship on U.S. state-level data on NO_x (nitrogen oxide) and SO_2 (sulfur dioxide) pollutants over the period 1929-1994. Our results indicate that conditional mean methods provide too optimistic estimates about emissions reduction of NO_x, as conditional-quantile methods suggest that the turning point of the relationship occurs at higher values of income; while the opposite is found for SO_2. Another important lesson drawn is that the income-pollution relationship is sensitive to the presence of outliers in the data.

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1 Introduction

What is the relationship between economic development and environmental quality? The Environmental Kuznets Curve (EKC) hypothesis tries to answer this question in terms of the income-pollution relationship. It is graphically represented by an inverted U shape: at the early stages of a country's development both (per capita) income and pollution increase, but after a certain level of income is attained, pollution starts to decrease. Several studies have found empirical evidence about the EKC hypothesis, starting with the seminal work of Grossman and Krueger (1991) and Shafik and Bandyopadhyay (1992), and followed by many others surveyed in De Bryun and Heintz (1999) and Dinda (2004).

The empirical literature has concentrated almost exclusively on estimation of the income-pollution relationship and its turning point at the (conditional) mean, usually employing longitudinal data on countries or U.S. states.[1] The estimated turning point is important for policy since, if it occurs at a very high level of income, it may be hard to attain and pollution may cause irreversible environmental damages. The typical empirical finding is an inverted U shaped relationship. However, the lack of robustness to different model specifications and data, along with a wide range of estimated turning points, have stimulated considerable criticism (e.g., Stern, 2004) and spurred the application of alternative methodologies such as semiparametric and nonparametric methods (e.g., Millimet, List, and Stengos, 2003; Flores, 2007; Zapata and Paudel, 2008). These alternative methods, though, also focus largely on the mean, leaving open questions about distributional heterogeneities as well as the potential impact of outlying observations.[2]

Distributional heterogeneities that can be present at higher and/or lower quantiles of the (conditional) emissions' distribution are important to analyze, as both humans and ecosystems are more seriously affected at high concentrations of pollutants (e.g., Chestnut et al., 1991). Additionally, it is of interest to analyze the sensitiveness of the income-pollution relationship to outliers. In the present context, atypical observations may be the result of actions in particular

[1] Exceptions are Khan (1997) and Maasoumi and Millimet (2005). The first paper documents the evolution of pollution in the U.S. over time at different quantiles, while the second applies stochastic dominance methods to analyze the evolution of the distribution of emissions in the U.S. over time.

[2] Harbaugh, Levinson and Wilson (2002) have analyzed the effect of outliers on the estimation of the income-emissions relationship. They employ a panel of cities worldwide (that updates the data used by Grossman and Krueger, 1995), a random effects model, and a rule that drops the 5% of the observations constituting the largest outliers. They find that these outliers have little effect on their results (which actually do not support the EKC hypothesis on their data).

locations (e.g., policies) that are not necessarily expected to arise naturally elsewhere. Examining these observations that reflect factors leading to success (or lack thereof) in the reduction of emissions is of interest for policy. While this last goal is beyond the scope of the present paper, identifying their effects on typical (mean) estimators of this relationship is a necessary first step.

To examine these issues inherent in mean estimation, we apply methods for (conditional) quantile regression estimation of panel fixed effects models (Koenker, 2004 and 2005) to the estimation of the EKC on U.S. state-level data on NO_x (nitrogen oxide) and SO_2 (sulfur dioxide) emissions over the period 1929-1994. Employing quantile methods allows us to examine the income-emissions relationship at different quantiles of the conditional distribution of emissions. It also allows analyzing the effects of outliers since quantile regression is a more robust method to their presence. To draw transparent implications from our exercise, we employ an identical specification to that used in previous studies employing the same data (e.g. List and Gallet, 1999; Millimet, List, and Stengos, 2003).

Our results indicate that methods that focus on the conditional mean typically provide estimates that are too optimistic about pollution reduction for NO_x, as conditional-quantile methods reveal that the turning point of the relationship occurs at a higher value of income per capita and the reduction in emissions seems to stop toward the high end of income levels. As for SO_2—where the EKC hypothesis seems to have failed in previous studies (e.g., Millimet, List and Stengos, 2003)—quantile regression offers a slightly more optimistic picture: the relationship is increasing but levels off at a medium level of income and offers prospects of starting a decline. Another important finding is that, for both pollutants, the shape of the income-pollution relationship is very similar across conditional quantiles. Consequently, our interpretation of the different results between conditional-mean and conditional-quantile methods is that they are mainly due to the robustness of the latter to outliers in the data.

The reminder of the paper is organized as follows: Section 2 provides some background that posits our study in context. Section 3 describes the data and the panel quantile methods employed. In section 4 we discuss our results and their differences from methods that concentrate on the conditional mean. Section 5 concludes.

