E C O N O M I C S   B U L L E T I N

Economic growth and environmental quality: a meta-analysis of environmental Kuznets curve studies

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Abstract

Meta-analysis is used to investigate systematic variation across Environmental Kuznets Curve (EKC) studies. Based on 588 observations, modeling results indicate that data characteristics, study methods, estimation techniques, and the chosen environmental quality degradation measure all significantly affect the absence or presence of the EKC, and any predicted income turning points (ITPs). With respect to anthropogenic activity-related greenhouse gases, the evidence does not support the presence of an EKC.

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1. Introduction

Debates about sustainable development involve questions about the relationship between economic growth and environmental quality. Within such debates, there has been persistent interest in exploring the Environmental Kuznets Curve (EKC) hypothesis, which poses an inverted-U relationship between some measure of environmental quality degradation (e.g., emission level of some pollutant) and some measure of economic growth (e.g., per capita income). Some sources use EKC evidence to draw broad conclusions (e.g., Beckerman 1992), while others caution that such evidence is not a substitute for policy, and that empirical support is mixed (e.g., Arrow et al. 1995). After the initial work in the early 1990s (e.g., Grossman and Krueger 1993, Selden and Song 1994), the literature has exploded to explore both the theoretical foundations and empirical EKC evidence. These studies vary widely in environmental quality measures, scope and time span, and methods, which together have produced a broad spectrum of findings. Several recent studies have reviewed both theoretical developments and the empirical evidence qualitatively (e.g., Yandle et al. 2004, Dina 2004, Stern 2004).

Extending Cavlovic et al. (2000), the objective of this study is to use meta-analysis to investigate empirical EKC studies from 1992 to 2005. Using a broader set of data characteristics and approximately tripling the number of studies used in Cavlovic et al. (2000), our analysis investigates the evidence from 77 studies and a total of 588 observations. Besides the data expansion, we improve on Cavlovic et al. (2000) by implementing two new modeling approaches. First, we use a multinomial logit model and control for various modeling and study characteristics to investigate the general pattern in the relationships between environmental degradation and economic growth. Second, we estimate income turning points (ITPs) by applying a tobit model, while accounting for heteroscedasticity. Given concerns over global climate change, we focus on the estimation of ITPs for categories of greenhouse gases. The list of study references is available upon request.

2. Background on the Empirical EKC Literature

Empirical EKC studies feature various pollutants or measures of environmental degradation. Although several studies have explored using comprehensive measures (e.g. Zaim and Taskin 2000), the lack of reliability on these composite indices make most EKC studies focus on some individual measure. Across these measures, it has been argued that the EKC hypothesis can be explained by several factors, including income elasticity of environmental quality demand (Beckerman 1992, Carson et al. 1997, McConnell 1997 and Chaudhuri and Pfaff 1998 and etc), scale, technological and composition effects (e.g. Grossman and Krueger 1991), international trade and the displacement hypothesis (e.g. Copeland and Taylor 1995), globalization (e.g. Wheeler 2000), international assistance (e.g. Dasgupta et al. 2002), and foreign direct investment and diffusion of technology (Reppelin-Hill 1999). However, as EKC studies rapidly accumulate (e.g., since the summary by Cavlovic et al. 2000), there remains considerable room for understanding systematic patterns for when an EKC might be observed.

Most commonly, EKC models start from a simple reduced-form quadratic function (1). After accounting for various factors, equation (2) has become a popular form, and sometimes polynomial terms on the income variable, usually the cubic level, are also included into the reduced form (3). Considering the polynomial feature of dependent variable, a logarithmic regression function (4) is also popular (Stern 2004):

$$y_{it} = \alpha_i + \beta_1 x_{it} + \beta_{21} x_{it}^2 + \varepsilon_{it}\,, \tag{1}$$

$$y_{it} = \alpha_i + \beta_1 x_{it} + \beta_{21} x_{it}^2 + \gamma z_{it} + \varepsilon_{it}\,, \tag{2}$$

$$y_{it} = \alpha_i + \beta_1 x_{it} + \beta_2 x_{it}^2 + \beta_3 x_{it}^3 + \gamma z_{it} + \varepsilon_{it}\,, \text{ and} \tag{3}$$