2 Background

Most of the work that estimates the income-emissions relationship employs reduced-form equations with income as the key explanatory variable. As a result, these empirical applications do not allow making causal inferences about this relationship, and thus the conceptual arguments about the EKC hypothesis are based primarily on theory. The theoretical underpinnings have been discussed extensively elsewhere (e.g., de Bruyn and Heintz, 1999; Stern, 2004; Dinda, 2004; Bartz and Kelly, 2008). We provide a brief discussion of some of the arguments and counter arguments of the EKC hypothesis, followed by a selective review of empirical work most relevant to the present work.

Arguments in favor of the EKC hypothesis are as follows: (i) Environmental quality is considered a luxury good having a greater than unit elasticity, such that people in an economy at the early stages of development do not have the luxury of caring about environmental quality. After reaching a level of income at which some basic needs are met, people are willing to pay for a cleaner environment (Selden and Song, 1994).[3] (ii) As education levels increase with income (a stylized fact), and people with higher education are more aware about the consequences of their economic activities, individuals increase their sensibility about environmental issues. (iii) A more open political system provides the opportunity for people to express their preferences regarding environmental protection. This argument strengthens (i) and (ii) since in a more open political system the population's environmental intentions and concerns are revealed through elections. (iv) Economic growth leads to stricter environmental regulation, perhaps through the strengthening of social institutions (Dasgupta et al., 2001). A number of studies note that governments of developed countries impose stricter environmental regulations than the governments of less developed countries (Dinda, 2004). (v) Improvements in technology–which occur with economic growth–affect environmental degradation either by increasing productivity or by developing processes to reduce specific types of emissions (Stern, 2004; Carrión-Flores and Innes, 2009).

Some of the counter arguments to the EKC hypothesis are as follows: (i) A number of empirical studies (e.g., Flores and Carson, 1995; Komen, Gerkin and Folmer, 1996; Kristom and Riera, 1996) have estimated the elasticity for environmental quality to be smaller than

[3] Alternatively, even if environmental quality is considered a normal good but the cost of abatement is convex, the inverted U shape implicit in the EKC hypotheis may arise (Kelly, 2003).

unity.[4] (ii) Empirical studies that investigate the influence of political systems and civil rights have produced conflicting evidence. For example, Shafik and Bandyopaohyay (1992) find evidence that SO_2 concentrations are higher in more democratic countries. (iii) Another counter argument relates to trade liberalization–which increases world production–and the transfer of pollution-intensive industries from developed to developing countries. This transfer may be due to economic specialization whereby manufacturing industries locate in developing countries, or to the developed countries establishing stricter environmental regulations (e.g., see Hettige, Lucas and Wheeler, 1992; Jaffe et al., 1995). Under this argument, environmental improvement might be noticed in developed countries but this is because the pollution has been "exported" to developing countries. Thus, environmental improvement may be just a local phenomenon.

Empirically, early evidence of an inverted U shape in the relationship between certain pollutants and income appeared in Grossman and Krueger (1991), who analyzed the environmental impacts of NAFTA. This study along with Shafik and Bandyopadhyay (1992) popularized the EKC and spurred a large number of follow-up studies (see the surveys in, e.g., De Bruyn and Heintz, 1999; and Dinda, 2004). Given the sometimes conflicting evidence reported in empirical studies, researchers have investigated the robustness of the EKC to different data sources, the inclusion of additional control variables, and to the utilization of different econometric techniques that relax various implicit assumptions in the canonical model (Dinda, 2004; Stern, 2004).

Studies that use the same data set as we do (a panel of U.S. states) and are thus directly comparable to ours are List and Gallet (1999), Millimet, List and Stengos (2003), and Flores (2007). The first examines whether income per capita might have a different effect on emissions in different cross-sectional units, thus estimating different coefficients on income per capita for each U.S. state and finding some parameter heterogeneity. The second study analyzes the issue of functional form misspecification by examining a less restrictive semiparametric model, while the third considers nonparametric estimation of both the relationship and its turning point. Both of these studies find that their methods provide more optimistic results towards the EKC hypothesis relative to parametric methods. In contrast to this previous work, the present study draws insights on the income-emissions relationship by analyzing it at different conditional quantiles of the emissions' distribution.

[4] While these studies may weaken the luxury good argument, they do not rule out an inverted U shape that could arise through Kelly's (2003) model. See footnote 3.

3 Data and Methods

3.1 Data

We use panel data at the U.S. state level covering the years 1929-1994 for emissions of NO_x and SO_2. The data contains 48 states and is identical to that originally used in List and Gallet (1999). The data on income comes from the State Annual Summary Tables, 1929-1994, constructed by the U.S. Department of Commerce, while the emissions' data was collected by the U.S. Environmental Protection Agency (EPA) and was included in the *National Air Pollutant Emission Trends, 1900-1994* report. For more details on the data set used see List and Gallet (1999) and Millimet, List and Stengos (2003).[5]

A recognized potential shortcoming of the data is that EPA changed the measurement scheme in 1985 (List and Gallet, 1999; Millimet, List, and Stengos, 2003). However, it has been found that this change in measurement does not result in marked differences in regards to the estimation of the income-emissions relationship (Millimet, List and Stengos, 2003). Given that our results are not qualitatively different from specifications that analyze the two sample periods (pre/post 1985) separately, we concentrate below in an analysis of the full sample 1929-1994. The interested reader is referred to Kapetanakis (2009) for the subsamples results.