$$\ln(y)_{it} = \alpha_i + \beta_1 \ln x_{it} + \beta_2 (\ln x)_{it}^2 + \beta_3 (\ln x)_{it}^3 + \gamma z_{it} + \varepsilon_{it}\,, \tag{4}$$

where y is the dependent variable representing a measure for environmental quality at time t for observation i, x is the income variable, z is a vector of other factors that influence y, α is the intercept term, the βs are the coefficients on the income terms, γ is the coefficient vector of z, and ε is the error term. In practice, y will be the gross level of pollution, or pollution per capita, or pollution density. The income variable can be the aggregate level of Gross Domestic Product (GDP) or GDP per capita, or national income (per capita). The vector z is a series of control factors, including population density, a trade measure, industrial intensity, poverty level, literacy rate, political openness, etc. The error term ε may not be white noise, i.e., it can be serially correlated across time or heteroscedastic among location-specific observations. Thus, when panel data is applied, modeling strategies and "deeper implications" can be explored (Stern 2004, p. 1423). The signs of the β coefficients determine the relationship between environmental quality degradation and income. The EKC relationship is only one of the possible outcomes, where $\beta_1>0$ and $\beta_2<0$ and $\beta_3=0$. If an EKC relationship exists, the ITP is calculated at $\tau = -\beta_1/2\beta_2$ for models (1 and 2), or $\tau = \frac{-2\beta_2 \pm \sqrt{4\beta_2^{\,2} - 12\beta_1\beta_3}}{6\beta_3}$ for model (3), and $\tau = \exp(-\beta_1/2\beta_2)$ for the logarithmic reduced form model (4) when $\beta_3=0$.

Consideration of the econometric framework includes concerns over heteroscedasticity, simultaneity, omitted variables bias and cointergration (Stern 2004). In the absence of robustness tests, various studies may lack predictive accuracy. Recent studies have implemented a range of methods such as Hausman, Chow, and Engel-Granger tests to address these concerns.

3. Meta-Regression Analysis and Data Design

Meta-analysis is a statistical approach to modeling related empirical studies, which are the observations in the data. The analyst attempts to collect all studies objectively, but chooses some response variables or summary statistics subjectively. Advantages include broad coverage and conclusions based on statistical analysis and hypothesis testing. Limitations include potential selection biases, and inherent variation across studies that may not be amenable to simple categorization. Meta-analysis is endorsed by statisticians (Hoffert 1997), and increasingly used in economics (e.g., Smith and Kaoru, 1990, Stanley 2001).

Using the base data of 25 studies through 1998 from Cavlovic et al. (2000), collecting additional observations began with an online search of the Journal of Economic Literature Database (Econlit). A request on "environmental Kuznets curve" from 1992 to 2005 traced 141 references, and netted 77 separate studies, including published papers (83%), book chapters (4%), and working manuscripts (13%), resulting in 588 observations. Definitions and descriptive statistics are presented in Table II. We report both significant and insignificant results with the selection of either based on robustness and those favored in a study (e.g., fixed versus random effects). Finally, a weighting variable is created so that each study is equally represented.

According to the signs of the β coefficients, the environment-income relationship can be categorized into 7 types including: (1) monotonic increasing (22 obs), (2) monotonic decreasing (20 obs), (3) inverted U-shape (EKC type) (333 obs), (4) U-shape (25 obs), (5) N-shaped (27 obs), (6) insignificance (INSIG) (124 obs) and (7) none (37 obs). Regarding relationship (6), insignificance means that the estimated β coefficients have consistent signs for an EKC relationship, but the results are not statistically significant. Relationship (7), NONE, refers to a situation where no relationship can be inferred. Based on examination of the final impact to the environment, these seven types of environment-income relationship can be collapsed into two groups: environmental quality worsens (WORSEN) and environmental quality improves (IMPROVE). Specifically, IMPROVE means that the environmental quality indicator eventually shows an improvement with continuing economic growth (353 obs). Improvements are demonstrated by monotonic decreasing and inverted-U scenarios. WORSEN refers to cases where economic growth will aggravate environment degradation (111 obs). WORSEN includes monotonic increasing, U-shape and N-shape cases. Meanwhile, the insignificant results remain in the INSIG category (124 obs), and those observations with no predicted relationship remain in the NONE category. We summarize these groups into a categorical variable, RELATION, which is the dependent variable used in the multinomial logit model. Descriptive statistics for the environment-income relationships are available online or upon request.