3.2 Methods

Following the specification used in most studies that estimate the relationship between emissions and income, we employ a third degree polynomial (Dinda, 2004). This specification is able to capture different possible relationships, such as an inverted U shape, N shape and monotonic functions. As usual in this literature, we work with variables in per capita terms. The specific functional form used for the conditional-mean fixed effects (FE) model is:

$$(E/cap)_{ij} = \alpha_i + \gamma_j + \beta_1(Income/cap)_{ij} + \beta_2(Income/cap)^2_{ij} + \beta_3(Income/cap)^3_{ij} + u_{ij}, \quad (1)$$

where (E/cap) is emissions per capita, which in our application are given by NO_x or SO_2 short tons per capita and represent environmental degradation. Income per capita, $(Income/cap)$, is measured in 1987 dollars, while α_i and γ_j are state and year fixed effects, respectively. In a

[5] List and Gallet (1999) discuss various advantages of the data. Among them: (i) U.S. data is considered more reliable than data from other sources; (ii) the length of the time dimension is large; (iii) we avoid dealing with exchange rate issues since we use data from a single country; (iv) the data measures emissions for the entire states and not solely those of urban areas. This last feature avoids underestimating pollution given that with development occurs decentralization, which reduces the emissions in urban areas and allocates them to the rest of the region.

first instance, we replicate the FE estimates in List and Gallet (1999) and Millimet, List and Stengos (2003) in order to compare them with the results from conditional-quantile methods. In addition, we also estimated–but do not present here–a random effects model which, as in previous studies, is soundly rejected in favor of FE by a Hausman specification test (Hausman, 1978) for both pollutants.

The approach used in this paper differs from the traditional conditional-mean approach in that it estimates the regression function parameters for different conditional quantiles of the emission's distribution. Thus, in general, instead of estimating the conditional mean equation

$$E(\mathbf{y}|\mathbf{X}) = \alpha + \mathbf{X}\boldsymbol{\beta} \tag{2}$$

we estimate

$$\mathrm{Quant}_\tau(\mathbf{y}|\mathbf{X}) = \alpha + \mathbf{X}\boldsymbol{\beta} \tag{3}$$

where τ represents selected quantiles.

The main advantage of considering (3) is that it allows analyzing the income-emissions relationship at different quantiles of the conditional distribution of emissions. Since (2) only analyzes the mean of the same distribution, quantile regression provides an opportunity to more fully explore the income-emissions relationship. For instance, it is of interest to evaluate whether the EKC hypothesis holds for low and high quantiles of the conditional distribution of emissions. In addition, quantile regression allows for some conditional heteroskedasticity in the model (Koenker and Portnoy, 1996), and is a method that is more robust to outliers (Koenker, 2005).[6]

One important practical difference in the estimation of equations (2) and (3) is that they represent different optimization problems. It is well known that the conditional mean model (2) can be estimated by minimizing the mean-squared errors given by the equation

$$\min_{\beta \in \Re^p} \sum_{i=1}^{n} (y_i - x_i^T \beta)^2. \tag{4}$$

Similarly, Koenker and Basset (1978) provided an estimation method for the conditional quantiles in (3) by minimizing

$$\min_{\beta \in \Re^p} \sum_{i=1}^{n} \rho_\tau (y_i - x_i^T \beta) \tag{5}$$

[6] See Koenker (2005) for an extensive treatment of quantile regression methods.

where $\rho_\tau = u(\tau - I(u < 0))$ is usually called the *check function* (Koenker and Basset, 1978; Koenker, 2005).

Estimation methods for the conditional-quantile regression model in (3) are well-developed, whereas corresponding methods for panel data–especially FE–have been developed only recently (see Koenker, 2004 and 2005; and Lamarche, 2006). The main reason for this is that although the extension of quantile regression to FE methods is straightforward with data containing a large number of cross-sections and time periods, the typical panel data set with a small number of time series or cross-sections yields the estimation of the multiple incidental FE parameters difficult. The difficulty arises because the method of differencing out fixed effects in the conditional-mean method does not carry over to the quantile method. As a result, penalized methods that shrink the FE coefficients toward a common value have been developed (Koenker, 2004; Lamarche, 2006).

Our data containing 48 U.S. states observed over 66 years, along with the parsimonious reduced-form specification of the relationship, allows us to estimate individual and time fixed effects at each conditional quantile with good precision. This specification is extremely flexible as it allows each conditional quantile to have its own fixed effects. Indeed, this flexibility is statistically justified in our data, as tests for the equality of state and year fixed effects across the conditional quantiles employed in the estimation below are strongly rejected. To our knowledge, this is one of the first unrestricted two-way fixed effects quantile regression models estimated.

The model is given by:

$$Q_{y_{ij}}(\tau|x_{ij}) = \alpha_i(\tau) + \gamma_j(\tau) + \mathbf{x}_{ij}\boldsymbol{\beta}(\tau), \tag{6}$$

where $\mathbf{x}_{ij}$ includes income per capita, its square and cube, and $\alpha_i(\tau)$ and $\gamma_j(\tau)$ are state and time (year) fixed effects that are allowed to vary across quantiles, respectively. This model dispenses the assumption that one or both types of fixed effects do not depend on the quantile, which is typically imposed when data restrictions (e.g., short panels) require constraining parameters for efficiency purposes. In addition, by avoiding the use of the penalized methods discussed above, we bypass the trade-off of allowing some bias (by shrinking the fixed effects) in order to achieve higher precision. By extension of (5), the minimization problem to solve in estimating the parameters in (6) is given by (Koenker, 2005):

$$\min_{(\alpha,\gamma,\beta)} \sum_{k=1}^{q} \sum_{j=1}^{n} \sum_{i=1}^{m_i} \rho_{\tau_k}(y_{ij} - \alpha_i(\tau_k) - \gamma_j(\tau_k) - x_{ij}^T \beta(\tau_k)). \tag{7}$$

4 Results

Table 1 presents descriptive statistics of the variables in our data, including selected quantiles of the unconditional distribution of the variables, showing that they are all skewed to the right by a considerable amount, especially the emissions variables. Table 2 contains results from the conditional-mean FE model for both pollutants. These results are identical to those from previous studies employing this data (List and Gallet, 1999 and Millimet, List and Stengos, 2003). All coefficients are highly statistically significant.[7] Given the nature of our study, we concentrate on the graphical appearance of the estimated income-emissions relationship. Figure 1 presents in the left panel the curve calculated from the estimated equation for NO_x, while the right panel–which employs a different vertical scale–adds to the corresponding curve a scatterplot of the observations in the sample. Both panels have a range of income per capita between zero and $22,500 which is approximately the range of this variable in our sample.

From the left panel of Figure 1 it is evident that the conditional-mean FE model offers support to the EKC hypothesis using NO_x, a result that replicates Millimet, List and Stengos (2003). The turning point for NO_x is estimated very precisely at $8,657 (standard errors obtained via the delta method). From the right panel, there seem to be a few outlier observations that may have an effect on the estimated parameters for this model.

The emissions per capita of SO_2 that are presented in the two panels of Figure 2 exhibit a very different behavior. The conditional-mean FE model produces a curve that is monotonically increasing in income per capita (also found in Millimet, List and Stengos, 2003). As a result, there is no estimated turning point for SO_2 and the EKC hypothesis is not supported for this pollutant. Relative to NO_x, the right panel of Figure 2 clearly shows that there is a larger amount of observations that can be considered outliers, which may be shifting the estimated curve upwards.

Next, we present the conditional quantile regression results for the FE model in (6) for the following quantiles $\{.05, .1, .25, .5, .75, .90, .95\}$. The estimated parameters (omitting the numerous fixed effects), are presented in Table 3 for each pollutant.[8] They reveal highly

[7] As mentioned in section 3.2, a random effects (RE) model is soundly rejected by the data employing a Hausman specification test, presented in Table 2 for each pollutant.

[8] All our panel quantile regressions results were obtained using Roger Koenker's R package "*quantreg*". The package is available at http://cran.r-projrct.org. The standard errors for the coefficients were obtained using the bootstrap option in that package.

statistically significant income per capita coefficients for all quantiles, as well as turning points.[9] The left panel in Figure 3 plots the estimated curves from the conditional-quantile FE model for NO_x for each of the quantiles considered. This figure allows a comparison of the curves across quantiles, which are all very similar in shape, although it is evident that the conditional distribution of NO_x is skewed to the right as the upper quantiles are farther away from the median than the lower ones. The figure also allows an examination of the amount of crossings among curves. A large number of curve-crossing is considered an indication of misspecification of the quantile model (Koenker, 2005). Except for a few instances, the curves do not cross despite the polynomial specification of the model that makes the occurrence of crossings more likely for extreme values of the income variable.[10]

The conditional-quantile FE model supports the EKC in the case of NO_x (left panel of Figure 3), but it evidences a number of important differences relative to the conditional-mean FE model. First, the conditional-quantile FE model turning points for the different quantiles (except the median) are all statistically significantly higher compared to the conditional-mean FE turning point. They range from \$10,282 to \$11,751–as can be seen from Table 3–and are between 19 and 36 percent higher than the conditional-mean turning point. Second, the rate of decrease after the turning point is attained in the conditional-quantile FE model is noticeably lower compared to the conditional-mean model (note that both figures have identical scales). Third, at very high levels of income per capita, the conditional-quantile FE model suggests that emissions actually stabilize and cease to decrease. Finally, the right panel of Figure 3 presents again the scatterplot of the data, which suggests that the conditional-mean FE model is influenced by outliers with low values of emissions at high values of income per capita.