The dependent variable in the censored tobit model is the ITP, converted to 2000 purchasing power parity dollars for comparison purpose (ITP00). About 45 percent of studies which support an EKC-type relationship do not report ITP values. We use the predicted ITP values from Cavlovic et al. (2000, p.37) to represent 32 percent of the missing ITPs.

Explanatory variables can be grouped into 4 subgroups: data-related, variable controls, statistical methods and pollutant categories. The data-related subgroup includes the characteristics of dataset in the study. Variable controls represent the set of explanatory variables used in an EKC study as statistical controls, as well as the measurement of these variables. Statistical methods include the type of econometric specifications used in estimations.

Four fundamental variables are included in the data-related subgroup: (1) time span of the data covered in logarithmic terms (LNTIME), (2) data size in logarithmic terms (LNOBS), (3) whether a study uses panel data (PANEL), and (4) the geographic coverage—whether the data uses information of more than one country (GLOBE). Since these typical pieces of information are often reported in individual studies, we use them to represent data characteristics.

The variable controls subgroup includes 8 variables to capture the major distinction between different studies: (1) whether the pollutant is measured by emission (EMISSION); (2) income measurement—whether a study uses GDP as the income indicator (GDP); (3) whether the income measurement is interacted with other factors, for example, trade or industrial output (INTINC); (4) economic activity—whether a study takes into account of scale or composition of economic activities, e.g., industrial output, manufacturing output (ECNACT); (5) international trade policy—whether a study controls for the impact of trade policies or not (TRADE); (6) population density—whether the study controls for population density (POPDEN); (7) institutional factor—whether a study includes poverty, literacy rate or other social developmental indices as control factors (INSTITUT); and (8) status of country development — whether a study includes data from developed countries only (DEVLPED). The effects of these variables on the relationships are not clear *a priori*. In addition to variable controls, the statistical subgroup attempts to capture recent criticisms concerning misspecification in EKC modeling. It includes three variables: (1) a study's goodness-of-fit measurement— usually R^2, adjusted R^2 or

Maddala's R^2 values (FITNESS); (2) evidence of robustness tests—whether a study performs robustness tests for heteroscedasticity, fixed effects and/or random effects, or cointergration, etc. (TEST); and (3) whether a study controls for a time trend effect (TREND).

While alternative categorizations of environmental indicators are possible, we are interested in isolating anthropogenic activity-related greenhouse gases (e.g., CO_2). For example, the United Nations' Framework Convention on Climate Change draws special attention to anthropocentric activity-related greenhouse gases (Kopp 2006). Thus, as detailed in Table I, we group indicators of environmental degradation into (1) anthropogenic activity-related greenhouse gases (ANTHPGH), including CO_2, CH_4, N_2O, PFC, HFC and SF_6, where in our data the dominant pollutant is CO_2; (2) chemically-active greenhouse gases (CHACTGR), which can assist or hinder the formation of other greenhouse gases via chemical interactions (e.g., SO_2); (3) biologically-related indicators (BIOREL); and (4) other environmental degradation indicators (OTHER) including various heavy metal pollutants and hazardous waste.

4. Modeling Considerations

RELATION is a categorical dependent variable for environment-income relationships (Table I): the base group (WORSEN and NONE); category 2 (IMPROVE); and category 3 (INSIG). A weighted multinomial logit model (MNL) model of the probability of RELATION is given by:

$$P(Y_i = j \mid C) = \frac{\exp(\beta_j ' x_i)}{\sum_{k \in C} \exp(\beta_k ' x_i)}, \tag{5}$$

where $P(Y_i = j \mid C)$ is the probability that the relationship category (Y) falls in alternative j within the choice set C, and C={IMPROVE, WORSEN+NONE, INSIG} for study i. β_j and β_k are vectors of coefficients, and x is a vector of attributes and study-specific modeling choices. To find the effect of each attribute, x_m, of choice k on the probability, P_j, we calculate the elasticities of the probabilities (Greene, 2003, p. 723).

A censored tobit model is used to estimate ITPs. Because an ITP is the calculated income threshold for a potential EKC relationship, to get an accurate view of ITP projections, we exclude monotonic increasing and U-shaped relationships as well as those observations falling into the NONE category. Of note, among those excluded, 28.6% are CO_2 studies, one of the major anthropocentric activity-related greenhouse gases. This gives us 504 observations in total (a detailed summary of environmental quality degradation categories across environment-income relationships is available online or upon request). Let $\ln ITP = y_i^*$, be the latent variable, and an observed dependent variable y transformed from $\ln ITP$ is defined as:

$$\begin{aligned} &y_i^* = x_i^{'}\beta + \varepsilon_i \\ &y = \ln T \quad if \;\; y^* \le \ln T, \\ &y = y^* \;\; if \;\; y^* > \ln T \end{aligned} \tag{6}$$

where $\boldsymbol{x}$ is a vector of explanatory variables for observation i, β is a parameter vector, ε_i is the random error which follows a normal distribution with $N(0, \sigma^2)$, and T is the left-censored value at ln(3950) =8.276, which is the logarithm of average GDP per capita in 2000 for upper-middle economies. A sensitivity analysis of the censored value is also performed at low-income ($399), middle-income ($1,793) economies and global average GDP per capita ($5,213); the estimation results are qualitatively consistent. The log-likelihood function is:

$$LnL = \sum_{y_i > T} -\frac{1}{2}\left[\log(2\pi) + \ln\sigma^2 + \frac{(y_i - x_i^{'}\beta)^2}{\sigma^2}\right] + \sum_{y_i \le T} \ln\left[1 - \Phi(\frac{x_i^{'}\beta}{\sigma})\right] \quad , \tag{7}$$

$$E[\ln ITP = y_i \mid x_i] = \Phi(\frac{x_i^{'}\beta}{\sigma})x_i^{'}\beta + \sigma\phi(\frac{x_i^{'}\beta}{\sigma}) \quad . \tag{8}$$

The *E[ITP]* is the exponential term of (8), and its standard error is calculated using the delta method (Greene, 2003, p. 173). To achieve consistent maximum likelihood estimators, given potential heteroscedasticity (Greene 2003, p. 723). We specify a general variance function as:

$$\sigma_i^2 = \exp(\alpha'\varpi_i), \tag{9}$$

where ω is the vector of potential explanatory variables, and α is the vector of parameters to be estimated. The log-likelihood function is similar to equation (7), except for replacing σ with $\boldsymbol{\sigma_i}$.

5. Results and Discussion

Estimation results of the MNL for explaining the pattern of environment-income relationships are shown in Table II. MNL coefficient estimates are difficult to interpret absent direct economic meaning. To clarify the effects of explanatory variables, the elasticities of probability are calculated and presented in the last two columns of Table II. For continuous variables, elasticities are calculated by a small increase to original mean values. For example, LNOBS is compared to the number of the observations increased by 100 (the logarithmic term of the number of observations plus 100). For the dummy variables, elasticities are calculated from 0-1.

We begin by examining the effects of data-related variables. Using more observations (LNOBS), longer time periods (LNTIME), panel data (PANEL), and data covering multiple countries (GLOBE) all significantly increase the probability of finding the IMPROVE category for the environment-income relationship (group 1). For instance, when the number of observations expands by 100, the probability of finding an IMPROVE relationship increases by 0.022, *ceteris paribus*. A similar pattern is detected for INSIG (group 2). When comparing the effect of these variables across the two groups, more observations and longer time periods have a greater effect on the IMPROVE group than the INSIG group.