The conditional-quantile FE model curves for the case of SO_2 are presented in Figure 4. While it is evident that the estimated curves do not convincingly support the EKC hypothesis, they offer a more optimistic picture relative to the monotonically increasing relationship estimated from the conditional-mean FE model. The left panel of Figure 4 shows that all of the estimated curves level off at about \$12,000. In addition, in four out of the seven conditional-quantiles considered (.05, .25, .75, and .90) the estimated relationship does exhibit a turning

[9] As already mentioned, we conduct tests of the equality of each variable's coefficients across the seven quantiles considered. In total, there are 65 year and 47 state FE plus the three income per capita variables. The vast majority of the tests are strongly rejected, with the exception of three FE coefficients in the case of NO_x and two in the case of SO_2. These results are available from the authors upon request.

[10] Recently, Chernozhukov, Fernández-Val and Galichon (2009) have devised a method based on rearrangement that corrects crossing in quantile regression.

point that ranges from $13,188 to $16,696 (all highly statistically significant, as shown in Table 3). Similar to the case of NO_x, the SO_2 curves show a small amount of crossing (two instances) and have similar shapes in every estimated conditional quantile. In contrast to NO_x, the conditional distribution of SO_2 is not as skewed as that of NO_x. The right panel of Figure 4 adds the scatterplot of the data, which suggests that the conditional-quantile FE model is not as heavily influenced by outliers with high values of emissions in the case of SO_2 as it was the case with the conditional-mean model in Figure 2.

As a final exercise, Figure 5 shows the curves from the conditional-median (0.5 conditional quantile) FE and conditional-mean FE models for each pollutant, along with their corresponding point-wise 95% confidence intervals computed using the delta method. In the case of NO_x in the left panel, their predicted curves are not statistically different from each other at conventional levels. This is consistent with the reported results in Table 3 for the median quantile and its estimated turning point. A different conclusion is reached for SO_2 in the right panel of Figure 5, as the conditional-median FE model produces a curve that is statistically different from the conditional-mean FE model for high levels of income per capita, despite the fact that for the median no turning point was found in Table 3. Additional figures comparing the conditional-mean with the rest of the conditional quantiles offer similar insights, although, as expected, showing more marked differences in line with their estimated coeffcients in Table 3.[11]

5 Conclusions

This paper estimates the income-emissions relationship employing conditional-quantile fixed effects (FE) methods to examine if the environmental Kuznets curve (EKC) hypothesis holds at different quantiles of the conditional distribution of emissions. In addition, since this methodology is more flexible and robust to outliers in the data relative to conditional-mean methods, it provides the opportunity to gauge the effects of those observations. We employ a U.S. state-level panel dataset for NO_x and SO_2 emissions from the Environmental Protection Agency (EPA) that includes annual observations for 48 states for the time period 1929 to 1994. These data are sufficiently rich to enable the estimation of a very flexible conditional-quantile panel specification that allows the fixed effects (both state and time) to vary freely across the conditional quantiles considered. For straightforward comparability of our estimates to conditional-mean

[11] We do not include these figures here in order to save space, but are available upon request.

FE methods, we employ a cubic polynomial specification for income per capita as in List and Gallet (1999) and Millimet, List, and Stengos (2003).

We find that the estimates from the conditional-quantile FE model provide new insights about the estimation of the income-emissions relationship and the EKC hypothesis. While for NO_x emissions both FE models support the EKC hypothesis, the method that focuses on the mean typically provides estimates that are too optimistic about pollution reduction, as conditional-quantile methods suggest that (i) the turning point occurs at income per capita levels that are 19-36 percent higher (and the difference is statistically significant), and (ii) the emissions cease to decrease after high levels of income per capita are reached. Conversely, for SO_2–where the EKC hypothesis seems to have failed in previous studies—quantile regression offers a more optimistic picture: the relationship is increasing but levels off at a medium level of income of about \$12,000. In addition, for four out of seven conditional quantiles computed we find statistically significant turning points (between \$13,188 and \$16,696 depending on the quantile) and the curve initiates a slight decline. Given that for both pollutants the use of conditional-quantile FE methods reveals that very similar shapes of the income-emissions relationship hold across conditional quantiles, our interpretation of the different results with respect to conditional-mean methods is that they arise mainly due to the robustness of quantile methods to outliers in the data. Lastly, conditional-quantile methods also reveal that the conditional distribution of NO_x is skewed to the right, while that of SO_2 is more symmetric.

A relevant lesson for the estimation of the income-emissions relationship that can be drawn from our results is that the presence of outliers in the data can have important consequences on inference. Therefore, careful examination of these outliers is warranted to determine if they are the result of particular policies or activities such as the "exporting" of pollution. Within our data, this is a task of interest that we leave for future research. Finally, our results add to the body of literature recognizing that the income-emissions relationship is often not robust to the methodology employed to estimate it. A natural next step in this line of research is to employ even more flexible methodologies, such as the quantile smoothing splines of Koenker, Ng, and Portnoy (1994) or the semiparametric quantile panel data procedure of Chen and Khan (2008).