The variable controls that significantly affect the probability of finding an IMPROVE relationship are EMISSION, ECNACT, TRADE and INSTITUT. Using an emission measurement, either emission level or emissions per capita, increases the probability by 0.207. For studies that control for economic activities, the probability of finding an improving environment-income relationship goes up by 0.16. On the other hand, controlling for the impact of trade policy and institutional factors (poverty level, literacy rate, etc.) lowers the probability of finding an IMPROVE relationship by 0.046 and 0.041, respectively. For the INSIG relationship group, TRADE, INSTITUT and INTINC all have a significant effect on the probability, while the EMISSION and INTINC have no significant effect. For both of the groups, the probabilities are not affected when taking into account population density (POPDEN), or evaluating only developed countries (DEVLPED). Interacting income with economic indicators (INTINC) does not affect the probability of an IMPROVE relationship, while it lowers the probability of an INSIG environment-income relationship by 0.09. For modeling procedures, if a study controls for a time trend effect, then it is more likely to find an IMPROVE relationship.

Estimation results on the dummy variables for the categories of environmental quality degradation are largely consistent for the improved (IMPROVE) and insignificant (INSIG) relationship groups. Relative to the base category (WORSEN+OTHER), the category of anthropocentric activity-related greenhouse gas pollutants (mainly CO_2) shows a significant decrease in the probabilities of finding both relationships (-0.16 for IMPROVE and -0.114 for INSIG). On the other hand, biologically-related degradation measures show an increase in the probability of finding both relationships (0.049 for IMPROVE and 0.278 for INSIG). Using chemically active greenhouse gases as the environment quality degradation measure does not appear to affect the probability of either relationship.

Tobit results are presented in Table III, including homoscedastic and heteroscedastic errors for T=8.27. A log-likelihood ratio test with a χ^2-of statistic 19 for T=8.27 is significant ($\chi^2_{df=5}$= 16 at the 0.01 significance level), and thus we reject the null of homoscedastic errors. We model heteroscedasticity directly by setting up a general variance function (9). Factors include dummy variables that indicate the environmental degradation categories (ANTHPGH, CHACTGH and BIOREL), and one continuous variable (LNTIME). Tobit results indicate that LNTIME, EMISSION, and higher R^2 (FITNESS) have a positive effect on the magnitude of the ITP. Results of the variance function indicate that longer time periods, chemically active greenhouse gases and biodiversity-related pollutants decrease variance.

Predicted ITP estimates from the heteroscedastic tobit model are presented in the last column of Table III. 96 percent of anthropocentrically-related greenhouse gases are CO_2 studies and 66% of the CO_2 studies claimed to find the evidence of an EKC, but only 27% of the CO_2 studies estimated an ITP. There is an absence of substantive information on the ITP of CO_2, and there is no monotonically decreasing environment-income relationship observed. MNL results indicate that the category of anthropocentric activity-related greenhouse gases is less likely to find an improved environment-income relationship. Thus, it is not surprising that the predicted ITP for general anthropocentric greenhouse gases is not statistically significant. Another group of greenhouse gases is the set of chemically active gases, where in our study this category includes SO_2 (47%), NO_x (34%), CO (9%), NO_2 (5%) and SO_x (5%). Numerous EKC studies have explored such pollutants. In this category, 71 percent of the observations support the existence of an EKC and 62 percent have reported ITP values. The estimated ITP is $37,217, which is relatively close to the sample mean ($34,645). The predicted ITP value for the broad grouping of biologically related pollutants is $8,995. There are 163 observations in the OTHER group, but 47 percent have missing ITP values. The predicted ITP for OTHER is $5,597.

Finally, greenhouse gases like CO_2 are transboundary pollutants, and their damages (i.e., global climate change) may accumulate and manifest in the future, which taken together may intensify global coordination costs., Using MNL and tobit modeling results, from what is by far the largest EKC meta-analysis to date, the evidence from studies from 1992-2005 does not support an EKC for anthropogenic activity-related greenhouse gases. For chemically-active greenhouse gases, the predicted ITP of $37,217 is seven times larger than the 2000 world average of GDP per capita. Thus there is no basis for predicting an EKC over any policy-relevant income range for the greenhouse gases.