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Table 1. Descriptive Statistics

Variable	Min	5^{th}	10^{th}	25^{th}	Median	Mean	75^{th}	90^{th}	95^{th}	Max	Std Dev
Income	$1,162$	$2,816$	$3,786$	$5,849$	$8,436$	$9,089$	$12,380$	$14,938$	$16,270$	$22,460$	$4,242$
NO_x	0.023	0.035	0.040	0.051	0.076	0.093	0.107	0.162	0.206	1.136	0.074
SO_2	0.002	0.025	0.036	0.059	0.097	0.165	0.184	0.335	0.544	1.618	0.206

Note: Income is measured in 1987 dollars per capita
NO_x and SO_2 emissions are measured in thousands short tons per capita.

Table 2. Estimated coefficients for the fixed effects model

	Dependent Variable			
	NO_x		SO_2	
Coefficient	Value	t-value	Value	t-value
$Income$ $(\times 10e5)$	3.070	9.465	11.351	13.330
$Income^2$ $(\times 10e10)$	-24.034	-8.241	-55.873	-7.296
$Income^3$ $(\times 10e15)$	48.556	5.453	107.880	4.614
Hausman test[a]	p-value = $<$ 2.2e-16		p-value $<$ 2.2e-16	
Estimated turning point [b]	8657(722)		-	

[a]Hausman test of H_0: RE vs. FE
[b]Standard errors in parentheses; estimated via delta method

Figure 1. Estimated EKC for NO_x employing fixed effects, with and without scatterplot