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Table I. Descriptive Statistics for Model Variables

	Variable	Descriptions	Obs.	Mean (std. dev.)
Dependent Variables	RELATION	Indicator variable of the environment-income relationship. If an inverted U-shape or a monotonically declining trend is found then =1; if an insignificant inverted-U shape exists then =2; else =3.	588	1.588 (0.788)
	ITP00	Real income turning point where the missing values are replaced with projections from Cavlovic (2000) (in 2000 purchase power parity dollars).	446	467946 (565954)
Data-Related	LNOBS	Logarithm of number of the observations.	588	5.441 (1.539)
	LNTIME	Logarithm of data coverage period.	588	2.351 (1.396)
	PANEL	Indicator variable of data in a study; if panel data is used, then PANEL=1, else 0.	588	0.73 (0.445)
	GLOBE	Indicator variable of using multi-country pollution data; if yes, GLOBE=1; else 0.	588	0.835 (0.371)
Variable Controls	EMISSION	Indicator variable of using emission as the pollution measurement, true=1, else=0.	588	0.532 (0.499)
	GDP	Indicator variable of using GDP as the income measurement in a study, true=1, else=0.	588	0.735 (0.442)
	INTINC	Indicator variable of including income interaction term(s) as exogenous variable in a study; if included INTINC=1, else 0.	588	0.075 (0.263)
	ECNACT	Indicator variable of including economic activities as exogenous variable(s) in a study; included ECNACT=1; else 0.	588	0.223 (0.416)
	TRADE	Indicator variable of including trade factor as exogenous variable in a study; included TRADE =1; else 0.	588	0.078 (0.269)
	POPDEN	Indicator variable of including population density as exogenous variable in a study; if included POPDEN=1, else 0.	588	0.24 (0.427)
	INSTITUT	Indicator variable of including institutional factor as exogenous variable in a study; if included INSTITUT=1, else 0.	588	0.213 (0.409)
	DEVLPED	Indicator variable of whether data comes from developed country or not. If yes, DEVLPED=1; else 0.	588	0.224 (0.149)
Statistical Methods	FITNESS	Fitness of the regression in a study (percentage).	588	0.399 (0.348)
	TEST	Indicator variable of applying robustness test for regression results; if applied, TEST=1, else 0.	588	0.447 (0.498)
	TREND	Indicator variable of including time trend as exogenous variable in a study; if included INST=1, else 0.	588	0.299 (0.458)
Environmental Quality Degradation Categories	ANTHPGR	Indicator variable of anthropogenic activity-related greenhouse gases; if yes, ANTHPGR =1, else 0.	588	0.284 (0.451)
	CHACTGR	Indicator variable of chemically-active greenhouse gases; if yes, CHACTGR =1, else 0.	588	0.228 (0.42)
	BIOREL	Indicator variable of biologically-related pollutants; if yes BIOREL=1, else 0.	588	0.163 (0.37)

Table II. Estimates of Multinomial Logit Model (Compared to Worsen + Other group)

Variables	IMPROVE	INSIG	Marginal Effects		
			IMPROVE	INSIG	Worsen +Other
Intercept	-0.29 (0.573)	-1.091 (0.808)	—	—	—
LNOBS[1]	**0.261***** **(0.085)**	**0.202*** **(0.12)**	**0.022**	**0.013**	**-0.035**
LNTIME[1]	**0.481***** **(0.147)**	**0.444**** **(0.187)**	**0.014**	**0.011**	**-0.025**
PANEL[1]	**-0.978**** **(0.428)**	**-2.2***** **(0.561)**	**0.019**	**-0.240**	**0.221**
GLOBE[1]	**-0.522*** **(0.326)**	0.578 (0.473)	**-0.154**	0.048	0.106
EMISSION[2]	**1.054***** **(0.363)**	**0.462** **(0.483)**	**0.207**	**0.068**	**-0.275**
GDP[2]	0.002 (0.137)	-0.026 (0.188)	0.004	-0.005	0.001
INTINC[2]	-0.255 (0.362)	**-1.182**** **(0.59)**	0.038	**-0.090**	**0.052**
ECNACT[2]	**0.94***** **(0.348)**	0.469 (0.438)	**0.160**	0.067	-0.227
TRADE[2]	**-0.736**** **(0.384)**	**-1.606**** **(0.637)**	**-0.046**	**-0.115**	**-0.161**
POPDEN[2]	-0.24 (0.263)	0.347 (0.341)	-0.087	0.040	0.047
INSTITUT[2]	**-0.742***** **(0.268)**	**-1.266***** **(0.373)**	**-0.041**	**-0.105**	**0.146**
DEVLPED[2]	-0.359 (0.332)	-0.226 (0.45)	-0.062	-0.024	0.086
TREND[3]	**-0.744**** **(0.306)**	0.158 (0.403)	**-0.189**	0.017	0.172
ANTHPGR[4]	**-1.142***** **(0.437)**	**-1.529***** **(0.603)**	**-0.160**	**-0.114**	**0.274**
CHACTGR[4]	-0.048 (0.35)	-0.554 (0.506)	0.033	-0.056	0.023
BIOREL[4]	**1.042***** **(0.393)**	**1.601***** **(0.462)**	**0.049**	**0.278**	**-0.327**
Number of Observations	588		588	588	588
Log-Likelihood ($\chi^2_{d.f.=596}$)	**825.89*****				

Notes:

1. Standard errors are included in parentheses.
2. Coefficients in **boldface** indicate significance level of at least at 10%.
3. *, **, and *** indicate that the estimated coefficients are significant at 10%, 5%, and 1% levels, respectively.
4. Marginal effects are calculated as discrete changes in predicted probabilities. Changes in LNOBS are measured by increasing every 100 observations; while that of LNTIME are measured by increasing one more year of data. All the dummy variables are measured by changing from 0 to 1.
5. Superscripts [1], [2], [3], [4] refer to data-related, variable controls, statistical and pollutant (environmental quality degradation) category factors, respectively.

Table III. Estimates of Weighted Tobit Models

Variables	Homoscedastic β(T=8.27)	Heteroscedastic β(T=8.27)	Heteroscedastic α(T=8.27)	Predicted ITP
INTERCEPT	2.224* (1.271)	3.65*** (1.19)	4.27*** (0.209)	
LNOBS[1]	0.32** (0.164)	0.115 (0.145)		
LNTIME[1]	0.486* (0.254)	0.016** (0.007)	-0.312*** (0.067)	
PANEL[1]	-2.245*** (0.761)	-0.582 (0.609)		
GLOBE[1]	0.269 (0.639)	-0.28 (0.475)		
EMISSION[2]	0.104 (0.631)	0.678 (0.504)		
GDPDEP[2]	2.837*** (0.546)	1.309*** (0.49)		
INTINC[2]	-0.77 (0.788)	-0.288 (0.735)		
ECNACT[2]	-1.659*** (0.617)	-0.44 (0.516)		
TRADE[2]	-0.427 (0.746)	-0.345 (0.656)		
PODEN[2]	0.975** (0.471)	0.609 (0.416)		
INSTITUT[2]	0.22 (0.536)	0.378 (0.454)		
DELVPED[2]	1.446** (0.641)	0.74 (0.561)		
FITNESS[3]	0.824 (0.652)	0.978* (0.581)		
TEST[3]	0.572 (0.466)	0.445 (0.358)		
TREND[3]	0.496 (0.551)	0.596 (0.464)		
ANTHPGH[4]	2.051*** (0.773)	1.926*** (0.786)	0.035 (0.218)	Statistically not significant
CHACTGH[4]	3.263*** (0.666)	3.329*** (0.563)	-2.209*** (0.217)	\$37,217** (16,299)
BIOREL[4]	1.247** (0.646)	1.3** (0.683)	-0.502** (0.229)	\$8,995* (4,751)
OTHER	—	—	—	\$5,597*** (2,404)
σ	4.464*** (0.169)	—		
McFadden's LRI	0.71	0.75		
(-2 LogL)	2569	2550.2		

Notes: 1. β is the vector of coefficients for explanatory variables, and α is the vector of coefficients of heteroscedasticity. 2. Standard errors are included in parentheses. 3. *, **, and *** indicate that estimated coefficients are significant at 10%, 5%, and 1%, respectively. 4. Superscripts [1], [2], [3], [4] refer to data-related, variable controls, statistical method and pollutant factors, respectively. 5. McFadden's LRI = $1 - LogL^{Unrestrict} / LogL^{Restrict}$.