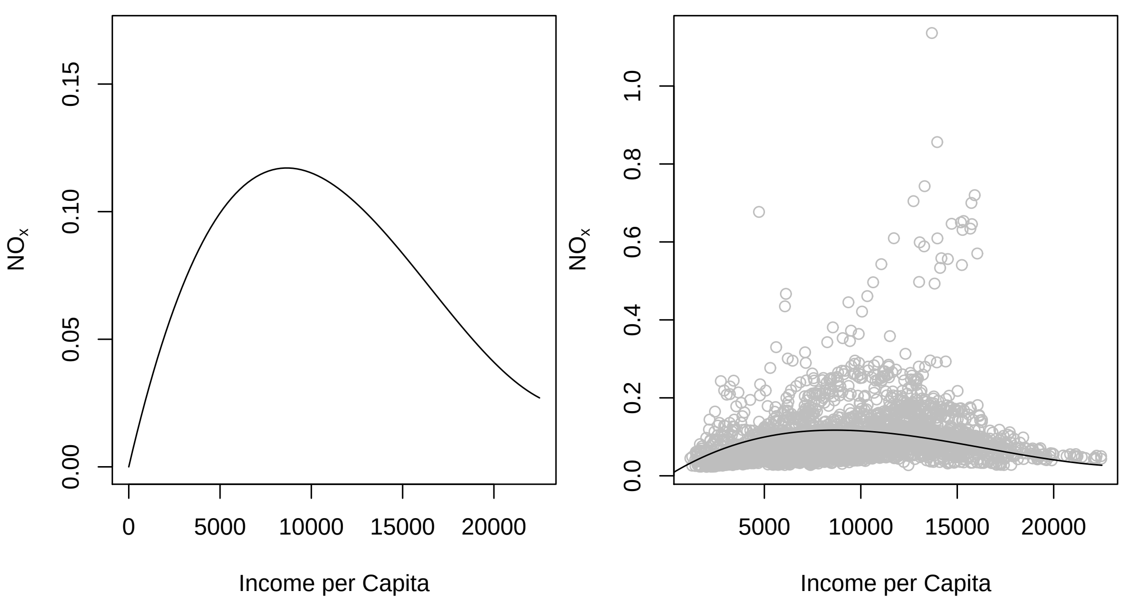

Table 3. Estimated coefficients for the quantile regression fixed effects model

	Dependent Variable			
	NO_x		SO_2	
Coefficient	Value	t value	Value	t value
5_{th} Percentile				
$Income$ $(\times 10e5)$	2.286	11.142	1.817	4.595
$Income^2$ $(\times 10e10)$	-15.295	-10.646	-10.447	-3.541
$Income^3$ $(\times 10e15)$	31.232	9.077	19.716	2.694
Estimated turning point	11,584 (658)***		15,472 (5,343)	
10_{th} Percentile				
$Income$ $(\times 10e5)$	2.409	12.660	2.374	6.261
$Income^2$ $(\times 10e10)$	-16.381	-12.292	-12.380	-4.457
$Income^3$ $(\times 10e15)$	33.456	10.385	22.168	3.015
Estimated turning point	11,188 (609)***		-	
25_{th} Percentile				
$Income$ $(\times 10e5)$	2.624	15.435	3.6049	9.361
$Income^2$ $(\times 10e10)$	-18.167	-14.250	-19.058	-6.558
$Income^3$ $(\times 10e15)$	37.786	11.362	33.148	3.964
Estimated turning point	10,991 (714)***		16,696 (4,664)	
Median				
$Income$ $(\times 10e5)$	2.532	15.331	4.694	12.588
$Income^2$ $(\times 10e10)$	-18.123	-13.403	-27.514	-10.028
$Income^3$ $(\times 10e15)$	37.689	9.893	55.296	6.728
Estimated turning point	10,282 (706)		-	
75_{th} Percentile				
$Income$ $(\times 10e5)$	2.635	12.042	3.6051	9.017
$Income^2(\times 10e10)$	-17.829	-10.360	-21.299	-8.115
$Income^3$ $(\times 10e15)$	34.166	7.468	38.574	5.225
Estimated turning point	10,649 (785)*		13,188 (1,307)	
90_{th} Percentile				
$Income$ $(\times 10e5)$	2.298	9.163	$4.4054e-05$	10.891
$Income^2$ $(\times 10e10)$	-14.065	-7.749	$-2.5184e-09$	-8.056
$Income^3(\times 10e15)$	24.336	5.128	$4.7417e-14$	5.293
Estimated turning point	11,751 (1,033)***		15,771 (2,327)	
95_{th} Percentile				
$Income$ $(\times 10e5)$	2.548	8.893	4.801	10.786
$Income^2$ $(\times 10e10)$	-16.894	-7.641	-27.662	-8.270
$Income^3$ $(\times 10e15)$	32.481	5.497	53.210	5.614
Estimated turning point	11,089 (1,110)*		-	

Note: For the estimated turning points standard errors are shown in parentheses, estimated via the delta method.
*** and * refer to the statistical significance (at the 1 percent and 10 percent level, respectively) of a test of significance of the difference between the corresponding quantile's estimated turning point and the one from the FE model shown in table **??**

Figure 2. Estimated EKC for SO_2 employing fixed effects, with and without scatterplot

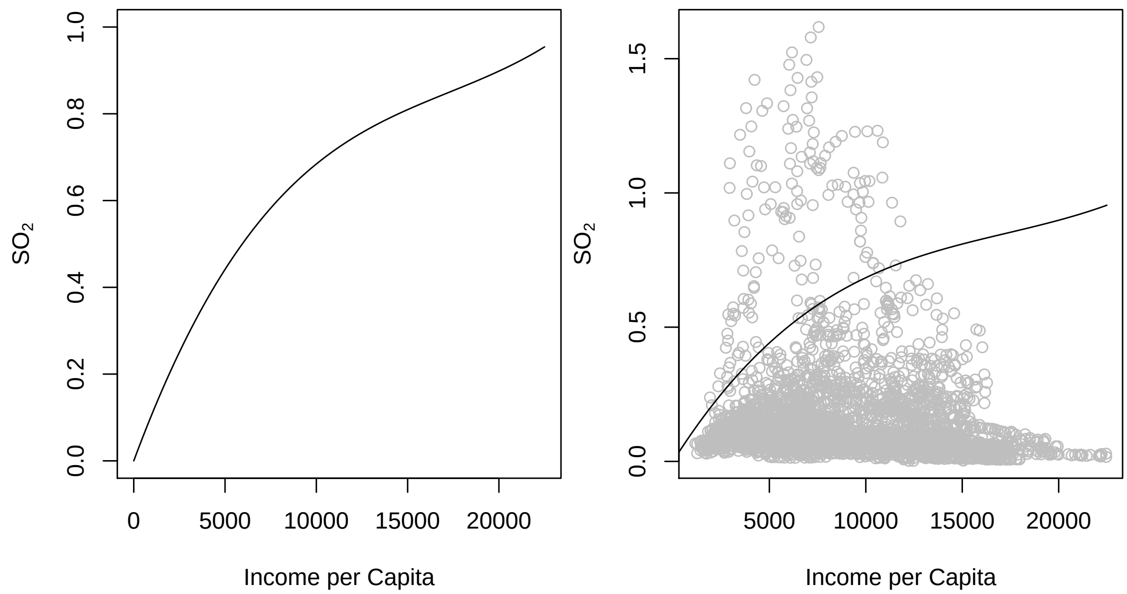

Figure 3. Estimated EKC for NO_x employing quantile regression fixed effects, with and without scatterplot

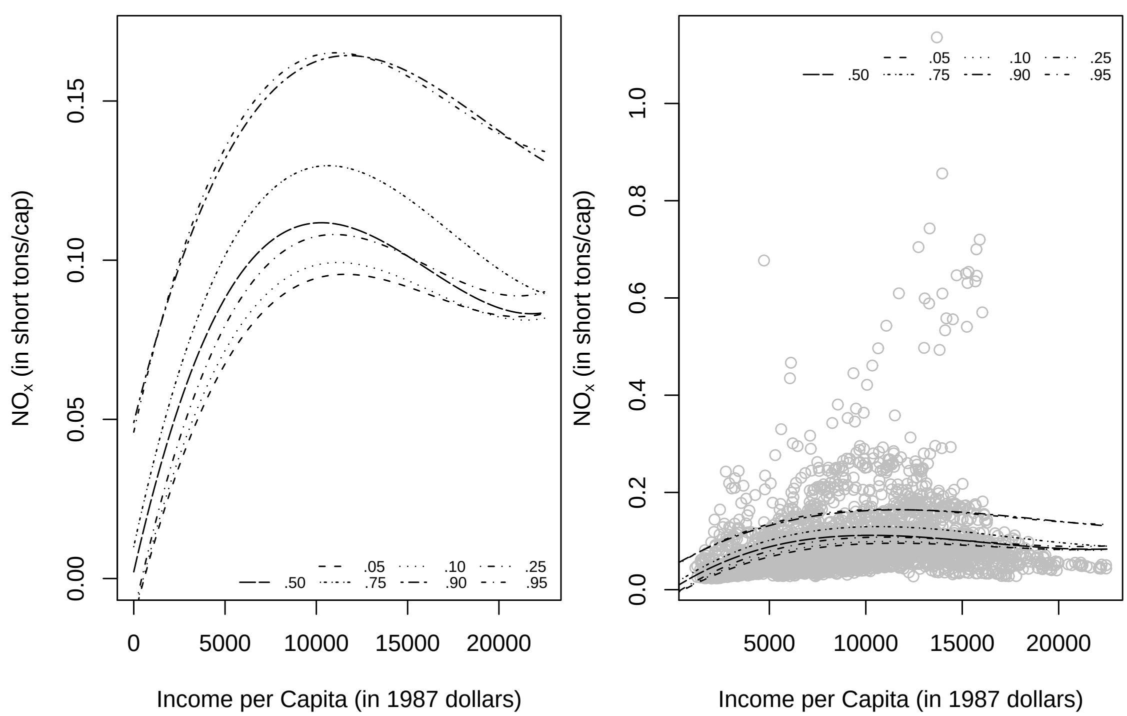

Figure 4. Estimated EKC for SO_2 employing quantile regression fixed effects, with and without scatterplot

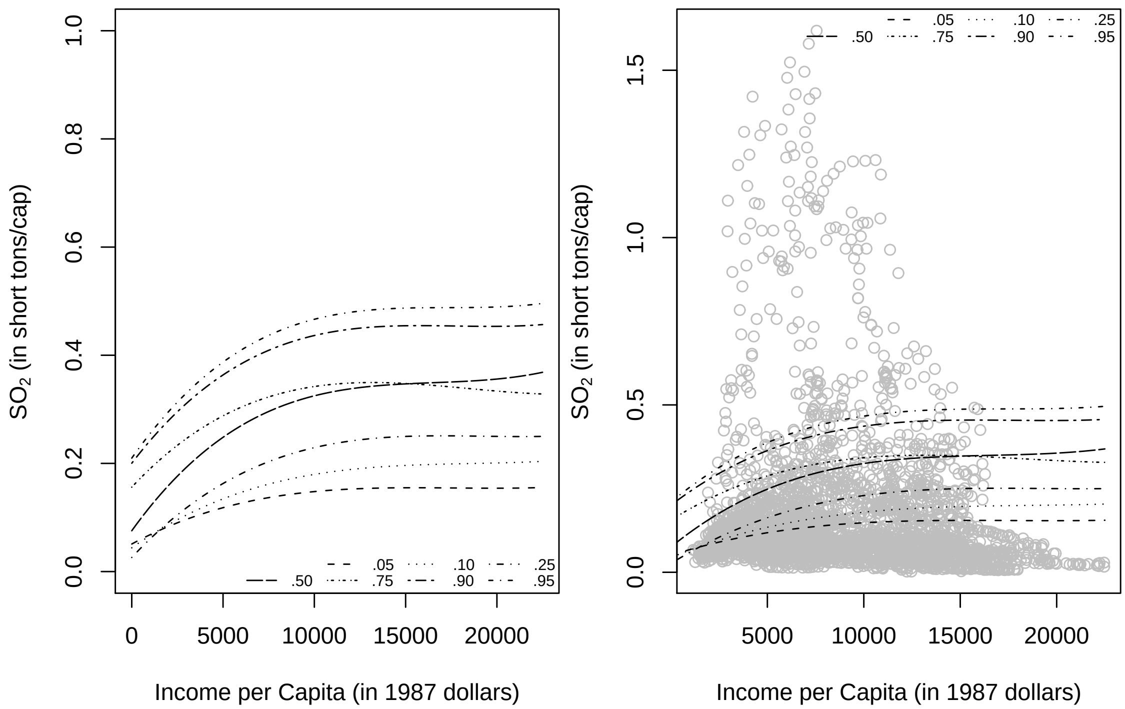

Figure 5. Estimated EKC for each pollutant for both fixed effects models with their 95% confidence intervals